Risk endogeneity at the lender/investor-of-last-resort*

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Abstract

To what extent can a central bank influence its own balance sheet credit risks during a financial crisis through unconventional monetary policy operations? To study this question we develop a risk measurement framework to infer the time-variation in portfolio credit risks at a high (weekly) frequency. Focusing on the Eurosystem's experience during the euro area sovereign debt crisis between 2010 and 2012, we find that the announcement and implementation of unconventional monetary policy operations generated beneficial risk spill-overs across policy portfolios. This caused overall risk to be nonlinear in exposures. In some instances the Eurosystem reduced its overall balance sheet credit risk by doing *more*, in line with Bagehot's well-known assertion that occasionally "only the brave plan is the safe plan."

Keywords: lender-of-last-resort; unconventional monetary policy; portfolio credit risk; longer-term operational framework; central bank communication.

JEL classification: G21, C33.

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1 Introduction

For at least 150 years, going back to Thornton (1802) and Bagehot (1873), central bankers have wondered to what extent they can actively influence rather than only passively accept their own balance sheet risks during a financial crisis. Theoretically, the possibility of the central bank influencing its own risk is uncontroversial. In the context of a pure illiquidity crisis without solvency concerns, for example, the simple announcement by a central bank to act as a generalized lender-of-last-resort (LOLR) to the entire financial system in line with Bagehot-inspired principles[1] could shift the economy from a 'bad' to a 'good' equilibrium, causing all illiquidity-related credit risks to quickly disappear at virtually no cost or additional central bank balance sheet risk; see e.g. Diamond and Dybvig (1983), Rochet and Vives (2004), Reis (2013), and Bindseil (2014). Additionally, the central bank's announcement to act as an investor-of-last-resort (IOLR) by purchasing stressed assets in malfunctioning markets could similarly shift expectations, possibly leaving the central bank's credit risk unaffected; see Calvo (1988), ECB (2014), Corsetti and Dedola (2016), and Acharya et al. (2018). Whether such possibilities are based on wishful "Münchhausen thinking,"[2] or are instead empirically relevant, is currently unclear. Empirical studies of central banks' financial risks are rare, primarily because the required data are almost always confidential. As a result, to our knowledge, the response of central bank credit risks to large-scale unconventional monetary policies has remained unexplored.

It is uncontroversial that lending freely in line with Bagehot (1873)-inspired principles as well as purchasing assets on stressed markets during a financial crisis can increase the overall credit risk of a central bank's balance sheet. How different LOLR and IOLR policies interact from a risk perspective, however, is currently unclear. Specifically, we ask: Can *increased* central bank liquidity provision or asset purchases during a financial crisis *reduce* bottom line central bank risks? This could happen if risk-taking in one part of the balance sheet

[1] Bagehot (1873) famously argued that the lender-of-last-resort should lend freely to solvent banks, against good collateral valued at pre-crisis levels, and at a penalty rate; see also Rochet and Vives (2004) and Freixas et al. (2004).

[2] This fictional German nobleman remarkably pulled himself, along with his horse, out of a morass by his own hair.

(e.g., more asset purchases) de-risks other balance sheet positions (e.g., the collateralized lending portfolio) by a commensurate or even larger amount. Focusing on the euro area during the sovereign debt crisis between 2010 and 2012, how economically important were such risk spillovers across monetary policy operations? Were the relevant financial buffers at all times sufficiently high? Finally, did unconventional operations differ in terms of beneficial economic impact per additional unit of risk?

We argue that the Eurosystem's experience during the euro area sovereign debt crisis is an ideal laboratory to study the impact of a central bank's LOLR and IOLR policies on the credit risk it assumes. Between 2010 and 2012, severe liquidity squeezes and market malfunctions forced the Eurosystem – the European Central Bank (ECB) and its then 17 national central banks (NCBs) – to act as a LOLR to the entire financial system; see e.g. ECB (2014), Drechsler et al. (2016), and de Andoain et al. (2016). Large-scale central bank lending to all banks helped avert a collapse of vital parts of the financial system and, with it, supported the transmission of monetary policy. Large-scale liquidity provision occurred via main refinancing operations (MROs), multiple long-term refinancing operations (LTROs), as well as two very-long-term refinancing operations (VLTROs), all backed by repeated expansions of the set of eligible collateral. In addition, the Eurosystem acted as an IOLR in stressed markets. For example, it purchased government bonds in malfunctioning secondary markets within its Securities Markets Programme (SMP) between 2010 and 2012, and committed to doing so again under certain circumstances within its Outright Monetary Transactions (OMT) program as announced in August 2012.

The Eurosystem's actions as a large-scale LOLR and IOLR to support stressed banks and sovereigns had a first-order impact on the size, composition, and, ultimately, the credit risk of its balance sheet. At the time, its policies raised substantial concerns about the central bank taking excessive risks (and supporting moral hazard) by helping troubled counterparties. Particular concerns related to the potential effect of a materialization of credit risk on the ECB's reputation, independence, and ultimately its ability to steer inflation towards its target of close to but below 2% over the medium term. The credit risk concerns were so pronounced at the time that some media outlets started referring to the ECB as the ECBB:

Europe's Central Bad Bank; see e.g. Brendel and Pauly (2011) and Böhme (2014).

By focusing on credit risk we do not intend to imply that other risk components — interest rate risk, exchange rate risk, liquidity risk, political risk, redenomination risk, and various other market risks — are not important. The credit risk component of central banks' balance sheets, however, has received particular and increasing attention from the public and the financial press since the global financial crisis; see e.g. Buiter and Rahbari (2012), Böhme (2014), and Bindseil and Laeven (2017). This attention has not waned given the complex and large balance sheets of currently all major central banks; see e.g. Greenlaw et al. (2013) and Reis (2018). Even in normal times, few central banks globally can afford to implement monetary policy simply by buying or selling (or lending against) entirely credit-risk-free financial assets.[3]

The methodological part of this paper introduces a reduced-form credit risk measurement framework that allows us to study the above questions. The framework is based on a tractable model for dependent defaults that can accommodate a large number of bank and sovereign counterparties simultaneously. The model allows us to capture extreme joint tail dependence, time-varying volatility and correlation parameters, as well as a potential asymmetry in the correlation dynamics. These empirical features are not unique to central bank portfolios but instead can apply to any large diversified asset or collateralized lending portfolio. We thus expect our risk framework to be of interest also for non-central-bank financial institutions that seek to repeatedly infer their portfolio credit risks at a high (weekly) frequency.

We stress that a central bank's risk management function is different from that of a commercial bank in at least three ways. First, risk and profitability are not first-order measures of success for a central bank. When taking monetary policy decisions the financial consequences for the central bank's bottom line are usually not a primary concern. If a central bank endures sustained losses, however, its independence may be, or perceived to be, impinged, which in turn may have adverse consequences for its ability to achieve its goals

[3] Risk concerns have remained a constant thorn in the side of monetary policy implementation. Historically, central banks have aimed to protect their balance sheets from unnecessary financial risks and avoid undue market non-neutrality through carefully designed collateral frameworks; see e.g. Cheun et al. (2009) for a survey.

and economic welfare.

