The Private Production of Safe Assets*

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Abstract

How fragile is the production of safe assets by the private sector? We answer this question using high-frequency data on certificates of deposit (CDs) issued in Europe. We show that only short-term CDs benefit from a safety premium. Using two identification strategies, we further show that the issuance of short-term CDs strongly responds to measures of safety demand. During periods of stress, this relation vanishes. However, high-quality issuers are still able to issue safe assets in periods of stress as investors distinguish between high- and low-quality issuers. Therefore, concerns about externalities arising from private safety production may be partially overstated.

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1 Introduction

A *safe asset* is an asset that is immune to adverse selection concerns and can thus be valued without expensive and prolonged analysis (Gorton, 2017). Such an asset, for example a Treasury, has money-like attributes and can serve as a store of value (Nagel, 2016). Traditionally, government debt has been the dominant form of safe asset (Krishnamurthy and Vissing-Jorgensen, 2012). However, recent decades have been characterized by an apparent shortage: Due to booming savings in emerging economies, the demand for public safe assets increased faster than its supply, pushing real interest rates to historically low levels and stimulating global imbalances (Caballero, 2006; Caballero, Farhi, and Gourinchas, 2016; Caballero and Farhi, 2018). To cater to investors' safety demand, private financial institutions started to issue assets with safety attributes similar to those of Treasuries (Bernanke et al., 2011; Gennaioli et al., 2013; Sunderam, 2015).

Several questions about the private production of safe assets remain open. First, while the private production of safe assets has been documented in aggregate (Sunderam, 2015), micro-level evidence is limited. For example, it remains unclear whether all financial institutions, or only a subset of them, cater to safety demand. Relatedly, among the set of securities they issue, we do not know which ones are truly considered safe. Second, and most importantly, the ability of the private sector to issue safe assets has been described as fragile and thus inefficient (Stein, 2012). However, no prior study investigates the ability of the private sector to issue safe assets in both stable and stress periods. Furthermore, we also do not know whether all issuers stop catering to safety demand during stress periods or whether time-series stylized facts arise from selection mechanisms. Answering these questions is important as it helps to distinguish between theories of safe assets.

In this paper, we shed some light on these questions using high-frequency data on 1.36 million Euro-denominated certificates of deposit (CDs) issued by commercial banks. Our data set covers most of the European short-term private debt and Treasury bill (T-bill) markets between 2008 and 2014. All these assets are reasonable safe-asset candidates: They have short maturities, up to one year, and are issued in liquid markets by borrowers with high credit quality.

Our first contribution is to show which securities issued by private institutions are considered safe by investors. We show that only short-term CDs, with maturities below or equal to one week, carry a *safety premium*: Their interest rates are below the risk-free rate, by 8 basis points per year (as compared to 15 basis points for one-month T-bills). The premium captures the non-pecuniary benefits associated with holding a safe asset (Krishnamurthy and Vissing-Jorgensen, 2012; Sunderam, 2015). It is economically large, since the average risk-free rate over our sample period equals 40 basis points. The fact that only short-term CDs are considered safe – while longer-term CDs carry a risk premium – is consistent with the view that assets with shorter maturities are less sensitive to the arrival of new information. We additionally show that the term structure of the CD safety premium exhibits a sharp discontinuity precisely at the one-week maturity, consistent with the view that investors clearly distinguish between safe and non-safe assets.

Our second contribution is to show that private issuers causally respond to measures of safety demand. The main challenge we face is to isolate the role of demand and supply forces. We improve over existing strategies in two respects. First, in contrast with previous work based on aggregate data, we are able to include issuer-fixed effects. Given that supply and demand curves can only be identified using time-series data, issuer-fixed effects alleviate the concern that estimates are contaminated by changes in the pool of issuers over time. Second, we suggest a novel instrumental variable (IV) that directly measures safety demand that is unmet by public supply. Specifically, we instrument the safety premium on private safe assets using the bid-to-cover ratio in T-bill auctions, that is, the ratio between total T-bill demand and T-bills eventually allotted. Our IV relies on the idea that the bid-to-cover ratio is a good measure for the excess demand for T-bills, and that excess T-bill demand directly affects the demand, but not the supply, of CDs. This instrument is supported by several features of T-bill auctions.

Using both identification strategies, we find that when the aggregate supply of T-bills goes down, the quantity of new short-term CDs goes up. Given that short-term CDs are precisely the ones that benefit from significant safety premia, this result is consistent with the view that the shortage of publicly issued safe assets creates a demand for privately issued assets with similar safety attributes. Notably, this substitution effect does not hold for longer-term CDs, which do not benefit from any safety premium. We further show that the negative relationship between quantities of publicly and privately produced safe assets also holds with issuer-fixed effects. We additionally exploit the exact timing of T-bill auctions to get further reassurance. Specifically, the quantity of T-bills auctioned is announced every Friday, and the auction takes place on Monday. Thus, investors learn about a potential shortage of T-bills on either of these two days. We show that these are precisely the days on which CD supply responds when safety demand is high. We find no significant differences on other days of the week.

Our third contribution is to study the fragility of private safety production. We do so by exploiting both the time-series and the cross-sectional dimensions of our data. Theoretically, if investors seek information-insensitive assets, then spikes in uncertainty or negative public news can imply that some assets become information-sensitive. If this is the case, adverse selection reappears and these assets are no longer appealing to safety-seeking investors. Some issuers should thus stop catering to safety demand because the assets they issue are no longer demanded by a certain clientele (Dang et al., 2012; Moreira and Savov, 2017).

Consistent with this idea, we show that while T-bills enjoy a safety premium at all times, CDs lose their safety status during periods of market stress. The main drop in private safety premia occurs in 2008, at the height of the financial crisis. In terms of quantities issued, we find that the substitution effect between the issuance of public and private safe assets disappears when market stress is high. However, while the substitution between public and private assets drops to zero, the CD market volume does not collapse. Thus, the time-series variation in our results is in line with a demand-driven mechanism: CDs continue to be issued, but investors no longer perceive them as substitutes for T-bills in periods of stress.

We additionally use cross-sectional issuer characteristics to distinguish between theories of safe asset fragility. If investors have public access to issuer-level information, they may still consider as safe issuers with high asset quality (Moreira and Savov, 2017). Instead, if they consider only information about the asset class as a whole, then all issuers may stop to be perceived as safe regardless of their balance-sheet characteristics (Dang et al., 2012). By estimating our baseline regressions conditional on measures of balance-sheet strength, we find that safety production persists, even in periods of high stress, for issuers that are large, profitable, and with high asset quality. We also show significant selection in the pool of issuers in good and bad times: Issuers with poor asset quality are more likely to be excluded from the market in periods of stress or, at least, to issue lower volumes. Thus, the aggregate time-series variation is driven by changes at both the intensive and extensive margins. Furthermore, we show that, during periods of high stress, issuers adjust more actively the maturity of new issues to cater to safety demand: While the share of short-term CDs is unrelated to safety demand in periods of low stress, it increases strongly with safety demand in periods of stress. All these findings suggest that adverse selection concerns are limited during periods of stress.

Finally, we assess the extent to which the private production of safe assets may cause negative externalities by imposing inefficient fire sales (Stein, 2012). We find that banks that cease being perceived as safe in stress periods indeed deleverage. That said, we also find that they substitute a significant part of their lost CD funding with both repo funding and, most importantly, central bank funding. Thus, it is reasonable to hypothesize that, absent central bank funding facilities, the deleveraging associated with private safety production would have been larger and more disruptive.

Our findings speak to two important policy questions. First, an active debate revolves around opacity in financial markets. For example, Gorton (2017) and Dang et al. (2017) argue that more opacity is desirable when manufacturing safe assets, because it makes information production more difficult, and thus reduces the potential for adverse selection. While this argument is valid ex ante, it also implies that, once some asset classes come under scrutiny by investors, all securities within a given asset class are likely to transition from safe to unsafe. This can lead to market-wide collapses, such as the meltdown of the securitization market in 2007-2008. Instead, we show that when basic issuer-level information (balance-sheet ratios or credit ratings) is available, investors use this information and markets are unlikely to collapse in aggregate. This difference in opacity is the key feature that, in our view, explains the difference between our results and standard narratives on the aggregate collapse of securitization. Second, there is a question whether the externality highlighted by Stein (2012) is likely to be large. While it is arguably very costly when all issuers (even high-quality ones) have to liquidate assets, it is presumably less costly if investors stop treating as safe only issuers with poor balance-sheet quality.

Our paper belongs to the fast-growing literature on safe assets, recently surveyed by Gorton (2017). Theoretically, the demand for safe assets arises from information asymmetries about the quality of the traded assets (Gorton and Pennacchi, 1990; Dang, Gorton, and Holmström, 2012). Relatedly, Holmstrom and Tirole (1998) model the link between the shortage of government bonds, the liquidity premium, and the production of private substitutes. Krishnamurthy and Vissing-Jorgensen (2015) model the response of financial intermediaries to a shortage of government safe assets and increased safety premium. Moreira and Savov (2017) model the market for safe assets within the shadow banking system and highlight the fact that shadow banks tend to collapse when uncertainty rises. Stein (2012) argues that privately issued safe assets may impose negative externalities on financial stability, which justifies the use of public asset supply as a policy tool.

Empirically, most of the literature examines safety in government assets (Krishnamurthy and Vissing-Jorgensen, 2012; Greenwood, Hanson, and Stein, 2015, 2016). A smaller literature analyzes privately issued assets. Gorton, Lewellen, and Metrick (2012) show that government debt and privately produced safe assets in the U.S. are strongly negatively correlated. Sunderam (2015) studies the determinants of aggregate net issuance of U.S. ABCP contracts prior to the 2008 crisis. Lei (2012) and Carlson et al. (2014) examine the issuance of private debt in response to changes in expected safety premium on T-bills. In contrast to these studies, we primarily focus on the fragility of private safety production. Furthermore, we do not use aggregate but micro-level data, which allows for cleaner identification. Finally, while our paper relies on similar data as Pérignon, Thesmar, and Vuillemey (2018), we are after a different question. They examine the cross-sectional determinants of bank-specific "dry-ups", that is, individual banks losing access to the CD market. In contrast, we study whether CDs are perceived as safe by investors, and how the ability of issuers to cater to safety demand varies over time and across issuers.

2 Hypotheses

In this section, we formulate testable hypotheses based on existing theoretical literature.

2.1 Ability to produce safe assets

A key premise of theories of safe assets is the existence of non-pecuniary benefits associated with the holding of certain financial securities. These benefits arise from the information insensitivity of assets (Gorton and Pennacchi, 1990; Gorton, 2017): Safety is valuable for uninformed investors who fear being adversely selected in markets for risky assets, that is, fear that informed investors will buy high-quality assets and that they will be left with lemons. The information insensitivity of assets implies that they have money-like features (e.g., they can easily be pledged as collateral) and are good stores of value (Nagel, 2016). In safe-asset pricing, the existence of non-pecuniary benefits implies a *safety premium*, further defined below. While publicly issued assets can be safe because they are backed by the taxing power of governments, privately issued assets can exhibit a safety premium if they are backed by collateral. However, our first hypothesis is that safety premia can also be expected on short-term uncollateralized securities.

Hypothesis 1. *Private assets can benefit from a safety premium if their maturity is short enough.*

Theoretically, a short maturity implies that a security is *de facto* senior relative to all other debt claims issued by an agent. In this sense, there are similarities between the tranching process in securitization and the issuance of short-term debt. In both cases, the allocation of early cash flows implies that securities can be made safe. All else equal, shorter-term securities should thus be safer.

The existence of a demand for safety that can be met either with public or private assets is the theoretical foundation for our second hypothesis.

Hypothesis 2. *Higher demand for safety is associated with higher issuance of private safe assets.*

While Hypothesis 2 is arguably the main prediction of theories of private safety production (Holmstrom and Tirole, 1998; Krishnamurthy and Vissing-Jorgensen, 2015), any test of this prediction raises significant identification issues. The main challenge is that the demand curve for safe assets is not observed, so that it is hard to disentangle demand and supply factors. To address this problem, existing papers have estimated the relationship between the issuance of public and private assets (Sunderam, 2015; Lei, 2012). The idea is that an exogenous decrease in the supply of T-bills leaves part of the safe asset demand unmet, which should increase the T-bill safety premium. If private assets are perceived by investors as providing safety, then the safety premium on private assets should also increase. Ultimately, this should induce private entities to issue more safe assets. While we partly rely on this strategy, we also use an alternative instrumental-variables approach that explicitly measures unmet safety demand.

2.2 Fragility of private safety production

Theory predicts potentially significant time-series variation in the ability of the private sector to issue safe assets (Gorton and Ordonez, 2014; Dang et al., 2012; Moreira and Savov, 2017). In Moreira and Savov (2017), investors seek information-insensitive assets to store value, and banks supply these assets by tranching cash flows from risky securities. Shadow banking in this model gives rise to fragile liquidity transformation: Securities are safe most of the time, but can suddenly become illiquid if uncertainty increases. Indeed, higher uncertainty means that securities become information-sensitive, so that adverse selection reappears, and these securities are no longer appealing to uninformed investors. This reasoning gives rise to our third hypothesis.

Hypothesis 3. *Aggregate substitution between issuance of public and private safe assets breaks down when market stress is high.*

While the collapse of securitization in 2007-2008 can be interpreted as supporting Hypothesis 3, the precise mechanism driving aggregate variation remains unclear. For example, the pool of issuers may have changed between calm and stress periods, for reasons unrelated to safety demand.