Second, commercial banks, by engaging in maturity transformation, are by their very nature exposed to liquidity shocks. By contrast, central banks are uniquely able to provide liquidity-support in a financial crisis owing to the fact that they are never liquidity-constrained in the currency they issue; see e.g. Bindseil (2014) and Reis (2015). Consequently, the default risk of the central bank itself on its domestic currency liabilities is negligible even during an existential financial crisis.

Finally, a small or medium-sized commercial bank is unlikely to be able to materially influence financial risks and risk correlations. Commercial banks are 'risk takers' in more than one sense — risk management is primarily about choosing exposures at *given* risks. This is inherently less true for central banks, as we show. Instead, point-in-time risk measures and risk correlations respond to a central bank's communication and large-scale actions, and are *endogenous* in this sense, particularly during a financial crisis. Philosophically, this requires a particular mindset of a central bank's risk management function, thinking as economists at least as much as as quants.

The empirical part of this paper applies our credit risk framework to the Eurosystem's consolidated conventional and unconventional monetary policy portfolios. We thus contribute to a growing literature that applies stress-testing methods to central banks' assets and income.[4] Exposures are taken from the Eurosystem's balance sheet and measured at a weekly frequency between 2009 and 2015. Standard point-in-time risk measures are obtained from Moody's Analytics (for banks) or are calculated from CDS spreads (for sovereigns), also at a weekly frequency. All risk model parameters are estimated by the method of maximum likelihood. Common portfolio risk measures, such as the expected loss and expected shortfall, are obtained through Monte Carlo simulation. We compare model-implied portfolio credit risks shortly before and after key policy dates. This 'high-frequency' weekly assess-

[4] For example, Carpenter et al. (2013) and Greenlaw et al. (2013) stress-test the Federal Reserve's ability to send positive remittances to the U.S. Treasury given that a large-scale government bond portfolio exposes the Fed (and thus indirectly the Treasury) to interest rate risk. Christensen et al. (2015) advocate the use of probability-based stress tests, and find that the risk of temporarily suspended Fed remittances to the Treasury is small but non-negligible (at approximately 10%). Finally, Del Negro and Sims (2015) consider conditions under which a central bank might need to withhold seigniorage, or request recapitalization from the treasury, in order to maintain its monetary policy commitments.

ment identifies the effect of each policy on its own and other portfolio credit risks; see e.g. Rogers et al. (2014) and Fratzscher and Rieth (2018) for similar event-study approaches.

We focus on three empirical findings. First, we find that LOLR- and IOLR-implied credit risks tend to be negatively related in our sample. Taking additional risk in one part of the central bank's balance sheet (e.g., the announcement and implementation of SMP asset purchases) tended to de-risk other positions (e.g., the collateralized lending exposures from previous LTROs). Vice versa, the allotment of two large-scale VLTRO credit operations each decreased the expected shortfall of the SMP asset portfolio. As a result of these risk spillovers, central banks' overall risks can be nonlinear in exposures. In bad times, additional lending or asset exposures can increase overall risk less than proportionally. Conversely, reducing balance sheet size after the crisis may not reduce total risk by as much as one would expect by linear scaling.

Second, some unconventional policy operations reduced rather than added risk to the Eurosystem's balance sheet in bottom line terms. For example, we find that the initial OMT announcement de-risked the Eurosystem's balance sheet by €41.4 bn in 99% expected shortfall (ES). The announcement of OMT technical details in September 2012 was associated with a further reduction in 99% ES of €18.1 bn. As another example, the allotment of the first VLTRO in late 2011 raised the 99% ES associated with VLTRO lending from zero to approximately €27.6 bn. However, the allotment also sharply reduced the need for shorter-term central bank funding, and in addition de-risked the SMP asset portfolio as banks funneled some of the additional central bank liquidity into government bonds, mitigating sovereigns' funding stress; see e.g. Drechsler et al. (2016). The overall 99% ES increased, but only marginally so, by €0.8 bn. The total expected loss decreased, by €1.4 bn. We conclude that, in exceptional circumstances, a central bank can remove excess risk from its balance sheet by doing *more*, in line with Bagehot (1873)'s well-known assertion that occasionally "only the brave plan is the safe plan."

A reduction in net risk is by no means guaranteed, however. A central bank's risk response can go either way. Which way it goes likely depends on market perceptions about the sustainability of and the central bank's commitment to its unconventional policies, and therefore its communication with the public. For example, the asset purchases that were implemented in the week following the SMP's initial announcement in May 2010 raised the 99% ES of the SMP portfolio from zero to approximately €7.3 bn. The policy announcement and the initial purchases spilled over and helped de-risk the collateralized lending book to some extent. The total 99% ES, however, still increased, by €5.1 bn. As a second example, the extension of the SMP to include Spain and Italy in August 2011 did not reduce total balance sheet risk. This time the effect did not even spill over to reduce the risks of the other monetary policy portfolios. This exception is likely related to the pronounced controversy regarding the extension of the SMP at that time. The full extent of the controversy became evident with the resignation of the Bundesbank President in February 2011 and an ECB Executive Board member in September 2011. The divided decision, as well as communication challenges associated with the unprecedented policy, may have caused market participants to doubt that the SMP would be active for long and substantial in size, lessening its economic and risk impact.

Third, our risk estimates allow us to study past unconventional monetary policies in terms of their ex-post 'risk efficiency.' Risk efficiency is the notion that policy impact should be maximal given a certain increase in balance sheet risk. Given an estimate of policy impact (e.g., a change in long-term inflation swap rates around the time of a policy announcement) and an appropriate estimate of risk (e.g., the change in 99% ES), it is possible to evaluate different policies ex-post by scaling the former by the latter. Doing so, we find that the ECB's OMT program was particularly ex-post risk efficient. Its announcement *increased* long-term inflation expectations away from deflationary tendencies towards the ECB's target of close to but below two percent, *decreased* sovereign benchmark bond yields of stressed euro area countries, while *removing* risk from the central bank's balance sheet (a win-win-win). Further, we find that the first allotment of VLTRO funds was more risk-efficient than its second installment. The SMP, despite its benefits documented elsewhere (e.g. Eser and Schwaab (2016), Ghysels et al. (2017)), does not appear to have been a particularly risk-efficient policy measure as defined above.

Our findings can have important implications for the design of central banks' post-crisis operational frameworks; see e.g. Reis (2018, 2019). As a first key takeaway, a certain amount of excess central bank liquidity for monetary policy purposes can be provided via both credit operations and asset purchases. We find that collateralized credit operations imply substantially less credit risks (by at least one order of magnitude in our sample) than outright government bond holdings per €1 of liquidity owing to the double recourse built into collateralized lending as well as the diversification over a much larger set of counterparties. Such pronounced differences in portfolio risk may be relevant for the decision whether to provide additional central bank liquidity via collateralized lending operations or via outright asset purchases. Second, expanding the set of eligible assets during a liquidity crisis could help mitigate the procyclicality inherent in some central bank's risk protection frameworks. Our results suggest that doing so does not necessarily increase a central bank's overall level of credit risk. Third, central bank communication on unprecedented monetary policy measures should, ideally, be unanimous and detailed to be effective and risk-efficient (see SMP versus OMT). Finally, risk spillovers across monetary policy portfolios may call for gradualism in reducing balance sheet size after a financial crisis.

The remainder of the paper is set up as follows. Section 2 presents our exposure data. Section 3 introduces our high-dimensional credit risk measurement framework. Section 4 applies the framework to a subset of the Eurosystem's balance sheet. Section 5 concludes. A Web Appendix presents additional results and technical details.

2 Eurosystem operations

We study the time variation in Eurosystem portfolio credit risks, with a particular focus on such risks just before and after key monetary policy announcements during the euro area sovereign debt crisis. We focus on six announcements that are related to three unconventional monetary policy operations: the SMP, the VLTROs, and the OMT. This section first discusses these operations, and then presents the relevant point-in-time exposure data.

The Eurosystem adjusts the money supply in the euro area mainly via so-called refinancing operations that usually take the form of repos. Eurosystem refinancing operations between 2009 and 2015 included main refinancing operations (MROs), various long-term refinancing operations (LTRO<1y, LTRO-1y), very-long-term refinancing operations (VLTROs), and targeted long-term refinancing operations (TLTROs). Between 2010 and 2012 the Eurosystem also conducted asset purchases within its SMP program. We collectively refer to the LTRO-1y, VLTROs, TLTROs, SMP, and OMT as unconventional monetary policy operations. The financial risks and profits associated with these policy portfolios have been shared across the Eurosystem since their inception. We refer to Web Appendix A for details on the SMP, the VLTROs, and the OMT.

Our study includes all exposures from refinancing operations and almost all asset portfolios held outright for monetary policy purposes within our sample. We exclude assets purchased within the Expanded Asset Purchase Programme (APP) commencing in March 2015 since the APP was unrelated to generalized lender-/investor-of-last-resort motivations. In addition, the risks and profits associated with the APP are subject to different risk sharing arrangements across the constituent Eurosystem national central banks.[5] We further exclude the first two covered bond purchase programmes (CBPP1 and CBPP2) because of their small sizes (€60 bn and €16.4 bn at their respective peaks) and low default rates. Finally, we exclude non-monetary policy related portfolios such as the ECB's Own Funds Portfolio.

Figure 1 plots selected items of the Eurosystem's weekly balance sheet between 2009 and 2015.[6] We distinguish five different liquidity operations: MRO, LTRO<1y, LTRO1y, VLTRO3y, and TLTRO. The figure also plots the par value of assets held in the SMP portfolio. Clearly, the Eurosystem's balance sheet varied in size, composition, and thus credit risk during the course of the global financial crisis and euro area sovereign debt crisis. A peak in total assets was reached in mid-2012, at approximately €1.5 trn, following two VLTROs and SMP asset purchases.

Figure 2 plots the Eurosystem's country-level collateralized lending exposures, aggregated over the five liquidity-providing operations of Figure 1. The largest share of collateralized

[5] We refer to ECB (2014, 2015). A discussion of the European institutional framework and euro area risk sharing arrangements across NCBs is beyond the scope of this paper.

[6] The Eurosystem's balance sheet is public; see `http://sdw.ecb.europa.eu/browse.do?node=9691110`.

Figure 1: Eurosystem collateralized lending and SMP exposures

Total collateralized lending exposures associated with different liquidity operations (MRO, LTRO<1y, LTRO1y, VLTRO3y, TLTRO), as well as government bond holdings from purchases within the Securities Markets Programme (SMP). Vertical axis is in trillion euro. Data is weekly between 2009 and 2015. Two black vertical lines refer to the initial announcement of the SMP on 10 May 2010 (SMP1) and the cross-sectional extension of the program to include Italy and Spain on 08 August 2011 (SMP2). Two red vertical lines mark the allotment of the first and second three-year VLTRO on 20 December 2011 and 28 February 2012, respectively. Two purple vertical lines mark the initial announcement of the OMT on 02 August 2012 (OMT1) and the announcement of its technical details on 06 September 2012 (OMT2).

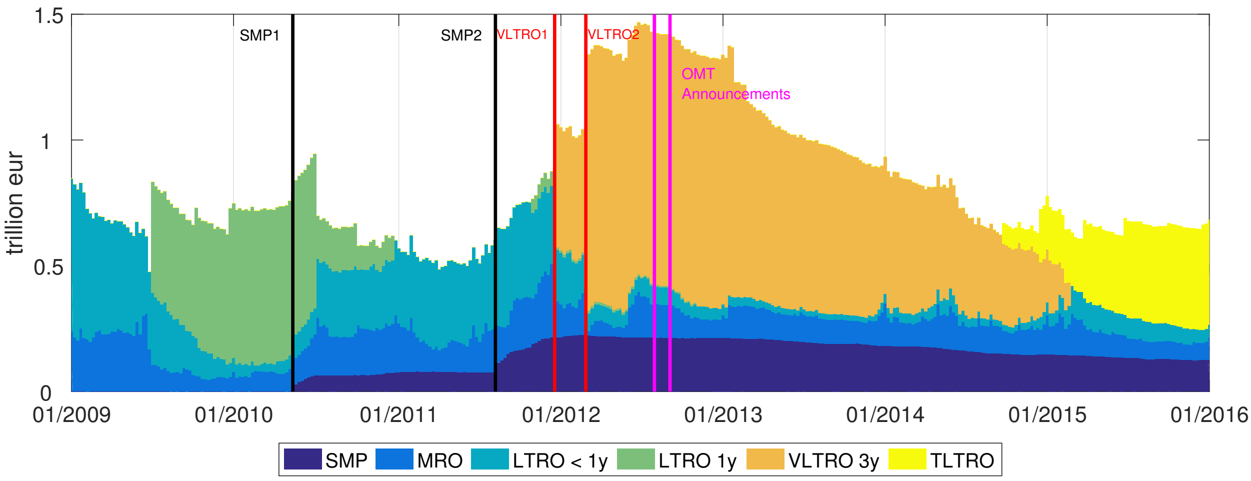
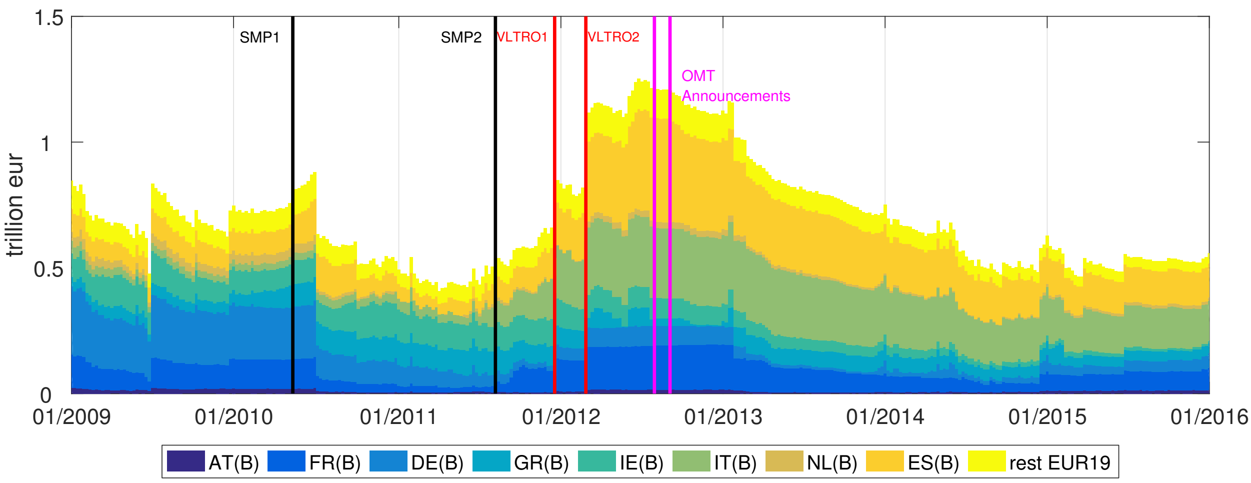