Finally, theory is ambiguous about whether the collapse of private asset issuance in periods of stress concerns all issuers, or a subset of them. In Moreira and Savov (2017), what determines the exposure of an issuer to a "crash" is the quality of the assets used as collateral to back the debt security. This suggests that, if investors have access to some public information about issuer quality (for example credit ratings), then issuers with high-quality assets may still be able to cater to safety demand in periods of stress. In contrast, alternative models (Dang et al., 2012) imply that if investors do not produce issuer-specific information, then we should expect the ability of all market participants to issue safe assets to vanish.[1] These theories motivate our fourth hypothesis.

Hypothesis 4. *In periods of high market stress, issuers with high asset quality keep catering to safety demand.*

Whether Hypothesis 4 holds or not is critical to assess policies discussed by Stein (2012). In his model, banks need to liquidate assets at fire-sale prices during periods of stress in order to honor safe (short-term) debt claims. Given that fire sales are associated with negative pecuniary externalities, the ex-ante issuance of private safe assets is excessive. Rejecting Hypothesis 4 indicates that all issuers will have to simultaneously engage in fire sales during financial crises, which would be a major source of concern. If instead the hypothesis is supported by the data, the concern may be less relevant—albeit not completely absent as long as fire sales are still present ex post.

[1] A related interpretation, suggested by Thakor (2015), is that bank-specific issuance patterns are more likely to be driven by insolvency risk, while market-wide issuance patterns are more likely to be driven by illiquidity risk.

3 Data

We build a data set with information on quantities and prices of public and private debt securities between January 1, 2008 and December 31, 2014. Our sample of private assets includes certificates of deposit (CDs) issued by European banks, and our sample of public assets includes European T-bills.

3.1 Certificates of deposit

We obtain daily issuance data on euro-denominated CDs from the Banque de France. CDs are unsecured short-term debt securities, with maturities ranging from one day to one year (see Pérignon, Thesmar, and Vuillemey, 2018, for a description of this market). To alleviate the impact of any country-specific effects, we focus our main analysis on the universe of CDs issued in the French market. French CDs are economically most relevant as they represent over 80% of the global market for euro-denominated CDs.[2] The sample covers 271 individual issuers. More than 90% of CDs are bought by money market funds; other buyers include pension funds and insurance companies. Our data include a number of security characteristics, such as the issuance and maturity dates, issuers' names, debt amounts, and yields. We further match issuance data with balance sheet and credit rating information from Bankscope. The data set contains 1,360,272 issues.

We provide details on the sample of CD issuers in Table 1. In Panel A, we present the geographic distribution of all issuers. French banks account for a significant fraction of the European CD market: 72.3% of issuers and 72.8% of issuances by volume. The second largest country by volume is the UK followed by the Netherlands. In Panel B, we provide information related to the issuers' balance sheets. Most issuers have high Tier-1 and total regulatory capital ratios, consistent with the view that CD issuers, on average, have strong balance sheets. Finally, Panel C shows that CDs make up an important part of banks' balance sheets, especially relative to equity and repo funding. In terms of total

[2] Further, the French market is the second largest market worldwide for CDs, behind the US but ahead of the London market. It is the largest market for CDs denominated in euros (see Banque de France, 2013).

liabilities, the share remains significant at 10%, on average.

3.2 Treasury bills

We also collect data on publicly issued assets. We restrict our attention to securities with maturities below one year, that is, T-bills, in order to match them with comparable privately issued securities. In our baseline analysis, we focus on French T-bills for the following reasons. First, the French government is the largest issuer of T-bills in the Euro area.[3] Second, most issuers in the European CD market are French. Third, CDs and French T-bills share a common investor base, primarily composed of money market funds. Fourth, the French Treasury is the only major European Treasury authority to issue one-month T-bills, which are directly comparable to CDs in terms of their maturity at origination. Finally, focusing on one country allows us to suppress any country-specific differences.

We append these data with information on 1,141 T-bill auctions between 2008 and 2014, obtained from the *Agence France Trésor*—the government authority in charge of the management of public debt in France. T-bills are auctioned every Monday for multiple maturities. For each of the 358 auction days, we record the maturity and volume of each issue and also retrieve the bid-to-cover ratio, further discussed below. Finally, for additional tests, we collect similar T-bill data for Germany, Italy, and Spain.

3.3 Summary statistics

We provide summary statistics on the issuance of public and private securities. In Panel A of Figure 1, we show the time-series variation in the outstanding amount of CDs and T-bills over our sample period. We observe that the CD market is significantly larger than the T-bill market (EUR 369 Bn versus 169 Bn, on average, between 2008 and 2014). The CD market started declining in size only towards the end of our sample period, when the

[3] As of year-end 2015, the outstanding amount of French T-bills was EUR174 Bn. In contrast, the outstanding amounts of German, Italian, and Spanish T-bills were equal to EUR19 Bn, 122 Bn, and 82 Bn, respectively. Data on these outstanding amounts are obtained from national Treasury administrations.

ECB policy rate dropped to zero. When breaking down volumes by maturity, in Panel B, we find that CDs with maturities below one month exhibit a significant variation in total volume over time. Among them, securities with maturities below or equal to one week are most prevalent. Most T-bills have maturities below or equal to 3 months.

In Table 2, we report additional details on the distribution of aggregate amounts outstanding (Panel A) and net issuance (Panel B) of T-bills and CDs. The amounts outstanding vary between EUR 249 Bn and EUR 466 Bn for CDs, and between EUR 78 Bn and EUR 210 Bn for T-bills. These statistics indicate a significant variation in aggregated quantities. Furthermore, issuance of CDs with maturities up to one week also displays a strong time-series variation at a weekly frequency: Net issuance ranges from EUR -29 Bn to EUR 27 Bn. Finally, Panel C shows the distribution of maturities for each asset type. The median maturity for T-bills equals 154 days, and 33 days for CDs. Figure 2 presents the distribution of maturities. We observe significant heterogeneity in CD maturities, with clustering at 1 day, 1 week, 1 month, and 3 months.

4 How safe are privately issued assets?

We test which private assets are considered safe by investors (Hypothesis 1). An asset that is considered safe should trade with a safety premium. While CDs are generally regarded as near safe, the empirical question remains whether they satisfy the strict safety condition, and whether there is any variation along relevant dimensions such as maturity.

4.1 Measuring safety

Following Krishnamurthy and Vissing-Jorgensen (2012) and Sunderam (2015), we define the safety premium on a security as the difference between its interest rate and a reference risk-free rate, r_f, which does not provide any non-pecuniary benefits. Safety premia on

T-bills and CDs are

$$P_{TB} = r_{TB} - r_f \quad \text{and} \quad P_{CD} = r_{CD} - r_f, \tag{1}$$

where r_{TB} and r_{CD} are respectively the interest rates on T-bills and CDs. A security is said to bear a safety premium whenever these quantities are *negative*.[4] Ample evidence shows that government-issued securities can benefit from safety premia, that is, $P_{TB} < 0$ (Greenwood, Hanson, and Stein, 2015). Prior research also suggests that private agents can produce safe assets, for example, through securitization (Sunderam, 2015). However, there is no direct evidence of a safety premium on privately issued assets.

To assess whether CDs carry a safety premium, the main empirical challenge is one of measurement. Indeed, while r_{TB} and r_{CD} in equation (1) are observed, the reference rate, r_f, must be carefully chosen. As in Sunderam (2015), we use overnight interest-rate swap rates for the following reasons. First, credit risk on interest rate swaps is extremely low, since no cash is exchanged upfront, and the notional amount of a swap contract is never exchanged. Moreover, interest rate swaps are fully collateralized an/or centrally cleared, which alleviates any remaining credit risk concerns. Second, the interest-rate swap market is very liquid. Therefore, liquidity premia are close to zero. Finally, the swap rate is not a rate at which investors can save, and swap contracts cannot be pledged as collateral. For these reasons, overnight interest rate swap rates are risk free, but they do not incorporate any safety premium.

Specifically, we use the Euro OverNight Index Average (Eonia) swap rate for the risk-free reference rate r_f. The Eonia swap rate is the European equivalent of the Overnight Indexed Swap (OIS) rate. While OIS rates are based on Libor, Eonia swap rates are based on Eonia, that is, the average rate on all overnight unsecured transactions within a sample of banks.[5] An Eonia swap is an interest rate swap in which one party agrees to receive or pay a fixed rate to another party, against paying or receiving Eonia. At a given

[4]We follow the literature when discussing the sign of safety premia: a *larger* safety premium refers to a *more negative* value of P_{TB} or P_{CD}.

[5]In contrast with Libor, Eonia is based on actual transaction prices.

maturity, the Eonia swap rate measures the market expectation of the average overnight unsecured rate.

To measure safety premia, we collect interest rate data for French T-bills and Eonia swap rates at multiple maturities (1w, 1m, 3m, 6m, 9m, and 12m) from Bloomberg. We obtain weekly data on CD interest rates at issuance from the Banque de France. We always match a security with the Eonia swap rate of the same maturity. Figure A1 shows the time-series evolution of the various Eonia rates.

4.2 Safety premia on CDs and T-bills

We begin by showing average safety premia on CDs and T-bills for various maturities in Panel A of Table 3, and their time-series variation in Figure 3.[6] The safety premium for CDs with a one-week maturity is negative for most of the sample period, and equals -8.1 basis points, on average. Hence, issuers of these assets borrow at a rate below the risk-free rate. Further, the magnitude of the safety premium on private assets is economically large: The average level of the risk-free rate over our sample period equals 40 basis points. Overall, the result indicates that very short-term private assets, even if uncollateralized, can be treated as safe by investors. This is consistent with Hypothesis 1.

For T-bills, we observe an average premium of -15 basis points for one-month T-bills. The safety premium on T-bills is negative over the entire time period, but displays significant time-series variation. The absolute value of the T-bill safety premium is highest during the Lehman crisis and in the second half of 2011 during European sovereign debt crisis. In turn, it is relatively low in the second half of 2009, and from 2013 onwards. In terms of magnitudes, this premium is smaller than the one documented by Greenwood, Hanson, and Stein (2015) for U.S. T-bills: around -40 basis points at a one-month maturity. Relatedly, Krishnamurthy and Vissing-Jorgensen (2012) find an average premium on Treasuries (across maturities) of -73 basis points over the 1926-2008 period. The difference in magnitudes with our estimates may be due to the fact that French government

[6] One-week T-bill rates are unavailable due to the lack of liquidity of the T-bill market for near-maturity securities. Data for 12-month CDs are too limited to compute the moments of interest.

securities are perceived as less safe than U.S. T-bills, or due to the difference in sample periods. Indeed, our sample period includes both the global financial crisis and the European sovereign debt crisis.

Overall, our results indicate that private assets can benefit from a safety premium, but this premium is lower than that on otherwise similar public assets.

4.3 The term structure of safety premia

Next, we show evidence on the term structure of safety premia, for both T-bills and CDs. For T-bills, Panel A of Table 3 shows that the difference in premia between the shortest and longest maturities equals 12.6 basis points. For CDs, this difference reaches an economically large 46.1 basis points. This term structure of the safety premium is consistent with theory: Shorter-term securities are *de facto* more senior, and are therefore less information sensitive.

This term structure has important implications: While T-bills benefit from a safety premium throughout the entire maturity spectrum, this is not the case for CDs. Specifically, the safety premium disappears for CDs with maturities beyond one week, that is, financial institutions borrow at a positive spread over the risk-free rate. Therefore, only short-term CDs can be considered as safe in an exact sense.

A distinct prediction of safe asset models is that safe assets should be priced discretely away from marginally non-safe assets. In other terms, there must be a discontinuity in the term structure at the point at which safety disappears. To examine this hypothesis, we investigate the average term structure for CD and T-bill safety premia and for the Eonia swap rate. In Figure 4, we see a large steepening of the CD term structure precisely between the 1 week and 1 month maturities, which is the point at which CDs stop to be perceived as safe. To formally test whether the change in slopes is statistically significant, we compute linear slopes of the term structure over three intervals: [1 week; 1 month], [1 month; 3 months], and [3 months; 6 months]. In Panel B of Table 3, we report these slopes and test for differences using t-tests. We see that the largest steepening of the CD safety premium term structure, both in magnitude and significance, occurs precisely over the [1 week; 1 month] interval.

5 Private production of safe assets

In this section, we use two different strategies to show that, in aggregate over the sample period, private institutions cater to safe asset demand.

5.1 Baseline estimation

Our first strategy to test Hypothesis 2 follows Sunderam (2015). Specifically, our baseline regression model is

$$\Delta \log(Q_{CD,i,t}) = \phi \cdot \Delta \log(Q_{TB,t}) + \rho \cdot Controls_{i,t-1} + \mu_i + \mu_t + \epsilon_{i,t}, \tag{2}$$

where $\Delta \log(Q_{CD,i,t})$ and $\Delta \log(Q_{TB,t})$ are respectively the log-difference of CDs outstanding by issuer i between t and $t-1$, and the log-difference of T-bills outstanding. Equation (2) additionally includes issuer and year-quarter fixed effects, as well as the following control variables: $\log(Q_{CD,t-1})$, $\Delta \log(Q_{CD,t-1})$, $\log(Q_{TB,t-1})$, and $\Delta \log(Q_{TB,t-1})$. Together with the first-difference specification, the inclusion of these lagged controls mitigates concerns arising from the autocorrelation of error terms. Our coefficient of interest is ϕ, which we expect to be negative if private issuers cater to safety demand.

For Equation (2) to identify the response of private issuers to safety demand, it must be that $\Delta \log(Q_{TB,t})$ is an exogenous measure of safety demand. We find this assumption reasonable for two main reasons. First, being backed by the taxing power of governments, T-bills should be one of the preferred form of safe assets for investors.[7] Second, changes in the supply of T-bills by the government are arguably unrelated to investors' demand for safety. Indeed, T-bills are mainly issued to manage stochastic government cash needs.