Figure 2: Eurosystem collateralized lending across countries

Exposures across different euro area countries from five liquidity-providing operations; see Figure 1. The vertical axis is in trillion euro. Vertical black, red, and purple lines indicate six monetary policy announcements as described in Figure 1. Data is weekly between 2009 and 2015.



lending was tapped by banks in Italy and Spain, and also Greece, Ireland, and Portugal. These sovereigns (and their banks) were perceived by markets to be particularly affected by the euro area sovereign debt crisis; see Section 3.2 below. Banks from non-stressed countries such as Germany and France were less liquidity-constrained and therefore relied less heavily on Eurosystem funding during the crisis.

3 Risk measurement framework

3.1 Portfolio risk measures

Credit losses at time $t = 1, \ldots, T$ over a one-year-ahead horizon are only known with certainty after the year has passed, and are uncertain (random) at time t. The probability distribution of ex-ante credit losses is therefore a key concern for risk measurement. We model total credit losses $\ell_t(k)$ associated with potentially many counterparties $i = 1, \ldots, N_t(k)$ as

$$\ell_t(k) = \sum_{i=1}^{N_t(k)} \ell_{it}(k) = \sum_{i=1}^{N_t(k)} 1(\text{default}_{i,t+1:t+52}) \cdot \text{LGD}_{i,t+1:t+52} \cdot \text{EAD}_{i,t+1:t+52}(k), \tag{1}$$

where $k = 1, \ldots, 6$ denotes monetary policy operations (e.g., LTRO lending or SMP asset holdings), $N_t(k)$ is the total number of both bank and sovereign counterparties that are relevant for operation k, $\ell_{it}(k)$ is the counterparty-specific one-year-ahead loss between week $t+1$ and $t+52$, $1(\text{default}_{i,t+1:t+52})$ is an indicator function that takes the value of one if and only if counterparty i defaults between $t+1$ and $t+52$, $\text{LGD}_{i,t+1:t+52} \in [0,1]$ is the loss-given-default as a fraction of $\text{EAD}_{i,t+1:t+52}(k)$, and $\text{EAD}_{i,t+1:t+52}(k)$ is the exposure-at-default associated with counterparty i and policy operation k. A default happens when the log-asset value of counterparty i falls below its counterparty-specific default threshold; see e.g. Merton (1974) and CreditMetrics (2007). The loss $\ell_{it}(k)$ is random because it is a function of three random terms: the default indicator, LGD, and EAD. Total losses from monetary policy operations are given by $\ell_t = \sum_{k=1}^{K} \ell_t(k)$. We focus on a one-year-ahead risk horizon to align our estimates with the common annual reporting frequency.

We adopt a static balance sheet assumption in our empirical study. This implies that risk parameters at time t are held constant between $t+1$ and $t+52$. In addition, exposures with maturities below the risk horizon are reinvested (for assets) or appropriately rolled over (for loans); see Section 3.4. As a result, the maturity structures of the policy portfolios are less relevant, and using a one-year risk horizon is without loss of much generality. Risk measures for different year-ahead horizons, when available, tend to be highly correlated.

Portfolio risk measures are typically based on moments of the ex-ante loss distribution. We focus on standard risk measures such as the expected loss and expected shortfall at a confidence level γ,

$$\begin{aligned} \mathrm{EL}(k)_t &= \mathbb{E}_t\left[\ell_t(k)\right], \\ \mathrm{ES}(k)_t^\gamma &= \mathbb{E}_t\left[\ell_t(k) \mid \ell_t(k) \geq \mathrm{VaR}^\gamma(\ell_t(k))\right], \end{aligned}$$

where $\Pr\left[\ell_t(k) \geq \mathrm{VaR}^\gamma(\ell_t(k))\right] \equiv 1-\gamma$ implicitly defines the value-at-risk at confidence level γ, and $\mathbb{E}_t\left[\,\cdot\,\right]$ is the conditional time t expectation over all sources of randomness in (1). Moments of the loss density can easily be obtained by simulation; see Section 4.2. The expected shortfall $\mathrm{ES}(k)_t^\gamma$ is often interpreted as the "average VaR in the tail," and is typically more sensitive to the shape of the tail of the loss distribution.

The remainder of this section reviews the modeling of the ingredients of (1) from left to right: marginal default probabilities and dependence, LGD, and EAD.

3.2 Bank and sovereign EDFs

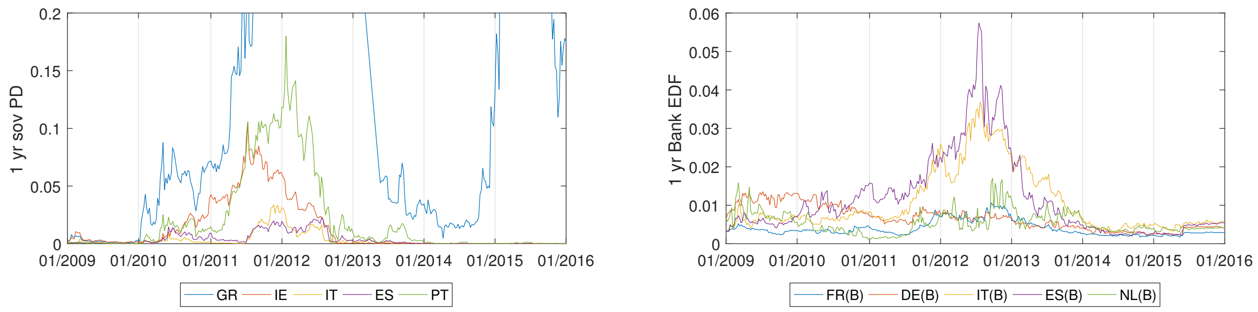
We rely on expected default frequency (EDF) data from Moody's Analytics, formerly Moody's KMV, when assigning point-in-time probabilities of default, p_{it}, to Eurosystem bank counterparties. One-year ahead EDFs are connected to (1) as

$$\mathbb{E}_t[1(\mathrm{default}_{i,t+1:t+52})] = \mathrm{EDF}_{it} = p_{it}, \tag{2}$$

where $\mathbb{E}_t[\,\cdot\,]$ denotes the expectations operator conditional on all information available at time t. EDFs are point-in-time forecasts of physical default hazard rates, and are based on

Figure 3: Sovereign and banking sector EDFs

Left panel: One-year-ahead CDS-implied-EDFs for five SMP sovereigns. Right panel: One-year-ahead banking sector EDF indices at the country level for the five largest euro area countries: Germany, France, Italy, Spain, and the Netherlands. Data is weekly between 2009 and 2015.



a proprietary firm value model that takes firm equity values and balance sheet information as inputs; see Crosbie and Bohn (2003). EDFs are standard credit risk measurements and are routinely used in the financial industry and credit risk literature; see for example Lando (2003) and Duffie et al. (2009).

EDF measures are available for listed banks only. Many Eurosystem bank counterparties, however, are not listed. At the same time, some parsimony is required when considering many bank counterparties. We address both issues by using one-year-ahead median EDFs at the country-level to measure point-in-time banking sector risk.[7] The right panel of Figure 3 plots our one-year ahead EDF indices for the 'big-5' euro area countries: Germany, France, Italy, Spain, and the Netherlands. During the crisis, most Eurosystem liquidity was taken up by banks located in these countries; see Figure 2. Banking sector EDF measures differ widely across countries, and peak around mid-2012. Our empirical setup uses nine banking sector EDFs that correspond to the countries shown in Figure 2.

Unfortunately, firm-value based EDF measures are unavailable for sovereign counterparties. We therefore need to infer physical PDs from observed sovereign CDS spreads. Web Appendix B provides the details of our approach. The left panel of Figure 3 presents one-year ahead sovereign risk measures for the five SMP countries. Most sovereign CDS-implied-EDFs

[7] EDF indices based on averages weighted by total bank assets are also available. These look similar but overall appear less reliable, and are not used for this reason.

are visibly correlated with their corresponding banking sector's EDF, and similarly tend to peak around mid-2012.

3.3 Multivariate model for dependent defaults

During and after the Great Financial Crisis the Gaussian dependence model (copula) was occasionally referred to as "the formula that killed Wall Street;" see e.g. Salmon (2009). Since then a consensus emerged that key features of appropriate risk models should include joint fat tails of individual risks, non-Gaussian dependence (to account for dependence in tail areas), instability or time variation in parameters, and potential asymmetries in dependence; see e.g. McNeil et al. (2015, Ch. 7). These concerns are not unique to central bank portfolios but instead apply to any large diversified asset or collateralized lending portfolio. Our model for dependent defaults presented in this section incorporates the above consensus.

Our risk model adopts the modeling framework developed previously in Creal et al. (2011) and Lucas et al. (2014, 2017). To tailor the model to the problem at hand, however, we modify it slightly to accommodate a large number of heterogeneous bank and sovereign counterparties. In addition, owing to high dimensions, we seek to capture joint tail dependence and a potential asymmetry in the copula in a computationally more straightforward way. Taken together, this yields a modeling framework that can be of use also to non-central-bank financial institutions.[8]

Following the seminal framework of Merton (1974) and CreditMetrics (2007), we assume that a counterparty i defaults if and only if its log asset value falls short of a certain default threshold. We assume that this happens when *changes* from current log asset values to future ones are sufficiently negative. Specifically, we assume that a default occurs with a time-varying default probability p_{it}, where

$$p_{it} = \Pr[\tilde{y}_{it} < \tau_{it}] = F(\tau_{it}) \Leftrightarrow \tau_{it} = F^{-1}(p_{it}), \tag{3}$$

[8] Other models to quantify a central bank's portfolio credit risks exist. For central-bank-specific through-the-cycle models of portfolio credit risk see e.g. ECB (2007, 2015). Our model measures credit risk at an uncommonly high frequency based on point-in-time risk measures. This is necessary given the questions at hand; see Section 4. For a discussion of model selection see Section 4.1.

where $\tilde{y}_{it}$ is a one-year-ahead change in log asset value, τ_{it} is a default threshold expressed as a log return, F is the CDF of $\tilde{y}_{it}$, and p_{it} is defined in (2). We stress that (3) is essentially a Merton (1974) model turned on its head in two ways. First, unlike Merton (1974), p_{it} is treated as an observed *input* in our model. In this way, point-in-time p_{it} and risk correlations can (and do) respond to market participant's expectations of future central bank actions. Second, τ_{it} does not have an economic interpretation in terms of debt levels of the firm. Rather, τ_{it} is chosen at each point in time and for each counterparty as the p_{it}-quantile of F such that the marginal default probability implied by the multivariate (copula) model coincides with the observed market-implied default probability for that counterparty at that time; see the last equality in (3).[9] The reduced form character of (3) ensures that the model can be used for sovereigns as well, for which asset values are a less intuitive notion.

When modeling dependent defaults, we link default indicators using a Student's t copula function. In particular, we assume that one-year-ahead changes in log-asset values $\tilde{y}_{it}$ are generated by a high-dimensional multivariate Student's t density with covariance matrix $\Omega_t^{(k)}$ and ν degrees of freedom. The covariance matrix depends on k because different counterparties participate in different monetary policy operations. The mean can be set to zero without loss of generality because copula quantiles shift linearly with the mean. We refer to Web Appendix C for all technical details.

The time-varying covariance matrix $\Omega_t^{(k)}$ is typically of a high dimension. For example, more than 800 banks participated in the Eurosystem's second VLTRO program. The high dimensions – and time-varying size – of $\Omega_t^{(k)}$ imply that it is difficult to model directly. We address this issue by working with block equi-correlations within and across countries. These block equi-correlations (Engle and Kelly, 2012) are gathered in a $D \times D$ matrix Σ_t, with $D \ll N_t(k)$, such that $\Omega_t^{(k)} = \Omega_t^{(k)}(\Sigma_t)$ is a function of the lower dimensional Σ_t. The smaller matrix Σ_t depends on a vector of latent factors $f_t \in \mathbb{R}^{D(D-1)/2}$ describing the transformed correlations, such that $\Sigma_t = \Sigma_t(f_t)$. The dynamics of f_t are given by the score-driven specification of Creal et al. (2013), such that the correlations adjust in an optimal way to

[9] The τ_{it}'s are not required at the estimation stage, and are constructed afterwards.

the data at every time t; see Blasques et al. (2015). The transition equation for f_t is

$$f_{t+1} = \bar{f} + A \cdot u_t + B \cdot f_t + C \cdot \text{asym}(y_t, f_t), \tag{4}$$

where $\bar{f}$ is a function of the unconditional correlations of the data and serves as a target for the level of f_t, u_t is a vector of innovation terms, A and B are scalar parameters determining the dynamics of f_t, and $\text{asym}(y_t, f_t)$ is a vector of asymmetry terms that allows for skewness in the unconditional dependence function, with corresponding scalar loading C; see Web Appendix C for more details on model specification and parameter estimation. The parameters A, B, and C need to be estimated. Our empirical application below considers nine banking sector risk indices and five SMP countries, thus $D = 14 \ll N_t(k) \approx 800$ at any t and k; see Sections 2 and 3.2. The correlation model is estimated based on weekly changes in log EDFs.