[7] Over our sample period, in spite of the European sovereign debt crisis in 2011-2012, France was always considered a core rather than a periphery country. Its S&P credit rating never fell below AA and its 5-year CDS spread never went above 250 basis points. Furthermore, as already shown, French T-bills benefited from a safety premium throughout the entire sample period, unlike Spain and Italy (see Figure 3).

Within our context of French data, about 5,000 public accountants draw on the government's account, making short-term cash needs unpredictable.[8] We verify this claim by regressing T-bills issued on the T-bill safety premium, and find no significant effect (see Appendix Table A4). Finally, while government cash needs may be higher in some periods when the ability of the private sector to issue CDs is lower (e.g., during a financial crisis), this concern is alleviated due to the inclusion of year-quarter fixed effects. Our estimation only exploits high-frequency (weekly) variation within a quarter. The intuition behind our identification is thus that, when government cash needs are lower in a given week for exogenous reasons, investors are seeking other forms of safe assets and private issuers cater to this demand.

We first estimate the model by aggregating all issuers and all maturities, and present the results in Panel A of Table 4. Using CDs with all maturities, we find that the ϕ coefficient is not statistically different from zero, both in univariate and multivariate models. However, the results change when we focus on short-term CDs (that is, with maturity up to one week). We find that ϕ is negative and statistically significant across specifications. Moreover, the effect is economically large: A one-standard-deviation decrease in the issuance of T-bills is associated with an increase by about 5% in the issuance of CDs, which corresponds to about 70% of the weekly standard deviation. When focusing on longer-term CDs (that is, above one week), we find that the coefficient switches its sign. Collectively, these results are consistent with Hypothesis 2. Indeed, short-term CDs are exactly the ones carrying a safety premium.

Another legitimate question is whether our results hold for a given issuer over time, or hold in aggregate due to selection of issuers over time. To address this concern, we estimate equation (2) at the issuer level and report the results in Panel B.[9] We restrict our sample to short-term CDs. The panel approach allows us to control for time-invariant differences across issuers using issuer fixed effects, and to control for time-varying issuer

[8]In 2016, the average daily cash outflow from the main State Account was EUR 17.8 Bn (see here).

[9]In unreported regressions, we verify that our estimation results hold when estimating equation (2) in log-level (rather than in first-differences) and with issuer fixed effects.

characteristics.[10] We cluster standard errors at the week level.[11] We find a negative and statistically significant effect of T-bill issuance on CD issuance. The effect is also economically significant: A one-standard-deviation decline in T-bill issuance is associated with an increase in CD issuance by 8 to 10%. The results are again consistent with the hypothesis that investors substitute into short-maturity CDs at times when public assets are less widely available.[12]

There are two potential alternative explanations for our results. First, the negative relationship between public and private asset issuance may be driven by standard crowding-out effects of public debt on private debt (Barro, 1974). Second, our results could be due to a "gap-filling" mechanism (Greenwood, Hanson, and Stein, 2010): When the government issues less debt at a given maturity, the private sector increases issuance at this maturity to cater to this neglected clientele. However, both explanations are unlikely to apply here. Indeed, the substitution effect we observe only affects short maturities, whereas the alternative two explanations should also apply to longer maturities.

5.2 Identification using the bid-to-cover ratio

To buttress our identification strategy, we use an alternative, instrumental-variables (IV) approach that relies on a more direct measure of excess demand for safety, that is, demand by investors that is not satisfied by government issuances. To understand the logic behind our IV approach, consider a linear system of CD demand and supply equations,

$$Q^d_{CD} = \alpha^d_{CD} + \gamma^d_{CD} P_{CD} + \epsilon^d_{CD} \tag{3}$$

$$Q^s_{CD} = \alpha^s_{CD} + \gamma^s_{CD} P_{CD} + \epsilon^s_{CD}. \tag{4}$$

[10] Our issuer-level control variables are total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans.

[11] We estimated the model with clustering at the issuer-, month-, quarter-level, and double clustering at issuer- and week-level. Clustering at the week level gives the most conservative standard errors.

[12] We further explore whether substitutability between public and private assets depends on the initial maturity of T-bills. We define short-term and long-term CDs as having maturity below and above 3 months, respectively. The magnitude of the effect varies markedly with T-bill maturity: It is twice as large for short-term T-bills, which suggests that issuers of private assets react more to changes in assets with similar maturity (see Table A3).

where Q^d_{CD} and Q^s_{CD} are respectively CD demand and CD supply, and P_{CD} is the CD safety premium. One instrument is sufficient to identify this system (the supply function). Our strategy is to introduce a measure of excess demand for T-bills in the CD demand equation (3). By construction, excess demand for T-bills does not directly affect CD supply.

Our proxy for the excess demand for T-bills is the weekly measured bid-to-cover ratio, which we denote as BTC. This ratio contrasts the aggregate demand for T-bills (numerator) with the T-bills eventually allotted in a given auction (denominator). Hence, it measures the degree of oversubscription by investors. Formally, it is defined as

$$BTC_t = \frac{\text{Bids for T-bills at } t}{\text{T-bills alloted at } t}. \tag{5}$$

Furthermore, BTC displays significant variation over time, as seen in Panel A of Table 5. We believe there are several reasons why BTC is a good measure of excess safety demand and does not merely capture auction-specific anomalies. First of all, even though French T-bill auctions are such that investors pay their bids, they cannot post bids for more than 1 billion euros at each quoted price. As a result, investors with high demand for T-bills must break down their demand into several bids. When doing so, they become more likely to be rationed. Indeed, the price listed in the secondary market is an upper bound on the auction price, so that additional bids are made at lower prices. This constraint is economically meaningful, since the increment between two listed prices is coarse (0.5 cents). Second, another concern could be that bids submitted at prices below the final auction price were unrealistically low, so that the corresponding bids cannot be treated as rationed. This concern is minor in our case, due to the specifics of French T-bill auctions. Indeed, participants in T-bill auctions are only 16 specialists who have strong incentives to send reasonable bids.[13] Among other incentives, each specialist receives an annual assessment by the Banque de France, based on whether their bids indeed enable them to buy T-bills. If the assessment is not successful, banks may lose their access to the auction. Taken together, these arguments suggest that BTC is a good measure of excess demand.

[13] The specialists include ten European banks, five American banks, and one Japanese bank.

To get further reassurance that BTC measures the demand for safety, we also show that BTC is primarily moved by demand, and not by supply, as the standard deviation of the numerator (demand) is more than three times as large as that of the denominator (supply), equal to EUR 4.7 and 1.4 Bn, respectively. Separately, we also regress monthly changes in average BTC and in T-bill bids on monthly flows into European money market funds.[14] In Panel B of Table 5, we report positive and significant coefficients (at the 5% level), even in specifications with year-quarter fixed effects that control for macroeconomic conditions. Therefore, changes in BTC are driven by changes in demand. Using BTC as an instrument yields the following system

$$Q^d_{CD} = \alpha^d_{CD} + \gamma^d_{CD} P_{CD} + \omega^d_{CD} \cdot BTC + \epsilon^d_{CD} \tag{6}$$

$$Q^s_{CD} = \alpha^s_{CD} + \gamma^s_{CD} P_{CD} + \epsilon^s_{CD}. \tag{7}$$

We can rewrite Q_{CD} and P_{CD} as functions of the exogenous variable BTC and of the error terms. We estimate the model using two-stage least squares, where the first-stage equation is

$$P_{CD} = \eta_1 + \pi_1 \cdot BTC + \epsilon_1, \tag{8}$$

and the second-stage equation is

$$Q_{CD} = \eta_2 + \pi_2 \cdot \hat{P}_{CD} + \epsilon_2. \tag{9}$$

In (9), $\hat{P}_{CD}$ is the predicted value of the CD safety premium from the first-stage equation.

The idea behind our instrument is that a high bid-to-cover ratio indicates high excess demand for safe assets and should therefore lead to a more negative CD safety premium. To support this relevancy condition, we expect a negative coefficient on BTC in the first stage. The identifying assumption (exclusion restriction) is that changes in the bid-to-cover ratio are not correlated with changes in supply of CDs, other than via the excess demand for safety. We consider this assumption quite natural, especially in the context

[14]Public data on fund flows are obtained from the ECB's Statistical Data Warehouse.

of high-frequency data.

In Panel C of Table 5, we show that the first-stage estimates are highly statistically significant, with the expected negative sign, and with a high F-statistic, of at least 11. In the second stage, we find a negative and statistically significant estimate of π_2, that is, changes in the CD safety premium induced by high safety demand lead banks to issue more CDs. In both models, the results hold with and without controls. Overall, the results from our IV identification strategy corroborate Hypothesis 2.

Finally, we get further reassurance that BTC is a measure of excess safety demand to which investors respond by exploiting the precise timing of T-bill auctions. In France, quantities issued in T-bill auctions are announced every Friday; auctions are held on the next Monday; and results are announced immediately at 2:50pm. Therefore, investors first learn about *potential* excess demand on Friday and about *actual* excess demand on Monday afternoon. If CD issuers cater to safety demand, then the demand for CDs should be particularly high on Fridays and Mondays whenever excess demand in the T-bill auction—as measured by the bid-to-cover ratio—is large. We test this idea by computing the average CD issuance (measured as $\log(Q_{CD,t}) - \log(Q_{CD,t-1})$) every day of the week, for both weeks with high and low BTC (defined by a ratio above or below its quarterly median). The results, displayed in Figure 5, show that the largest difference in issuance between high-BTC and low-BTC weeks is indeed realized on Mondays. The second largest difference is realized on Fridays. We separately check whether these differences are significant using two-sample t-tests, and find that the difference is statistically significant only on Mondays (p-value of 0.082) and near-significant on Fridays (p-value of 0.166). This result lends additional support to Hypothesis 2.

6 The fragility of private safety production

In this section, we study the fragility of private safety production in periods of stress. We show that, while the aggregate relation between issuances of public and private assets collapses, there is significant cross-sectional heterogeneity. In particular, high-quality issuers are able to cater to safety demand at all times.

6.1 Time-series variation in safety premia

We start by comparing CD safety premia in periods with high and low uncertainty. Our findings so far point towards the existence of safety premia among short-term CDs and for all T-bills. We now examine time-series variation in the level and term structure of safety premia. To this end, for each maturity bucket and asset type, we estimate a time-series regression model with the safety premium as a dependent variable and a set of indicator variables for each individual year as regressors. We report the estimated coefficients in Table 6. First, the previously reported term structure of the safety premium can be observed for almost all years, both for T-bills and CDs. Second, we observe significant time-series variation in the magnitude of the safety premium for each maturity and asset type.[15] For T-bills, the safety premium is generally larger around periods of stress. For CDs, the biggest retrenchment from safety can be observed in 2008, which is one of the years in which T-bills have enjoyed the largest safety premium. Therefore, safety premia on public and private assets follow diverging dynamics in periods of stress. At times, the safety premium on short-term private assets even disappears and can turn into a risk premium.

6.2 Aggregate variation in substitution effect

Next, we examine the time-series variation in the ability of private assets to serve as substitutes for public assets. We start by studying the aggregate variation in the substitution effect. Specifically, we test Hypothesis 3 by estimating equation (2) with interaction terms between $\Delta \log(Q_{TB})$ and indicators of market stress. Exploiting the variation with regard to market stress is natural given the role that safe asset theories assign to uncertainty shocks (Moreira and Savov, 2017). We classify periods of market stress using option im-

[15] To assess whether the cross-sectional patterns in safety premia may be due to differences in respective Eonia swap rates, we separately investigate the time-series variation in the rates. Figure A1 shows no significant differences across swap rates with different maturities. Hence, we conclude that the patterns in the data cannot be explained by variation in swap rates.

plied market volatility (VIX), past returns on Euro stoxx 50 index, or Euribor-Eonia swap spread. To account for different levels of stress, we divide each measure of market stress into quartiles, based on their conditional sample distribution. Our sample is well suited to study the economic consequences of market stress as it includes episodes of unconditionally high market stress—the 2008 financial crisis as well as the European sovereign debt crisis. We report the results in Table 7.

Consistent with Hypothesis 3, we find that the relationship between changes in issuance of T-bills and issuance of CDs is most negative during periods of low market stress. In turn, the relationship is close to zero in times of high market stress, regardless of the measure we use. This result suggests that privately issued safe assets are considered close substitutes to T-bills mostly at times of low aggregate market uncertainty.

Finally, we check that our time-series results are not driven by flight-to-quality episodes in which the CD market freezes. Specifically, we plot in Figure 1 the aggregate volume in the European CD market. As can be seen, lenders continue to be active in the European CD market throughout both the global financial crisis and the European sovereign debt crisis. We conclude that our time-series results are solely driven by a change in investors' views about the substitutability between T-bills and CDs. Hence, our results identify a time-series change in perceived safety of private assets. This alternative definition of a flight-to-quality is consistent with models of safe asset demand.

6.3 Cross-sectional variation in substitution effect

We next turn to tests of Hypothesis 4, that is, we want to understand whether all banks, or only a subset of them, stop catering to safety demand in periods of higher uncertainty. There are two dimensions which could drive the aggregate effect: Either (i) there are changes in the substitution effect for some or all issuers with constant CD volumes (intensive margin), or (ii) there are differential changes in CD volumes across issuer types (extensive margin). We start by studying the intensive margin. To do so, we evaluate the cross-sectional variation in the ϕ coefficients in regression (2). In Figure 6, we observe a significant variation in coefficients across individual issuers.