3.4 Loss-Given-Default (LGD) and Exposure-At-Default (EAD)

Portfolio risk levels depend substantially on the modeling of the loss fraction given default. We distinguish two separate cases: bank and sovereign counterparties.

Collateralized lending to banks within the Eurosystem's liquidity facilities implies a double recourse. If a bank defaults, the central bank can access the pledged collateral and sell it in the market to cover its losses. Conservatively calibrated haircuts on the market value of pledged assets ensure that a sufficient amount of collateral is almost always available to cover losses. Haircuts are higher for more volatile, longer duration, and more credit-risky claims. For example, so-called non-marketable assets carry valuation haircuts of up to 65%. As a result, historical counterparty-level LGDs have been approximately zero for most central banks.

The case of Lehman Brothers can serve as an (extreme) example. Its German subsidiary, Lehman Brothers Bankhaus, defaulted on the Eurosystem on 15 September 2008. In the weeks leading up to the default, a large quantity of mortgage-backed-securities had been posted as collateral that were highly non-liquid and non-marketable at the time. In addition, an untypically large amount of central bank liquidity had been withdrawn just prior to the default. Even so, the posted collateral was ultimately sufficient to recover all losses. The workout-LGD was zero as a result; see Bundesbank (2015).

A substantial loss to the central bank may nevertheless occur in extreme scenarios when both banks and their collateral default simultaneously. This was a valid concern during the sovereign debt crisis. A subset of banks pledged bonds issued by their domestic government, or bank bonds that were eligible only because they were also government-guaranteed. This exposed the central bank to substantial "wrong way risk," as bank and sovereign risks are highly positively dependent in the data.

We incorporate the above observations as follows. For a bank counterparty i, we model LGD stochastically as

$$\mathrm{LGD}_{i,t+1:t+52} = 0.02 + 0.58 \cdot 1\left\{\tilde{y}_{jt} < \tau_{jt} \text{ for at least one SMP country } j\right\}. \tag{5}$$

i.e., $\mathrm{LGD}_{i,t+1:t+52} = 0.02$ if bank counterparty i defaults but no SMP counterparty defaults. The 2% value for bank workout LGDs is not unrealistically low, as explained above. The LGD increases to 60% if bank i defaults and at least one SMP sovereign defaults as well (in the same simulation).[10] The 60% value reflects the conservative assumption that a sovereign credit event could be associated with significant spillovers across all euro area banks and sovereigns, leading to an impaired market value for all posted collateral.[11] The 60% stressed LGD is furthermore approximately in line with international evidence on government bond haircuts (Cruces and Trebesch (2013, Table 1)), Moody's (2018, p. 8)'s long-horizon LGD estimates for senior unsecured bonds, and the Foundation-IRB approach as referred to in the E.U.'s CRR (2013).

In case of a sovereign counterparty, e.g., for government bonds acquired within the SMP,

[10] The multivariate model allows the defaults of banks and sovereigns to be positively correlated. As a result, the adverse feedback loop between banks and sovereigns does not just work through 5.

[11] Web Appendix E.2 explores what happens to portfolio credit risk if a less conservative LGD specification is adopted. While the multivariate risk model is nonlinear in parameters, its implied EL and ES99% estimates *are* linear in LGD; see (1).

only a single recourse applies. We set the LGD to 60% should such a default be observed,

$$\text{LGD}_{j,t+1:t+52} = 0.60 \cdot 1\left\{\tilde{y}_{jt} < \tau_{jt} \text{ for SMP country } j\right\}. \tag{6}$$

More elaborate specifications for LGD are clearly also possible. The present approach, however, is parsimonious and conservative, while still sufficiently flexible to capture the issues of systematic variation of LGDs with defaults as well as wrong-way risk between banks and sovereigns.

Exposures-at-default $\text{EAD}_{i,t+1:t+52}(k)$ in (1) can, but do not have to, coincide with currently observed exposure $\text{EXP}_{it}(k)$. Recall that in the case of Lehman Brothers Bankhaus, exposures increased substantially in the weeks prior to the observed default. Similarly, the OMT would likely be activated in extremely bad states of the world. To keep things simple and interpretable, however, we set $\text{EAD}_{i,t+1:t+52}(k) = \text{EXP}_{it}(k)$, also in line with the static balance sheet assumption in Section 3.1. We refer to Web Appendix C for further details.

4 Empirical results

Our empirical study is structured around five interrelated questions. What were the relevant portfolio credit risks associated with each Eurosystem unconventional monetary policy operation during the sovereign debt crisis? How important were risk spillovers across different monetary policy operations? Were the tail risks at all times covered by financial buffers? To what extent did unconventional policies differ in terms of ex-post risk efficiency? Finally, do other central banks' policy announcements materially affect the Eurosystem's risks?

4.1 Model specification

For model selection, we are most interested in whether non-Gaussian dependence as well as the asymmetry term in (4) are preferred by the data. Table 1 reports parameter estimates for three different specifications of the copula model (3)–(4). The model parameters are estimated from $D = 9+5 = 14$ multivariate time series of daily log changes in banking sector

Table 1: Parameter estimates

Parameter estimates for the copula model (3)–(4) fitted to weekly log changes in $D = 14$ banking sector and sovereign EDFs between 03 October 2008 and 11 March 2016 ($T = 389$). The same univariate models are used; see Web Appendix C. The first model specification enforces a multivariate Gaussian copula by setting $C = 0$ and $\nu^{-1} = 0$. The second and third specifications refer to a symmetric and asymmetric t copula, respectively. Standard errors in parentheses are constructed from the numerical second derivatives of the log-likelihood function.

	Gaussian copula	Student's t copula	
		symmetric ($C = 0$)	asymmetric ($C \neq 0$)
A	0.007	0.007	0.008
	(0.003)	(0.003)	(0.002)
B	0.864	0.953	0.969
	(0.082)	(0.034)	(0.013)
C	-	-	-0.555
	-	-	(0.206)
ν	-	11.964	11.970
	-	(0.991)	(0.982)
logLik	1487.61	1629.49	1631.83
AICc	-2969.2	-3251.0	-3253.6

and sovereign EDFs. Univariate Student's t models with time-varying volatility and leverage are used to model the marginal dynamics for each series separately; see Web Appendix C.

Gaussian dependence is a special case of our model, with $\nu^{-1} = 0$ and $C = 0$. This joint restriction, however, is strongly rejected by the data in a likelihood-ratio test.[12] Turning to the two t copula specifications, allowing for an asymmetric response of the correlation factors is preferred by the data based on the log-likelihood fit and information criteria. The increase in log-likelihood is significant at the 5% level. This model choice has an economically small effect on the expected shortfall estimates, and almost no effect on the mean loss estimates. The degree-of-freedom parameter $\nu \approx 12$ allows for a moderate degree of joint tail dependence in the copula.[13] Parameter $C < 0$ implies that correlations *increase* more quickly in bad times than they decrease in good times.[14] Experimenting with block-specific C parameters did not lead to significantly improved log-likelihoods. We select the asymmetric t copula

[12]Web Appendix E.1 presents and discusses EL and ES99% estimates based on the simpler Gaussian model.

[13]The degree-of-freedom parameters ν for the marginal univariate models are substantially lower, and vary between approximately three and eight; see Web Appendix D. The Web Appendix further reports diagnostic checks for all D marginal models. The diagnostic checks are in line with the substantial increase in log-likelihood fit when moving from Gaussian to Student's t models.

[14]This is related to the use of polar coordinates (cosines) when mapping f_t into Σ_t; see Web Appendix C.

specification for the remainder of the analysis based on likelihood fit and information criteria. Using this specification, we combine model parsimony with the ability to explore a rich set of questions given the data at hand.

4.2 Expected shortfall

A large number of studies focus on the beneficial impact of Eurosystem unconventional monetary policies during the euro area sovereign debt crisis on financial markets and macroeconomic outcomes, including Eser and Schwaab (2016), Ghysels et al. (2017), Krishnamurthy et al. (2018), Fratzscher and Rieth (2018), De Pooter et al. (2018), among many others. By contrast, the risk implications and potential downsides of unconventional policies have received less attention.

Figure 4 plots estimated one-year-ahead ES99% from Eurosystem collateralized lending operations (top panel) and SMP asset purchases (bottom panel). Portfolio-specific estimates are (sub)additive across operations, and stacked vertically in the top panel of Figure 4. The loss density is obtained by simulation, using 200,000 draws at each time t; see Web Appendix C.6 for details. For each simulation, we keep track of exceedances of $\tilde{y}_{it}$ below their respective calibrated thresholds at time t as well as the outcomes for LGD and EAD, as described in Section 3. The risk estimates combine all exposure data, marginal risks, as well as all 14(14-1)/2=91 time-varying correlation estimates into a single time series per operation.

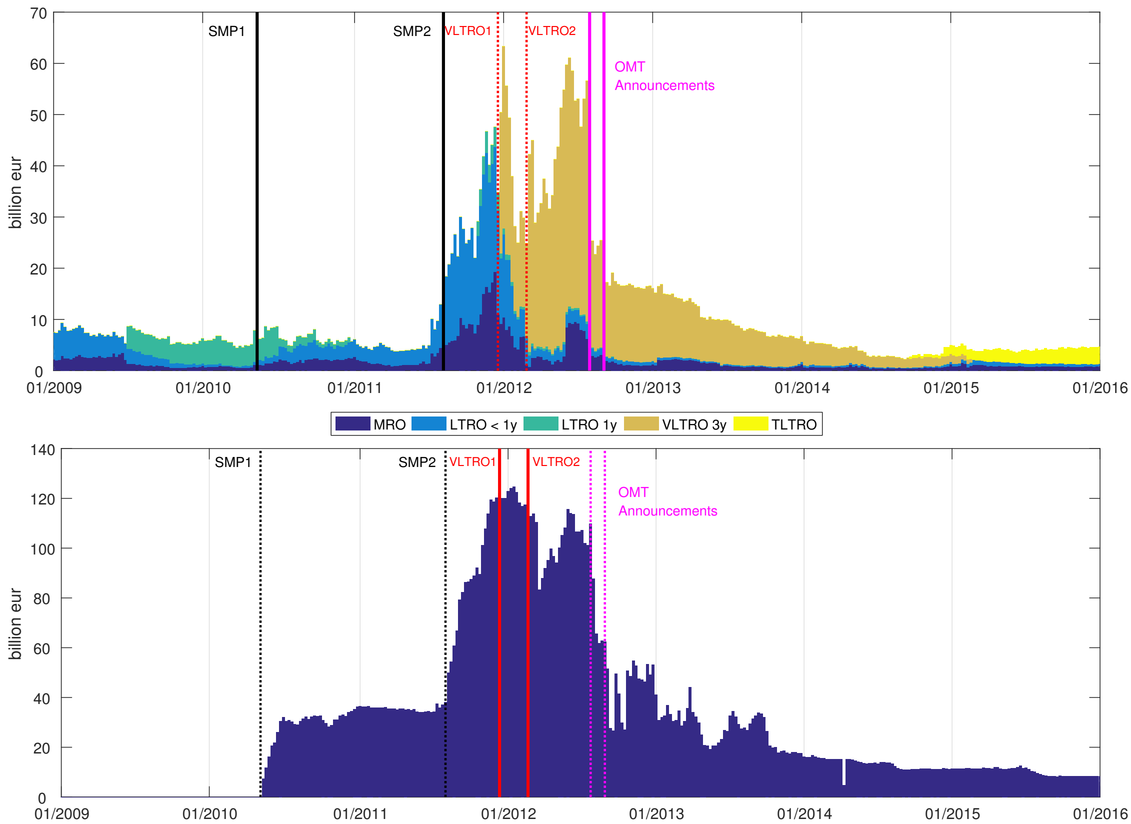
The ES99% estimates in Figure 4 exhibit pronounced time series variation, peaking in 2012 at approximately €60 bn for the collateralized lending operations and at approximately €120 bn for the SMP portfolio. All portfolio tail risks collapse sharply following the OMT announcements.[15]

Figure 5 provides the ES99% scaled per €1. The changes in portfolio credit risks around key policy dates can be decomposed into a risk (PD and correlation) component and an exposure component. Figure 5 suggests that the risk component is the main driver. For

[15]To the extent that redenomination risk is priced in sovereign CDS contracts, redenomination risk is a part of the portfolio credit risks as plotted in Figures 4 and 5. Redenomination risk is most likely relevant for the SMP portfolio; the collateralized lending portfolios may be sensitive to redenomination risk via the LGD specification (5).

Figure 4: ES99% for collateralized lending and SMP portfolios

Top panel: ES99% in €bn for five Eurosystem collateralized lending operations. Bottom panel: ES99% for SMP asset portfolio. Six vertical lines mark the events described in Section 2. Data is weekly between 2009 and 2015.