To enhance our understanding of the cross-sectional variation, we explore how the strength of the substitution effect changes conditional on the quality of the issuers' fundamentals. Specifically, we consider size, bank equity, level of impaired loans, ROA, and credit rating as measures of issuer quality. We estimate the following regression model:

$$\Delta \log(Q_{CD,i,t}) = \phi_1 \Delta \log(Q_{TB,t}) + \sum_{j=1}^{4} \phi_j \Delta \log(Q_{TB,t}) * q_j + \rho \cdot Controls_{i,t-1} + \mu_t + \epsilon_{i,t}, \quad (10)$$

where q_j denotes the quartile of the distribution to which a given characteristic of issuer i belongs at time t. The model is estimated separately for periods with low and high VIX (defined as periods in which the VIX is below or above its sample median). We do not include issuer fixed effects in this regression, so as to identify differential effects in the cross-section of issuers. Estimates are reported in Table 8 and yield three main findings.

First, we observe a negative value for most of the ϕ coefficients in both low and high VIX periods, which suggests that, to some degree, investors consider short-term CDs to be substitutes to public safe assets. Second, we observe a significant variation in the cross-sectional response of issuers to safety demand even in low-VIX periods (Panel A). In particular, issuers that are larger in size, better capitalized, have higher asset quality, and higher ROA respond more. For lower-quality issuers, we find no significant response of issuance to safety demand even in low-stress periods. Third, we find strikingly similar patterns in periods of high uncertainty (Panel B). Banks with the strongest balance sheets are still able to supply safe assets to meet investors' demand. Moreover, only issuers in the highest-quality quartiles display statistically significant negative coefficients. This preliminary evidence is thus inconsistent with the idea that markets for safe assets collapse as a whole, and instead suggests that investors can discriminate between issuer types.

We further evaluate these findings using our instrumental-variables approach. Results in Table 9 are broadly consistent with those using OLS estimation. However, we observe some differences. First, in periods of high uncertainty, the ϕ coefficient for the lowest-quality quartiles becomes positive though it remains statistically insignificant. Second, the ϕ coefficient for highest-quality quartiles is negative and statistically significant in both low and high-uncertainty periods for most quality measures. Overall, these results suggest that investors' demand for private safety is sensitive to changes in the underlying information.

6.4 Cross-sectional variation in volumes

Next, we turn to the extensive margin, that is, we want to understand whether CD issuance changes differentially across issuer types during periods of stress. As a first test, we classify banks every year into high- and low-quality banks based on whether their ratio of impaired loans to total assets is below or above the sample median. Among all our sample years, we then classify 2008, 2009, 2011, and 2012 as years of stress. These are the years with the highest average level of VIX, due to the global financial crisis and to the European sovereign debt crisis. By contrast, 2010, 2013, and 2014 are classified as non-stressed. We compute the probability that high- and low-quality banks issuing CDs in a given year t are still issuing CDs in year $t+1$, when we transition from non-stressed periods to stressed periods, or vice-versa. The untabulated results show that conditional on issuing at t, a high-quality bank has a probability of issuing at $t+1$ equal to 0.867 when transitioning from non-stressed to stressed periods, while low-quality banks have a visibly lower probability of 0.775. Thus, periods of high uncertainty are associated with lower issuance volumes by low-quality banks. Instead, when computing the same probabilities when transitioning from stressed to non-stressed periods, we find no difference in issuance probabilities at $t+1$ between high- and low-quality banks (0.707 versus 0.717 respectively). This gives further reassurance that investors are distinguishing issuers based on their quality particularly during periods of stress.

While the preceding test focuses on a dummy variable based on whether banks issue any CD during the year, we use a similar variable based on a continuous measure of issuance. Based on the same definitions of high- and low-quality banks as before, we compute every week the share of outstanding short-term CDs that come from high-quality banks. We then regress this weekly share on the weekly averaged VIX. We find a positive coefficient, significant at the 1% level, together with an adjusted R^2 of 11%. Thus, the finding that the share of high-quality banks increases in periods of stress is confirmed when using a continuous measure of volumes.

Lastly, the selection of issuers conditional on stress periods should imply that issuers with good fundamentals are more likely to issue CDs in high-uncertainty states. To provide additional evidence, we plot the kernel densities of fundamentals of issuers in high and low-uncertainty states in Figure 7. Specifically, we present the densities for size, book equity to assets, impaired loans to assets, and ROA. We find that the distribution of fundamentals in stress periods shifts in the direction of better fundamentals relative to that in low-uncertainty states, particularly for size and the fraction of impaired loans. In turn, the results are less pronounced for book equity and net income. These results are consistent with significant selection of issuers with respect to fundamentals in times of high uncertainty. Notably, the observed shifts are inconsistent with the mechanical explanation according to which fundamentals of all issuers deteriorate.

6.5 Safety production via maturity adjustments

As a next step, we study an alternative channel through which issuers may cater to safety demand: the maturity of CD issuances. Specifically, in periods of high safety demand, issuers may shorten the maturity of new issues to benefit from a safety premium. Furthermore, we expect this effect to be stronger in periods of high uncertainty. Indeed, when uncertainty is moderate, the distinction between safe and marginally non-safe assets may be less clear, so that longer-term CD may be considered as partial substitutes for short-term CDs. Instead, when uncertainty is high, only short-term CDs should be considered safe, and the distinction with marginally non-safe assets should be starker. To evaluate this hypothesis, we estimate the following regression model, separately for the two subsamples based on whether the VIX is below or above its sample median:

$$Issuance^{CD}_{i,t} = \alpha_0 + \phi \cdot \Delta \log(Q_{TB,t}) + \rho \cdot Controls_{i,t-1} + \mu_i + \mu_t + \epsilon_{i,t}, \qquad (11)$$

where $Issuance^{CD}_{i,t}$ is the share of CDs issued with maturity below one week. Control variables include: $\log(Q_{CD,t-1})$, $\Delta\log(Q_{CD,t-1})$, $\log(Q_{TB,t-1})$, $\Delta\log(Q_{TB,t-1})$, total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans. We cluster standard errors by date. Our coefficient of interest is ϕ.

We present the results from the estimation in Table 11. In column 1, we display the estimates from the univariate regression, while in columns 2-5, we sequentially add controls, issuer fixed effects, and year-quarter fixed effects. The top panel shows the results for periods with low VIX, while the bottom panel presents the results for periods with high VIX. Estimated coefficients for ϕ are negative in both VIX regimes and for all specifications. However, the effect is twice as large and statistically significant only during high-VIX periods, which is when the market puts more scrutiny on issuers. The idea that maturities shorten in periods of stress, and that the distinction between safe and non-safe assets sharpens, is consistent with theory.

6.6 Dynamics of fundamentals

So far, our results show that, in periods of stress, the CD market did not collapse in aggregate. Instead, investors were still distinguishing between high- and low-quality banks, both in terms of the intensity of the substitution effect (intensive margin) and in terms of issuance decisions (extensive margin). If investors are seeking information-insensitive securities, these findings suggest that adverse selection risk for them was limited. However, to better understand the market dynamics during periods of stress, we study whether all banks have fundamentals that are equally sensitive to uncertainty shocks.

To do so, we study the dynamics of fundamentals for high- and low-quality issuers. As before, we measure issuer quality based on whether its fraction of impaired loans to total assets is above or below the sample median in any given year.[16] We then conduct a test akin to a difference-in-difference estimation. We define an indicator variable $Treat_i$ equal to 1 for low-quality banks. The events we use as treatments are shifts from non-stressed to

[16]The findings are quantitatively similar if we define high- and low-quality issuers based on medians over the entire sample period. Indeed, yearly transition probabilities from high-to low-quality or vice-versa are small (respectively 0.096 and 0.058).

stressed years ($Post_{t+1}$), where stressed years are 2008, 2009, 2011, and 2012. To evaluate the differential dynamics of fundamentals during periods of stress, we estimate:

$$\begin{aligned} Fundamental_{CD,i,t+1} &= \phi_1 Treat_i + \phi_2 Post_{t+1} + \phi_3 Treat_i * Post_{t+1} \\ &\quad + \rho \cdot Controls_{i,t} + \epsilon_{i,t+1}. \end{aligned} \tag{12}$$

Our coefficient of interest is ϕ_3. We focus on the following fundamentals as dependent variables: size, total loans to assets, liquid assets to assets, ROA, and impaired loans to assets.

We present the estimation results in Table 10. In the top panel, we include all years in which $t+1$ is a high-uncertainty period. Our results indicate that, when transitioning into high-uncertainty periods, the fundamentals of low-quality issuers deteriorate more than those of high-quality issuers. In the middle panel, we further show that the effect holds when we restrict the sample to years when t is a non-stressed year. The combination of the first two panels indicates that the differential dynamics of fundamentals during high-uncertainty periods amplifies when stress is long-lasting. Finally, in the bottom panel, we show the results from a placebo test when year $t+1$ is a low-uncertainty year. We find no significant differences in fundamentals between high-quality and low-quality issuers during such transitions. Thus, fundamentals evolve differentially across types of issuers only in periods of stress. The fact that the fundamentals of high-quality banks are less sensitive to uncertainty may explain why investors have limited incentive to produce information about them, and thus why adverse selection seems limited.

6.7 Balance-sheet rebalancing

Finally, we assess the potential for significant externalities arising from the private production of safe assets. So far, our results are inconsistent with the idea of a widespread disruption affecting the whole CD market, as we show that high-quality issuers are still able to issue safe assets in periods of stress. However, a more direct test is to assess whether issuers which lose the ability to issue safe assets are forced to deleverage, or whether they can substitute CDs with other sources of funds and thus avoid engaging in fire sales. Indeed, based on Stein (2012), the key market failure in the private production of safe assets arises from the existence of ex-post fire sales.

We reproduce the difference-in-difference estimation of equation (12) by replacing the dependent variables with variables related to sources of funds for issuers. As before, "treated" banks are those with below-average asset quality (measured using impaired loans to total assets), while the "post" periods are years with high stress (2008, 2009, 2011, 2012). We report the results in Table 12. In the first column, we confirm that in periods of stress low-quality banks issue fewer CDs relative to high-quality banks. The second column shows that total debt of these banks also drops significantly relative to that of the control group. Thus, the theoretical idea that the fragility of private safety production is associated with ex-post deleveraging is empirically verified. In terms of magnitude, however, the deleveraging is slightly smaller than the drop in CD funding. Columns 3 and 4 show that banks are able to substitute part of their lost CD funding with (arguably more expensive) repo funding and, more importantly, with central bank funding. Indeed, central bank borrowing increases significantly more for lower-quality banks. This finding makes any definite lesson on the inefficient private production of safe assets difficult to draw. Indeed, based on Stein (2012), the excessive production of private safe assets calls for the central bank to intervene and guarantee financial stability. However, the fact that central bank refinancing facilities were in place during our sample period implies that the deleveraging was arguably less pronounced than it would have been otherwise.

7 Conclusion

Our empirical study on the private production of safe assets yields several important findings. First, we show that privately issued debt securities can benefit from a safety premium, but only if their maturity remains very short. Consistent with the existence of a demand for safe stores of value, we show that the private sector produces more safe assets when safety demand is not met with public safe assets. However, the ability of the private sector to issue safe assets exhibits significant variation, both in the time series and across issuers. Specifically, the substitutability between public and private assets weakens during periods of high aggregate uncertainty. That said, even though the substitution effect wanes, aggregate issuance does not collapse, contrary to evidence from the ABCP market in the US. Moreover, the weakening substitutability is not uniform across issuers and is strongly related to issuers' observable quality. In uncertain times, high-quality institutions are more likely to produce safe assets, and to adjust the maturity of new issues to do so. Overall, these results are consistent with investors seeking information-insensitive stores of value but also processing some issuer-specific information, as in Moreira and Savov (2017).

Our results have potentially important policy implications. The finding that the private production of safe assets, at least for some assets, can break down in periods of market stress implies that public and private safe assets are not perfect substitutes. Thus, the heavy reliance of the financial system on privately-issued safe assets can become problematic in when uncertainty spikes. At the same time, the negative externality resulting from the possible overproduction of safe assets in good times may not be as severe as argued in the literature (e.g., Stein, 2012). Our findings suggest that the market can distinguish between good and bad types. If so, markets for private assets do not collapse in aggregate and financial stability is preserved. This finding should lead us to reassess the claim that higher opacity of a security's payoff is always a desirable feature that increases safety by detering information production. Access to basic information, such as ratings, can be a stabilizing feature for the market as a whole, even though it also implies that some issuers cross-sectionally will not be considered safe.

Our results also show that issuers of private assets that lose their safety status may find it difficult to replace CD financing with debt coming from other private sources, and thus turn to the central bank. Hence, from an aggregate perspective, the role of banks as capital providers can be impeded and the real sector may suffer in periods of high uncertainty. Monetary policies that affect incentives to produce public versus private safe assets may help mitigate any residual over-production of private assets in the economy (Stein, 2012; Gourinchas and Jeanne, 2012; Greenwood et al., 2016). How important should these policies be is difficult to qualify without an explicit specification for the optimal leverage economy-wide. We consider these links to the real sector as a promising avenue for future research.

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Table 1 – Description of the sample of CD issuers

This table describes the sample of CD issuers. Panel A shows the share of issuers and CD amounts issued by country. Panel B provides descriptive statistics on the distribution of balance sheet characteristics of CD issuers. Means and quantiles are as of end of December of each year and are computed from the pooled sample over the period from 2008 to 2014. Panel C relates CD outstanding amounts as of end of December of each year to other balance sheet characteristics, in the pooled sample. Statistics are conditional on the issuer having a non-zero amount of CD outstanding. Calculation of CD / (CD + Repo) is also conditional on the issuer having a non-zero amount of repurchase agreements outstanding. All variables are defined in Table A1.

Panel A: Geographic distribution of issuers

	Banks		% Issued	
	# issuers	% Issuers	amount	Largest issuer
All	271	100.00	100.00	—
Austria	2	0.74	0.20	Oesterreich. Kontrollbank
Belgium	2	0.74	6.26	Dexia Credit Local
Denmark	3	1.11	0.56	Jyske Bank
France	196	72.32	72.83	BNP Paribas
Germany	12	4.43	1.08	HypoVereinsbank
Ireland	7	2.58	0.48	Allied Irish Banks
Italy	14	5.17	3.18	Unicredit
Netherlands	8	2.95	5.42	Rabobank
Spain	2	0.74	0.58	BBVA
Sweden	4	1.48	0.89	Svenska Handelsbanken
Switzerland	2	0.74	0.44	UBS
UK	11	4.06	7.36	HSBC
Others	8	2.95	1.12	—

Panel B: Balance sheet characteristics

	10th	25th	Mean	Median	75th	90th	Std.	Obs.
Size (log Total assets)	20.82	22.07	23.50	23.34	24.71	26.70	2.09	1,449
Loans / Assets	0.27	0.48	0.63	0.69	0.82	0.88	0.23	1,445
Customer deposits / Assets	0.03	0.20	0.37	0.35	0.57	0.66	0.23	1,422
Short-term debt / Assets	0.05	0.13	0.29	0.24	0.48	0.60	0.21	1,422
ROA (%)	-0.20	0.15	0.32	0.40	0.74	1.04	1.15	1,443
ROE (%)	-3.88	2.52	3.57	5.42	8.32	13.27	12.36	1,443
Net interest margin / Assets	0.00	0.01	0.01	0.01	0.02	0.03	0.01	1,411
Impaired loans / Loans (%)	1.04	2.24	5.42	3.91	6.59	11.89	5.08	1,056
Equity / Assets	0.03	0.04	0.08	0.07	0.11	0.13	0.05	1,449
Tier 1 capital (%)	7.60	9.20	13.07	11.20	14.30	18.25	7.29	458
Total regulatory capital (%)	9.90	11.60	16.12	13.70	16.91	21.4	10.27	486

Panel C: Size of CD funding

	10th	25th	Mean	Median	75th	90th	Std.	Obs.
CD / Equity	0.01	0.05	1.17	0.21	0.69	2.25	0.33	971
CD / (CD + Repo)	0.01	0.05	0.34	0.22	0.61	0.85	0.39	218
CD / Short-term debt	0.00	0.01	0.16	0.05	0.18	0.49	0.23	971
CD / Total liabilities	0.00	0.01	0.09	0.03	0.09	0.22	0.10	1,007

Table 2 – Descriptive statistics on short-term debt securities

This table describes our data on the issuance of short-term debt securities. The universe of assets includes T-bills issued by the French Treasury and CDs issued by European banks. Panel A shows the amount of securities outstanding. Panel B shows net issuances, defined as the change in outstanding amounts between Fridays of two consecutive weeks. Panel C shows the maturity of new issues, measured in days, both unweighted and weighted by the amount of the issue. Unweighted moments are computed based on the sample of all issuances. Weighted moments are computed as averages by day. Short-term CDs are defined as those with maturity below or equal to 7 days at issuance.

Panel A: Aggregate T-bill and CD amounts outstanding (in EUR Billion)

	Min	10pc	25pc	Median	Mean	75pc	90pc	Max	Std.	Obs.
Total T-bill outstanding	78.4	111.6	165.6	174.6	167.4	183.4	196.4	209.9	29.7	365
Total CD outstanding	248.9	285.3	340.2	373.8	369.7	412.2	433.0	465.9	52.5	365
Short-term CD outstanding	1.0	9.1	19.1	31.2	30.8	40.9	50.6	75.2	15.7	365

Panel B: Aggregate T-bill and CD net issuance (in EUR Billion)

	Min	10pc	25pc	50pc	Mean	75pc	90pc	Max	Std.	Obs.
Total T-bill net issuance	-15.2	-1.3	-0.5	0.0	0.3	1.2	2.3	5.9	1.8	364
Total CD net issuance	-29.0	-7.0	-3.7	-0.3	-0.4	3.0	7.1	26.9	6.5	364
Short-term CD net issuance	-28.4	-7.7	-4.2	-0.1	-0.2	3.8	7.1	29.6	7.2	364

Panel C: Maturity of new issues (in days)

	Min	10pc	25pc	50pc	Mean	75pc	90pc	Max	Std.	Obs.
Pooled data										
T-bill	7	84	91	154	185	337	357	365	111	1,145
CD	1	2	13	33	66	92	181	367	76	841,636
Volume weighted (daily)										
T-bill	53	129	154	164	161	173	182	227	23	359
CD	5	13	18	26	40	39	79	365	44	2,185

Table 3 – Safety premium on T-bills and CDs

This table displays the safety premium on T-bills and CDs with maturities between one week and one year. The safety premium is defined by equation (1). In Panel A, the safety premium is computed over the whole sample period (2008-2014) for each maturity. In each sub-panel, the last column shows the difference between the safety premium at the longest and at the shortest available maturity. In Panel B, we compute linear slopes of the weekly CD safety premium over three intervals ([1 week; 1 month], [1 month; 3 months], and [3 months; 6 months]). The first three columns display the average slopes and their standard-deviations. The last two columns report differences and standard deviations obtained from a two-sample t-test. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Whole sample period

	T-bills					CD				
	1m	3m	6m	12m	12m - 1m	1w	1m	3m	6m	6m - 1w
	-0.150***	-0.120***	-0.068***	-0.023***	0.126***	-0.081***	0.115***	0.239***	0.374***	0.461***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.005)	(0.036)	(0.024)	(0.025)	(0.025)
Obs.	338	338	338	338	338	338	338	338	338	338

Panel B: Slope of CD safety premium

Average slopes			Differences in slopes	
[1w, 1m]	[1m, 3m]	[3m, 6m]	[1w, 1m] − [1m, 3m]	[1m, 3m]−[3m, 6m]
0.049***	0.024***	0.017***	0.024***	0.008***
(0.003)	(0.001)	(0.001)	(0.002)	(0.001)

Table 4 – CD issuance and T-bill issuance: OLS estimation

In this table, we regress CD issuance on T-bill issuance. Panel A is with aggregate issuance data with Panel B is at the issuer level. The data are at a weekly frequency. Short-term (resp. long-term) CDs are defined as having a maturity below or equal to (resp. above) 7 days at issuance. Control variables include: $\log(Q_{CD,t-1})$, $\Delta\log(Q_{CD,t-1})$, $\log(Q_{TB,t-1})$, $\Delta\log(Q_{TB,t-1})$. In Panel B, we also control for total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans. Panel C reproduced the same regression as in Panel B with different measures of public safe assets, either both French and German T-bills (which bear a safety premium) or Italian and Spanish T-bills (which do not bear any safety premium). I and YQ denote issuer and year-quarter fixed effects. The time period is from January 2008 to July 2014. Robust standard errors (Panel A) and standard errors clustered at the week level (Panels B and C) are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Time-series evidence

	Dependent variable: $\Delta\log(Q_{CD,t})$					
	All CD		Short-term CD		Long-term CD	
$\Delta\log(Q_{TB,t})$	0.073	0.085	-2.696**	-2.832***	0.482**	0.370**
	(0.116)	(0.132)	(1.128)	(0.868)	(0.197)	(0.179)
Controls	No	Yes	No	Yes	No	Yes
R^2	0.132	0.276	0.031	0.221	0.109	0.234
Observations	342	341	342	341	342	341
FE	YQ	YQ	YQ	YQ	YQ	YQ

Panel B: Panel evidence

	Dependent variable: $\Delta\log(\text{Short-term } Q_{CD,i,t})$					
$\Delta\log(Q_{TB,t})$	-2.772***	-3.732***	-4.534***	-3.599***	-4.208***	-5.076***
	(0.817)	(1.043)	(1.109)	(1.284)	(1.340)	(1.424)
Controls	No	No	No	Yes	Yes	Yes
R^2	0.001	0.004	0.003	0.002	0.005	0.006
Observations	16,083	16,083	16,007	9,870	9,906	9,870
FE	I	YQ	I, YQ	I	I, YQ	I, YQ

Panel C: Evidence from other European issuers

	Dependent variable: $\Delta\log(Q_{CD,i,t})$					
	France + Germany			Italy + Spain		
$\Delta\log(Q_{TB,t})$	-2.285***	-3.605***	-4.456***	-0.492	-0.127	-0.225
	(0.779)	(1.045)	(1.078)	(0.849)	(0.911)	(0.949)
Controls	No	No	Yes	No	No	Yes
R^2	0.001	0.003	0.005	0.000	0.002	0.003
Observations	16,083	16,083	16,007	16,083	16,083	16,007
FE	I	I, YQ	I, YQ	I	I, YQ	I, YQ

Table 5 – CD issuance and T-bill issuance: IV estimation

In this table, we regress changes in log CDs outstanding on the CD safety premium, where the CD safety premium is instrumented using the T-bill bid-to-cover ratio (BTC). Panel A displays some descriptive statistics on the BTC and on its two components (bid = T-bill demand and cover = T-bill supply). In panel B, we study the dynamics of the instrument by regressing in on monthly flows into European money market funds. Panel C shows the regression estimates for the two stages of the instrumental variables estimation. The CD safety premium is computed using Equation (1), in which we use the Eonia swap rate as the risk-free rate r_f. Observations are at a weekly frequency. Short-term CDs are defined as having a maturity below or equal to 7 days at issuance. Control variables include: $\log(Q_{CD,t-1})$, $\Delta \log(Q_{CD,t-1})$, total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans. Standard errors are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Descriptive statistics

	Min	10pc	25pc	Median	Mean	75pc	90pc	Max	Std.	Obs.
Bid-to-cover ratio	1.62	2.14	2.37	2.67	2.69	2.94	3.36	4.41	0.47	358
Bid (EUR Bn.)	6.20	14.80	17.60	20.60	20.40	23.20	26.60	42.30	4.70	358
Cover (EUR Bn.)	2.90	6.40	7.30	8.00	7.90	8.60	9.60	11.50	1.40	358
Fund flows (EUR Bn.)	-77.80	-24.30	-15.00	-4.00	-3.40	8.30	15.50	81.50	19.80	83

Panel B: Variation in the instrument

	ΔBTC_t	ΔBTC_t	$\Delta \log(Bids_t)$
$Flow_t$	0.344*	0.708*	1.837*
	(0.161)	(0.337)	(0.852)
$\log(Cover_t)$	-0.003	-0.096	
	(0.193)	(0.317)	
R^2	0.007	0.009	0.011
Observations	83	83	83
FE	-	YQ	YQ

Panel C: Instrumental variables estimation

	First stage		*Second stage*	
	Dependent variable			
	$P_{CD,t}$		$\Delta \log(\text{Short-term } Q_{CD,i,t})$	
Bid-to-cover ratio$_t$	-0.006***	-0.005***		
	(0.002)	(0.002)		
Instrumented $P_{CD,t}$			-8.187**	-9.619*
			(4.061)	(5.315)
Controls	No	Yes	No	Yes
F statistic	11.48	55.65	-	-
R^2	0.010	0.011	-	-
Observations	14,725	14,649	14,725	14,649

Table 6 – Time-series variation in safety premia

This table displays the safety premium on T-bills and CDs with maturities between one week and one year. The safety premium is defined by equation (1). We regress the safety premium on a set of indicator variables for each individual year, with no intercept. Standard errors are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	T-bills					CD				
	1m	3m	6m	12m	12m - 1m	1w	1m	3m	6m	6m - 1w
2008	-0.168***	-0.162***	-0.077***	-0.029***	0.138***	0.040***	0.372***	0.639***	1.216***	1.196***
	(0.014)	(0.015)	(0.010)	(0.011)	(0.016)	(0.014)	(0.112)	(0.069)	(0.072)	(0.074)
2009	-0.089***	-0.039***	0.010	0.030***	0.120***	-0.164***	0.072	0.318***	0.394***	0.558***
	(0.014)	(0.015)	(0.010)	(0.011)	(0.016)	(0.011)	(0.088)	(0.054)	(0.050)	(0.050)
2010	-0.151***	-0.138***	-0.097***	-0.072***	0.078***	-0.115***	0.048	0.089	0.197***	0.312***
	(0.014)	(0.015)	(0.010)	(0.011)	(0.016)	(0.011)	(0.088)	(0.054)	(0.050)	(0.050)
2011	-0.278***	-0.220***	-0.133***	-0.049***	0.229***	-0.059***	0.374***	0.352***	0.404***	0.464***
	(0.014)	(0.015)	(0.010)	(0.011)	(0.016)	(0.011)	(0.088)	(0.054)	(0.050)	(0.050)
2012	-0.189***	-0.161***	-0.113***	-0.047***	0.142***	-0.091***	0.010	0.237***	0.443***	0.535***
	(0.014)	(0.015)	(0.010)	(0.011)	(0.016)	(0.011)	(0.088)	(0.054)	(0.050)	(0.050)
2013	-0.077***	-0.056***	-0.039***	-0.003	0.074***	-0.058***	-0.024	0.054	0.108**	0.167***
	(0.014)	(0.015)	(0.010)	(0.011)	(0.016)	(0.011)	(0.088)	(0.054)	(0.050)	(0.050)
2014	-0.042**	-0.007	0.012	0.031**	0.073***	-0.072***	-0.020	0.044	0.231***	0.303***
	(0.019)	(0.021)	(0.013)	(0.015)	(0.022)	(0.016)	(0.126)	(0.076)	(0.069)	(0.051)
R^2	0.735	0.615	0.599	0.232	0.584	0.604	0.068	0.361	0.627	0.673
Obs.	338	338	338	338	338	338	338	338	338	338

Table 7 – CD and T-bill issuance conditional on stress

In this table, we regress changes in log short-term CDs outstanding at the bank level on changes in log T-bills outstanding, interacted with measures of market stress. Short-term CDs are defined as having a maturity below or equal to 7 days at issuance. Observations are at the bank-week level. The baseline coefficients are for "Low stress" periods, defined as a VIX, 50-days past stock returns on the Euro stoxx 50, or the Euribor-Eonia swap spread in their first quartile over the sample period. Other interaction terms are for the three top quartiles. Control variables include: $\log(Q_{CD,t-1})$, $\Delta\log(Q_{CD,t-1})$, $\log(Q_{TB,t-1})$, $\Delta\log(Q_{TB,t-1})$, total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans. I and YQ denote issuer and year-quarter fixed effects. Each regression also includes fixed effects associated with quartiles of the market stress variable used to construct interaction terms. The time period is from January 2008 to July 2014. Standard errors clustered at the week level are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $\Delta\log(\text{Short-term } Q_{CD,i,t})$					
	VIX		Past returns Euro stoxx 50		Euribor - Eonia swap spread	
$\Delta\log(Q_{TB,t})$	-11.188***	-11.891***	-7.477***	-8.179***	-6.861**	-7.403**
	(3.263)	(3.295)	(2.060)	(2.076)	(3.099)	(3.097)
$\Delta\log(Q_{TB,t}) \ast$ Mid-low stress	2.666	2.927	-2.970	-2.108	-2.219	-1.728
	(4.548)	(4.544)	(3.355)	(3.363)	(3.969)	(3.969)
$\Delta\log(Q_{TB,t}) \ast$ Mid-high stress	7.218**	7.096**	4.584*	4.357	3.651	3.640
	(3.663)	(3.660)	(2.754)	(2.772)	(3.646)	(3.670)
$\Delta\log(Q_{TB,t}) \ast$ High stress	10.322***	10.074***	7.459***	7.359***	4.568	3.875
	(3.568)	(3.573)	(2.587)	(2.631)	(3.371)	(3.386)
Controls	No	Yes	No	Yes	No	Yes
R^2	0.004	0.005	0.004	0.006	0.004	0.005
Observations	16,083	16,007	16,083	16,007	15,901	15,825
FE	I, YQ	I, YQ	I, YQ	I, YQ	I, YQ	I, YQ

Table 8 – CD and T-bill issuance conditional on balance sheet and VIX: OLS regression

In this table, we regress changes in log short-term CDs outstanding at the bank level on changes in log T-bills outstanding, interacted with dummies for quartiles of balance sheet characteristics. We do so for two subsamples based on whether the VIX is below or above its sample median (respectively "Low VIX" and "High VIX"). The regression does not include a constant. Observations are at the bank-week level. Short-term CDs are defined as having a maturity below or equal to 7 days at issuance. Control variables include: $\log(Q_{CD,t-1})$, $\Delta\log(Q_{CD,t-1})$, $\log(Q_{TB,t-1})$, $\Delta\log(Q_{TB,t-1})$, total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans. I and YQ denote issuer and year-quarter fixed effects. Each regression also includes fixed effects associated with quantiles (above or below median) of the balance sheet variable used to construct interaction terms. The time period is from January 2008 to July 2014. Standard errors clustered at the week level are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $\Delta\log(\text{Short-term } Q_{CD,i,t})$				
Panel A: Low-VIX periods					
	Size	Equity	Impaired	ROA	Rating
$\Delta\log(Q_{TB,t})$ ∗ First quartile	-4.552	-4.302	-7.058*	-7.044	-6.342
	(7.776)	(6.426)	(3.796)	(4.830)	(5.516)
$\Delta\log(Q_{TB,t})$ ∗ Second quartile	-5.636	-6.083	-10.160*	-4.353	-6.335*
	(5.629)	(4.459)	(5.377)	(4.766)	(3.676)
$\Delta\log(Q_{TB,t})$ ∗ Third quartile	-5.781	-6.460*	-6.213	-8.255*	-29.062**
	(5.421)	(3.890)	(5.315)	(4.277)	(13.486)
$\Delta\log(Q_{TB,t})$ ∗ Fourth quartile	-8.399**	-17.092**	-3.270	-9.286	-24.094
	(3.660)	(7.522)	(6.888)	(6.843)	(33.606)
Controls	Yes	Yes	Yes	Yes	
R^2	0.010	0.002	0.002	0.002	0.001
Observations	4,254	4,254	4,254	4,254	3,490
FE	YQ	YQ	YQ	YQ	YQ
Panel B: High-VIX periods					
$\Delta\log(Q_{TB,t})$ ∗ First quartile	-1.654	-2.597	-2.285	-2.076	-1.828
	(2.190)	(2.292)	(2.351)	(2.484)	(3.152)
$\Delta\log(Q_{TB,t})$ ∗ Second quartile	-4.751	-3.145	-5.123*	-3.696	-10.087
	(3.597)	(2.375)	(2.839)	(2.543)	(7.266)
$\Delta\log(Q_{TB,t})$ ∗ Third quartile	-4.537	-4.391	-3.893	-4.412*	-3.683
	(3.153)	(3.240)	(2.588)	(2.597)	(2.340)
$\Delta\log(Q_{TB,t})$ ∗ Fourth quartile	-6.341**	-9.181**	-5.163	-7.045*	29.350
	(2.697)	(4.025)	(3.420)	(3.890)	(85.522)
Controls	Yes	Yes	Yes	Yes	Yes
R^2	0.002	0.002	0.002	0.002	0.003
Observations	5,840	5,840	5,840	5,840	4,322
FE	YQ	YQ	YQ	YQ	YQ

Table 9 – CD and T-bill issuance conditional on balance sheet and VIX: IV regression

In this table, we regress changes in log short-term CDs outstanding at the bank level on changes on the CD safety premium, where the CD safety premium is instrumented using the T-bill bid-to-cover ratio (BTC). We do so for two subsamples based on whether the VIX is below or above its sample median (respectively "Low VIX" and "High VIX"), and after interacting the main coefficient with dummies for quartiles of balance sheet characteristics. The regression does not include a constant. Observations are at the bank-week level. Short-term CDs are defined as having a maturity below or equal to 7 days at issuance. Control variables include: $\log(Q_{CD,t-1})$, $\Delta\log(Q_{CD,t-1})$, $\log(Q_{TB,t-1})$, $\Delta\log(Q_{TB,t-1})$, total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans. I and YQ denote issuer and year-quarter fixed effects. Each regression also includes fixed effects associated with quantiles (above or below median) of the balance sheet variable used to construct interaction terms. The time period is from January 2008 to July 2014. Standard errors clustered at the week level are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $\Delta\log(\text{Short-term } Q_{CD,i,t})$				
Panel A: Low-VIX periods					
	Size	Equity	Impaired	ROA	Rating
Instrumented $P_{CD,t}$ ∗ First quartile	-3.207	-1.158	-10.999**	-5.721	-1.117
	(4.286)	(5.531)	(5.001)	(6.639)	(4.320)
Instrumented $P_{CD,t}$ ∗ Second quartile	-2.853	-4.563	-7.854*	-6.003	-6.988
	(5.398)	(6.884)	(3.643)	(7.004)	(6.804)
Instrumented $P_{CD,t}$ ∗ Third quartile	-7.983*	-8.885*	-4.481	-8.965	-12.240*
	(3.901)	(4.421)	(5.632)	(7.665)	(6.121)
Instrumented $P_{CD,t}$ ∗ Fourth quartile	-12.760**	-14.751**	-5.600	-9.514*	-7.742
	(6.111)	(6.901)	(5.798)	(4.607)	(6.709)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	4,254	4,254	4,254	4,254	3,490
FE	YQ	YQ	YQ	YQ	YQ
Panel B: High-VIX periods					
Instrumented $P_{CD,t}$ ∗ First quartile	1.207	-2.877	-4.001*	-2.117	2.208
	(5.559)	(7.884)	(2.009)	(3.465)	(7.809)
Instrumented $P_{CD,t}$ ∗ Second quartile	-1.237	-3.085	-6.606*	-2.285	-3.401
	(4.007)	(5.219)	(3.340)	(6.773)	(4.330)
Instrumented $P_{CD,t}$ ∗ Third quartile	-3.437	-1.201	-1.143	-3.404	-6.601
	(5.553)	(5.098)	(4.211)	(5.763)	(6.997)
Instrumented $P_{CD,t}$ ∗ Fourth quartile	-7.652*	-8.806*	0.054	-7.005*	-4.331
	(3.807)	(4.453)	(6.770)	(3.564)	(4.441)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	5,840	5,840	5,840	5,840	4,322
FE	YQ	YQ	YQ	YQ	YQ

Table 10 – Balance sheet quality: Difference-in-differences

This table estimates a difference-in-differences model with several balance sheet characteristics as dependent variable. In the first two panels, "Post" correspond to years $t+1$ in which market stress is high (2008, 2009, 2011, and 2012), while year t is either stressed or non stressed (first panel) or non stressed (second panel). "Treated" equals one for banks with above-median non-performing loans to total assets over the sample period. The third panel is a placebo, as we estimate the same difference-in-differences models with $t+1$ being non stressed. All regressions are at a yearly frequency. The time period is from January 2008 to July 2014. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Size	Loans	Liquid assets	ROA	Impaired loans
	Year $t+1$ is stressed				
Post ∗ Treated	-0.019*	-0.011*	-0.014	-0.002**	0.017*
	(0.010)	(0.007)	(0.015)	(0.001)	(0.009)
R^2	0.010	0.009	0.010	0.011	0.010
Observations	807	805	749	804	712
	Year $t+1$ is stressed, t is not stressed				
Post ∗ Treated	-0.022*	-0.016*	-0.017*	-0.002**	0.021**
	(0.012)	(0.009)	(0.009)	(0.001)	(0.010)
R^2	0.011	0.010	0.010	0.012	0.011
Observations	401	400	372	201	351
	Placebo: Year $t+1$ is not stressed				
Post ∗ Treated	0.011	0.007	-0.011	0.001	0.008
	(0.015)	(0.012)	(0.016)	(0.004)	(0.009)
R^2	0.008	0.007	0.009	0.008	0.008
Observations	601	588	547	597	352

Table 11 – CD maturity and T-bill issuance conditional on VIX

In this table, we regress the share of CDs issued with maturity below one week on changes in log T-bills outstanding. We do so for two subsamples based on whether the VIX is below or above its sample median (respectively "Low VIX" and "High VIX"). Observations are at the bank-week level. Control variables include: $\log(Q_{CD,t-1})$, $\Delta\log(Q_{CD,t-1})$, $\log(Q_{TB,t-1})$, $\Delta\log(Q_{TB,t-1})$, total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans. I and YQ denote issuer and year-quarter fixed effects, respectively. The time period is from January 2008 to July 2014. Standard errors clustered at the week level are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Share of CDs issued with maturity below 1 week				
			Low VIX		
$\Delta\log(Q_{TB,t})$	-0.309	-0.115	-0.363	-0.102	-0.291
	(0.383)	(0.432)	(0.470)	(0.285)	(0.309)
Controls	No	No	Yes	No	Yes
R^2	0.001	0.010	0.010	0.030	0.030
Observations	18,231	18,231	18,231	18,231	18,231
FE	-	YQ	YQ	I, YQ	I, YQ
			High VIX		
$\Delta\log(Q_{TB,t})$	-0.495**	-0.591**	-0.641**	-0.589***	-0.633***
	(0.194)	(0.257)	(0.280)	(0.177)	(0.193)
Controls	No	No	Yes	No	Yes
R^2	0.001	0.007	0.007	0.013	0.013
Observations	26,646	26,646	26,464	26,646	26,464
FE	-	YQ	YQ	I, YQ	I, YQ

Table 12 – Financing and balance-sheet quality: Difference-in-differences

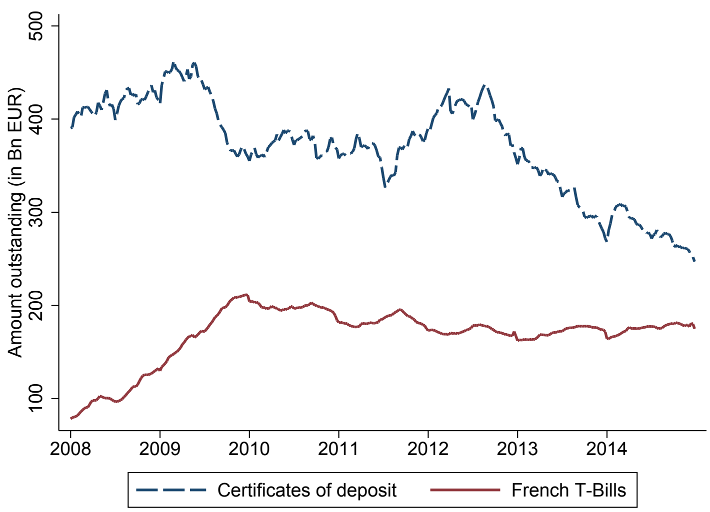
This table estimates a difference-in-differences model with several balance-sheet characteristics (all normalized by total assets) as dependent variable. In the first two panels, "Post" correspond to years $t+1$ in which market stress is high (2008, 2009, 2011, and 2012), while year t is either stressed or non stressed (first panel) or non stressed (second panel). "Treated" equals one for banks with above-median non-performing loans to total assets over the sample period. The third panel is a placebo, as we estimate the same difference-in-differences models with $t+1$ being non stressed. All regressions are at a yearly frequency. The time period is from January 2008 to July 2014. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	CD	Debt	Central bank	Repo	Deposits
	Year $t+1$ is stressed				
Post $*$ Treated	-0.049**	-0.042**	0.051**	0.031*	-0.002
	(0.023)	(0.020)	(0.024)	(0.017)	(0.016)
R^2	0.011	0.010	0.012	0.013	0.007
Observations	807	631	578	122	801
	Year $t+1$ is stressed, t is not stressed				
Post $*$ Treated	-0.058**	-0.051**	0.072**	0.038**	-0.004
	(0.026)	(0.023)	(0.034)	(0.016)	(0.011)
R^2	0.013	0.011	0.013	0.013	0.009
Observations	401	308	260	60	395
	Placebo: Year $t+1$ is not stressed				
Post $*$ Treated	0.023	0.012	0.008	-0.009	0.005
	(0.024)	(0.016)	(0.013)	(0.017)	(0.021)
R^2	0.009	0.008	0.009	0.007	0.006
Observations	601	442	402	78	599

Figure 1 – Outstanding amounts of safe securities

This figure plots the outstanding amounts of safe securities in the European market. We plot certificates of deposit issued by European banks and T-bills issued by the French government. Panel A plots amounts aggregated over all maturities, and Panel B a breakdown across maturities.

Panel A: Aggregate amounts



Panel B: Breakdown by maturity

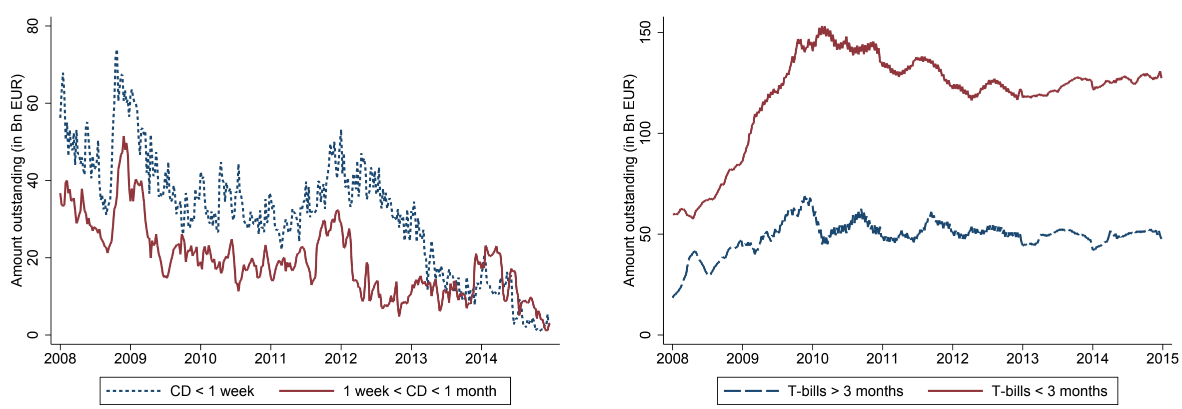


Figure 2 – Distribution of the maturity of short-term debt securities

This figure plots the maturity at issuance of short-term securities in the European debt market. We plot histograms of maturity at issuance for certificates of deposit issued by European banks (left panel) and for T-bills issued by the French government (right panel), both in the pooled sample.

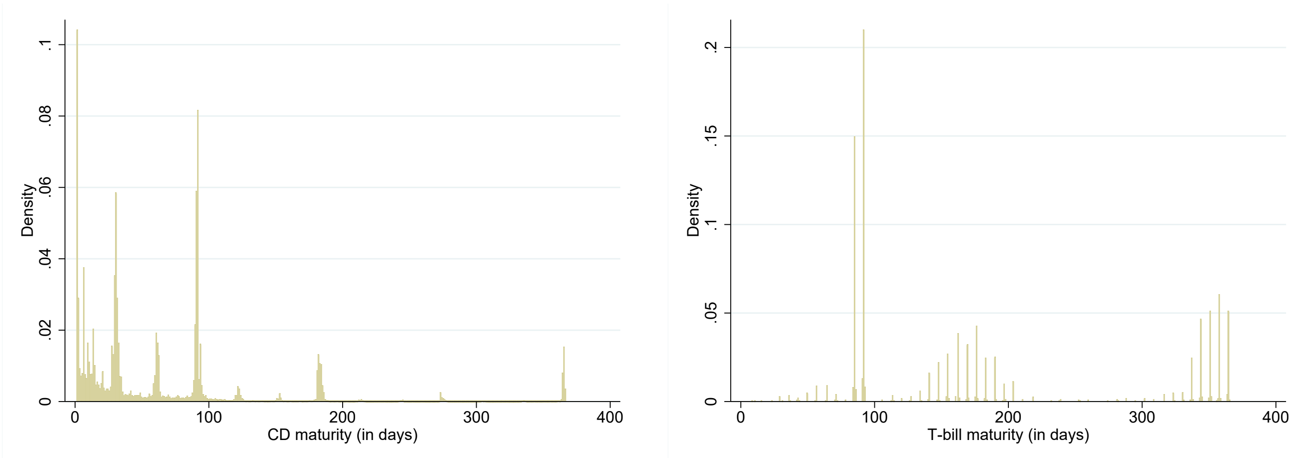
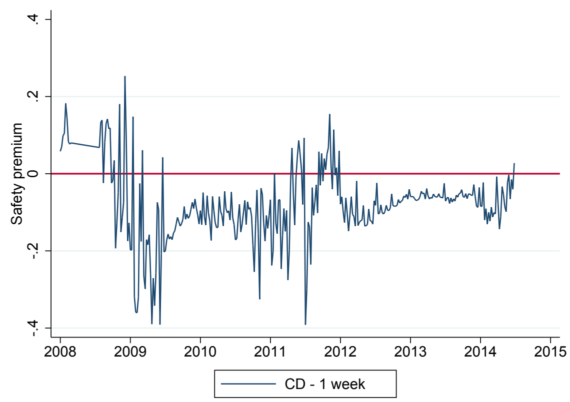
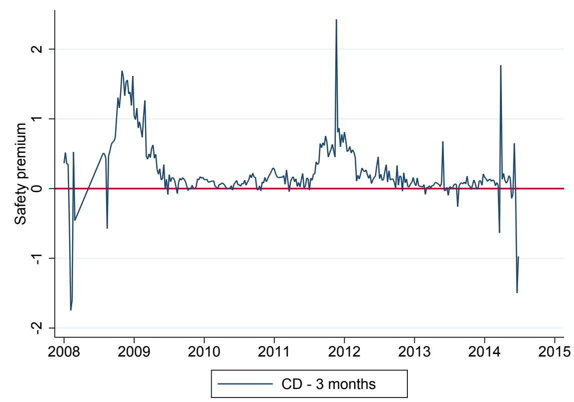


Figure 3 – Safety premium across maturities and countries

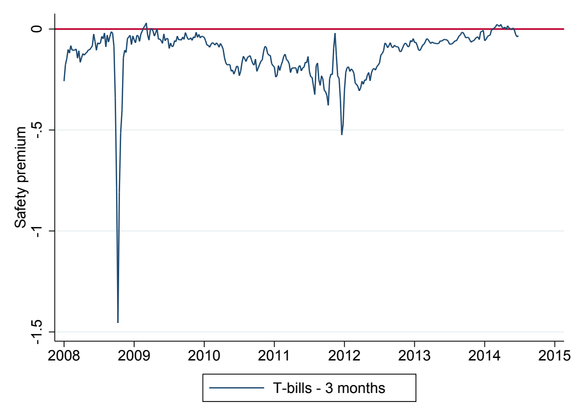
This figure plots the safety premium on safe securities in the European market. We plot the safety premium for certificates of deposit issued by European banks and T-bills issued by the French, German, Italian and Spanish governments.

Panel A: Certificates of deposit

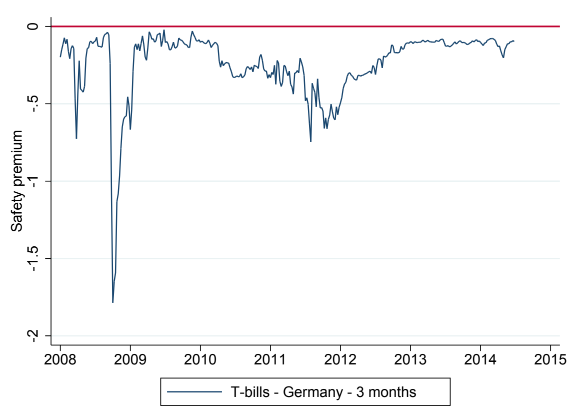




Panel B: T-Bills (France)



Panel C: T-Bills (Germany, Italy, Spain)



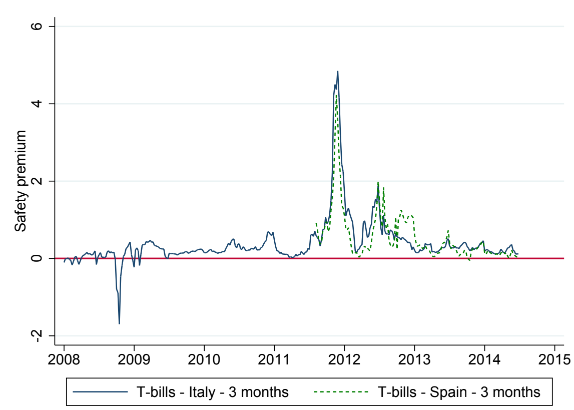


Figure 4 – Term structure of safety premia and Eonia swap

This figure plots the term structure of the safety premia on CDs (solid line) and T-bills (dotted line). It also plots the term structure of the Eonia swap rate (dashed line). All values are averages over the entire sample period (2008-2014). The one-year safety premium on CD and the one-week safety premium on T-bills are not available.

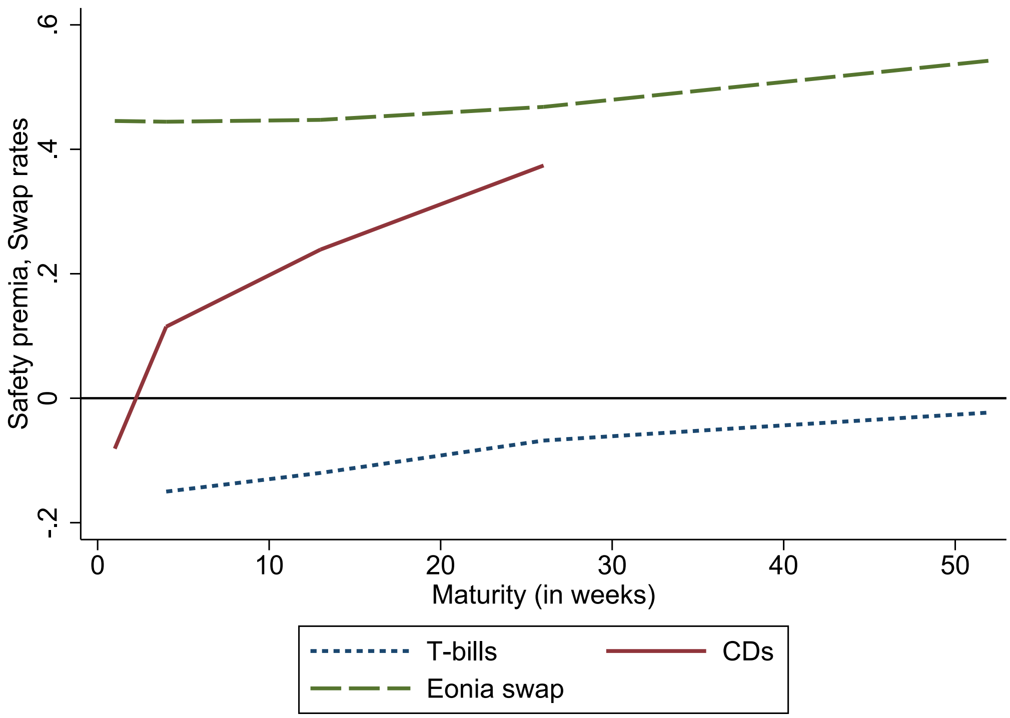


Figure 5 – CD issuance on T-bill auction days

This figure plots the average CD issuance, measured as $\log(Q_{CD,t}) - \log(Q_{CD,t-1})$, for every day of the week. We further break down the data between weeks in which the T-bill bit-to-cover ratio (BTC) is above or below its quarterly median. Monday corresponds to the day on which T-bill auctions are held. The time period is from January 2008 to July 2014.

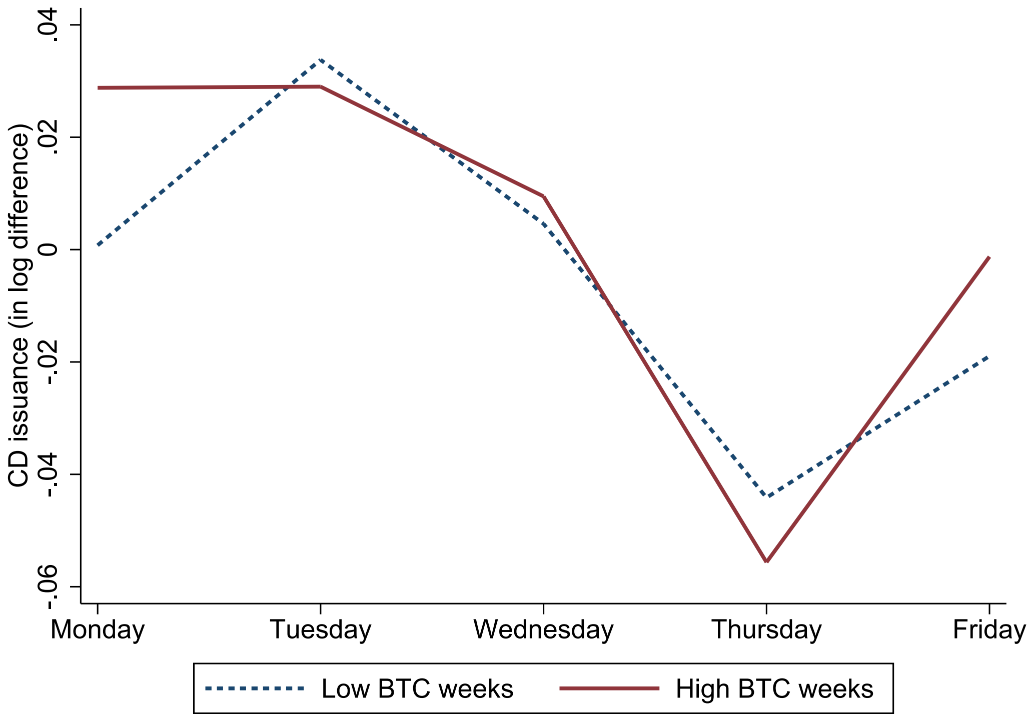


Figure 6 – Cross-sectional variation in CD issuance response to T-bill issuance

This histogram plots the distribution of the coefficients estimated by regressing the change in log CDs outstanding at the issuer level on the change in log T-bills outstanding. The regression is estimated separately for each issuer. The time period is from January 2008 to July 2014.

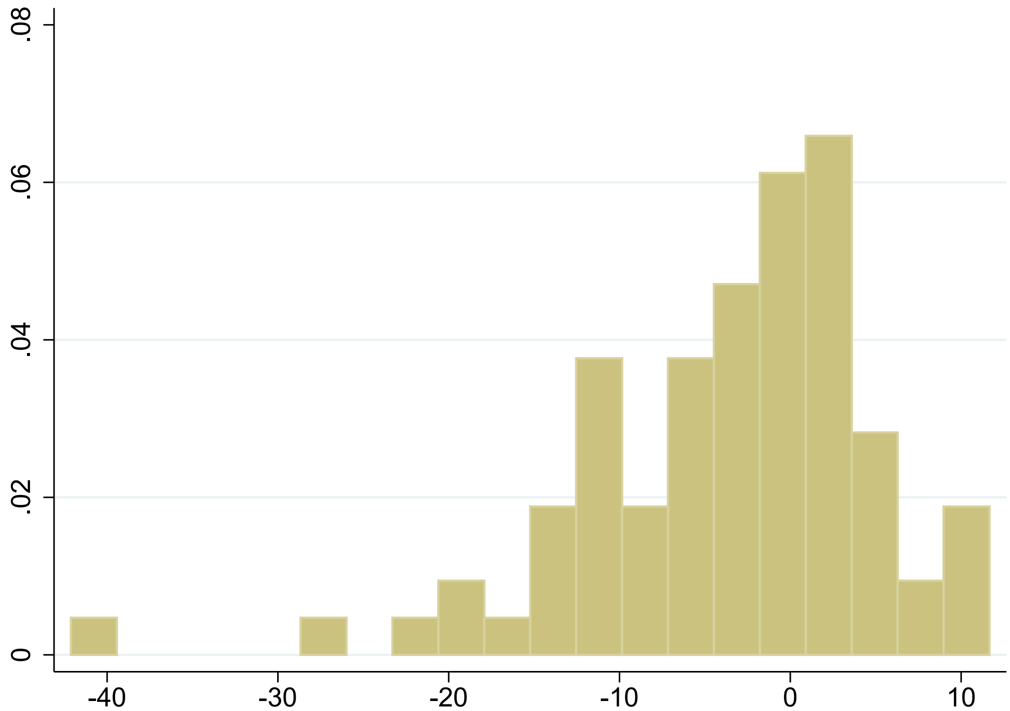
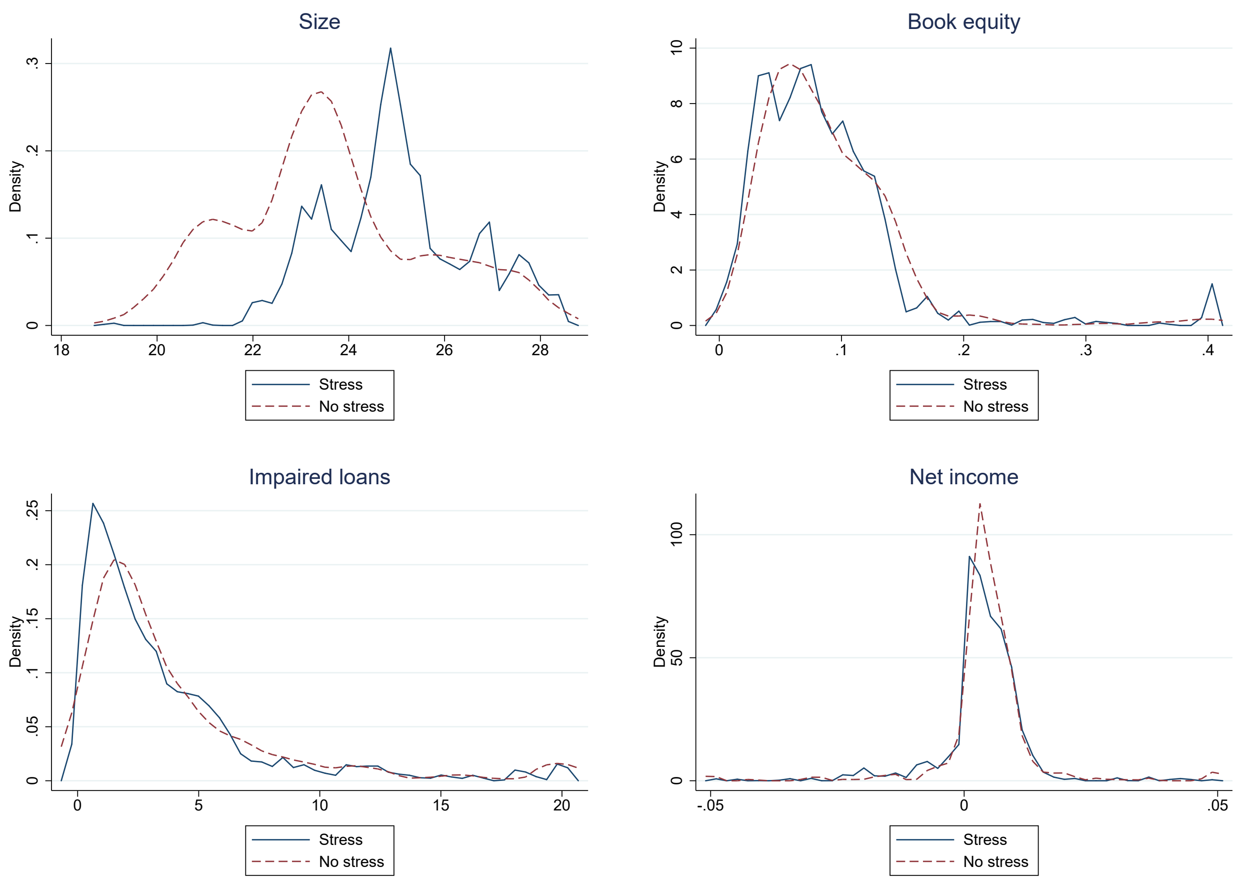


Figure 7 – Cross-sectional characteristics of CD issuers, conditional on market stress

This figure plots the kernel distribution of four balance sheet characteristics (size, book equity to total assets, impaired loans to total assets, net income to total assets). Stress years are 2008, 2009, 2011 and 2012. No stress years are 2010, 2013 and 2014.



Appendix

Table A1 – Variable definitions

This table defines the variables used in the empirical analysis, for both CD and CP issuers. The "id" code is the index number in Bankscope or to the variable tickers in Bloomberg. Variables related to issuer profitability and asset quality are winsorized at the 1st and 99th percentiles. We also provide the source for macroeconomic data.

Variable	Definition	Data source
	Data on CD issuers	
Assets	Total assets (id: 11350).	Bankscope
Book equity	Common Equity (id: 11800).	Bankscope
Loans	Gross loans (id: 11100).	Bankscope
Customer deposits	Total customer deposits: Current + Savings + Term (id: 11550).	Bankscope
Net income	Net income (id: 10285).	Bankscope
ROA	Return on average assets (id: 4024).	Bankscope
Impaired loans / Gross loans	Impaired Loans over Gross Loans (id: 18200).	Bankscope
Short-term credit rating	Encoded on a scale from 1 to 5 ("B"=1; "F3"=2; "F2"=3; "F1"=4; "F1+"=5)	Fitch Ratings / Moody's or S&P if Fitch unavailable
	Data on CP issuers	
Assets	Total assets (id: *BS_TOT_ASSET*).	Bloomberg
Equity	Total equity (id: *TOTAL_EQUITY*).	Bloomberg
Total debt	Short-term debt (id: *BS_ST_BORROW*) + Long-term debt (id: *BS_LT_BORROW*).	Bloomberg
Net debt	Net debt (id: *NET_DEBT*).	Bloomberg
ROA	Net income (id: *NET_INCOME*) divided by total assets.	Bloomberg
ROE	Net income (id: *NET_INCOME*) divided by total equity.	Bloomberg
	Macroeconomic data	
VIX	CBOE Volatility Index: VIX (id: *VIXCLS*)	FRED
Eonia swap rates	Eonia swap rates at all maturities between 1 week and 1 year	Bloomberg
Euribor - Eonia swap spread	Euribor from EMMI minus Eonia swap rate, both with 1 month maturity	European Money Market Institute (EMMI)
Eurostoxx 50	Eurostoxx 50 Index	Bloomberg

Table A2 – CD issuance and T-bill safety premium

In this table, we regress changes in the natural logarithm of CDs outstanding on the T-bill safety premium. Panel A estimates time-series regressions, where issuances are aggregated across issuers, while Panel B uses panel data. The T-bill safety premium is computed using Equation (1), where we use the Eonia swap rate as the risk-free rate r_f. In the last two columns of Panel B, the T-bill safety premia is measured using an alternative variable: the difference between the actual T-bill rate and the T-bill rate predicted using the term-structure model by Gürkaynak, Sack, and Wright (2007). Observations are at a weekly frequency. Short-term (resp. long-term) CDs are defined as having a maturity below or equal to (resp. above) 7 days at issuance. Control variables include: $\log(Q_{CD,t-1})$, $\Delta\log(Q_{CD,t-1})$, $\log(Q_{TB,t-1})$, $\Delta\log(Q_{TB,t-1})$. In Panel B, we also control for total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans. I and YQ denote issuer and year-quarter fixed effects. The time period is from January 2008 to July 2014. Standard errors clustered at the week level are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Time-series evidence

	Dependent variable: $\Delta\log(Q_{CD,t})$		
	All CD issues	Short-term CDs	Long-term CDs
$P_{TB,t}$	-0.013	-0.263***	0.004
	(0.012)	(0.069)	(0.018)
Controls	Yes	Yes	Yes
R^2	0.278	0.221	0.231
Observations	336	336	336
FE	YQ	YQ	YQ

Panel B: Panel evidence

	Dependent variable: $\Delta\log(\text{Short-term } Q_{CD,i,t})$						
	Eonia					Term-structure model	
$P_{TB,t}$	-0.254***	-0.272*	-0.321**	-0.276*	-0.328**	-0.214*	-0.192*
	(0.077)	(0.150)	(0.160)	(0.152)	(0.164)	(0.131)	(0.127)
Controls	No	No	Yes	No	Yes	Yes	Yes
R^2	0.001	0.002	0.003	0.002	0.003	0.003	0.004
Observations	16,091	16,091	14,349	16,091	14,349	14,349	14,349
FE	-	YQ	YQ	I, YQ	I, YQ	YQ	I, YQ

Table A3 – CD issuance and T-bill issuance by maturity

In this table, we regress changes in log CDs outstanding on changes in log T-bills outstanding. We break down the supply of CD and T-bills in two maturity buckets. Observations are at a weekly frequency and aggregate CD issuances of all sample banks. Short-term (resp. long-term) CDs are defined as having a maturity below or equal to (resp. above) 7 days at issuance. Short-term (resp. long-term) T-bills are defined as having a maturity below or equal to (resp. above) 3 months at issuance. Control variables include: $\log(Q_{CD,t-1})$, $\Delta\log(Q_{CD,t-1})$, $\log(Q_{TB,t-1})$, $\Delta\log(Q_{TB,t-1})$, total assets, return on assets, loans over assets, customer deposits over assets, common equity over assets, and impaired loans over total loans. I and YQ denote issuer and year-quarter fixed effects. The time period is from January 2008 to July 2014. Standard errors clustered at the week level are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable:			
	$\Delta\log$(Short-term $Q_{CD,i,t}$)		$\Delta\log$(Long-term $Q_{CD,i,t}$)	
$\Delta\log$(Short-term $Q_{TB,t}$)	-1.048***		0.284***	
	(0.251)		(0.071)	
$\Delta\log$(Long-term $Q_{TB,t}$)		-0.540**		0.008
		(0.035)		(0.029)
Controls	Yes	Yes	Yes	Yes
R^2	0.004	0.009	0.002	0.003
Observations	16,007	16,007	16,007	16,007
FE	I, YQ	I, YQ	I, YQ	I, YQ

Table A4 – T-bill issuance and T-bill safety premium

In this table, we regress T-bill issuance (the numerator in BTC) over the T-bill safety premium. Observations are at a weekly frequency. YQ denotes year-quarter fixed effects. The time period is from January 2008 to July 2014. Robust standard errors are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: T-bill cover	
$p_{TB,t}$	0.078	-0.294
	(0.107)	(0.187)
Controls	No	No
R^2	0.001	0.520
Observations	351	351
FE	-	YQ

Figure A1 – Eonia swap rate

This figure displays the Eonia swap rate measured in percentage points between 2008 and 2014. We consider Eonia swap rates with 1-week, 1-month, 3-month, 6-month, and 12-month maturities.