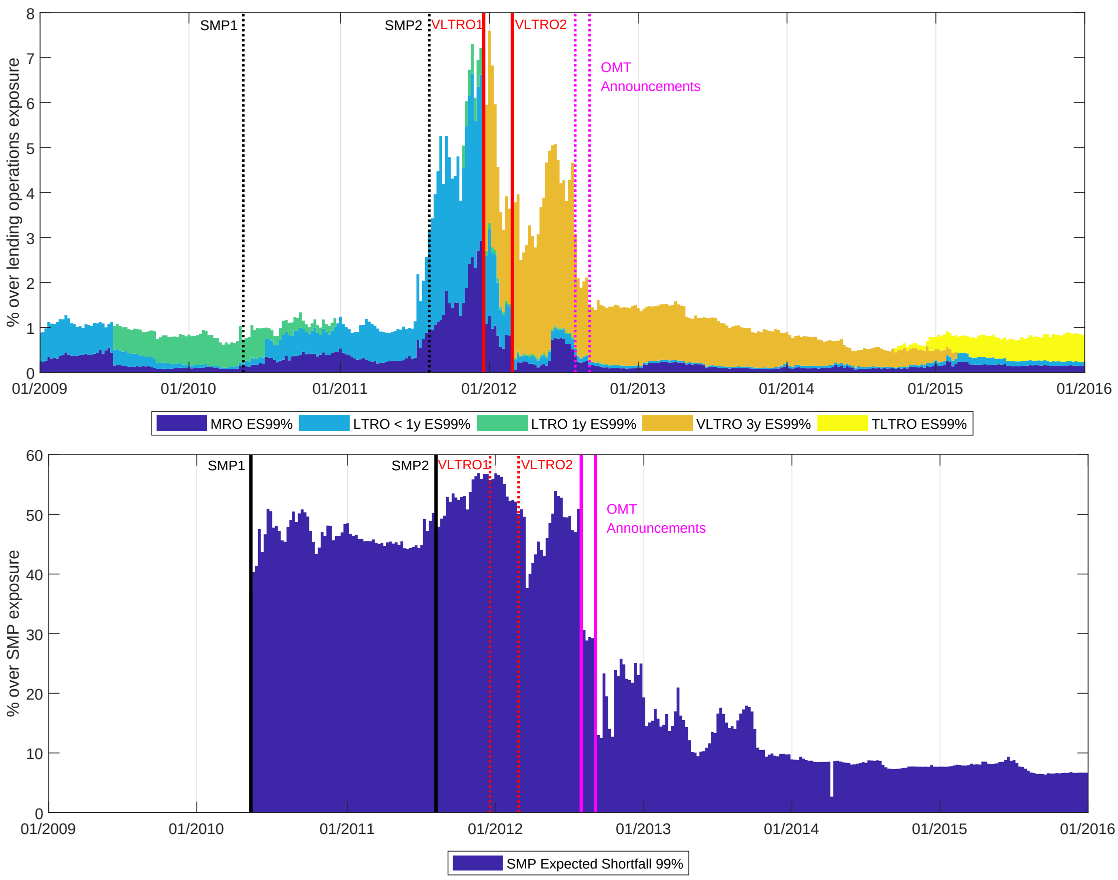


example, the ES99% decreases from approximately 55 cent per €1 of SMP exposures before the allotment of the first VLTRO to less than 40 cent following the allotment of the second VLTRO. As another example, the ES99% collapses from approximately 50 cent per €1 of SMP exposures before the OMT announcements in mid-2012 to less than 20 cent per €1 afterwards. Regarding collateralized lending, the ES99% decreases from approximately 4.5 cent per €1 of exposures before the OMT announcements to less than 2 cents following the second announcement.

When comparing the top and bottom panels of Figure 5, portfolio risk per €1 of exposure differs by approximately one order of magnitude. The risk differential between collateralized lending and outright holdings is even more pronounced at the center of the loss distribution;

Figure 5: ES99% in percent of exposures

Top panel: ES99% for five collateralized lending portfolios in percent of total collateralized exposures, stacked vertically. Bottom panel: ES99% for SMP assets in percent of total nominal (par) value. The vertical lines mark the events described in Section 2. Data is weekly between 2009 and 2015.



see Web Appendix F. Such pronounced differences in portfolio risk may be relevant for the decision whether to provide additional central bank liquidity via collateralized lending operations or via outright asset purchases. Implementing monetary policy via credit operations could be preferable in settings when the respective economic benefits are comparable.

Finally, Figures 4 and Figures 5 strongly hint at the presence of beneficial spillovers across monetary policy operations. For example, the OMT announcements had a pronounced impact on the ES99% associated with the collateralized lending and the SMP asset portfolios. As another example, the weeks around the first VLTRO allotment coincide with peak SMP ES99% in percent of exposures.

4.3 Financial buffers

This section studies whether the Eurosystem was at all times sufficiently able to withstand the materialization of a 99% ES-sized credit loss.

For a commercial bank, financial buffers against a large portfolio loss typically include accounting items such as the current year's projected annual income, revaluation reserves in the balance sheet, general risk provisions, and paid-in equity capital. We adopt a similar notion of financial buffers for the Eurosystem. We recall, however, that a central bank is never liquidity constrained in the currency they issue, so that the notion of solvency buffers is much less appropriate.

Since the financial crisis in 2008, the Eurosystem as a whole has built up relatively large financial buffers, including from part of the stream of seignorage revenues generated by banknote issuance. Those buffers are mainly in the form of capital and reserves (i.e., paid-up capital, legal reserves and other reserves), revaluation accounts (i.e., unrealized gains on certain assets like gold) and risk provisions. These items stood at €88 bn, €407 bn and €57 bn, respectively, at the end of 2012; see ECB (2013, p. 44). The overall financial buffers therefore stood at €552 bn. Comparing these balance sheet items with our ES estimates in Figure 4 we conclude that the Eurosystem's aggregate buffers were at all times sufficient to withstand an ES99%-sized credit loss, even at the mid-2012 peak of the euro area sovereign debt crisis.

4.4 Risk spillovers across policy operations

The credit risk of the Eurosystem's balance sheet depends on the financial health of its counterparties, which in turn depends on expectations about the central bank's liquidity provision to and asset purchases from those same counterparties. This interdependence can give rise to a pronounced nonlinearity in the central bank balance sheet risks, e.g. as the economy switches from a 'bad' equilibrium to a 'good' one; see e.g. Calvo (1988), Reis (2013), and ECB (2014). This section studies how a central bank's credit risk respond to the announcement (and subsequent implementation) of unconventional monetary policies.

Table 2: Portfolio credit risks around six key policy announcements, I/II

Portfolio credit risks for different monetary policy operations around six policy announcements: the SMP announcement on 10 May 2010, the cross-sectional extension of the SMP on 08 August 2011, and the allocation of the first VLTRO on 20 December 2011. Square brackets [] contain 99% confidence intervals obtained from 200,000 simulation runs. Web Appendix G presents the analogous results in percent of the respective exposures. The table continues on the next page.

SMP1	07/05/2010		14/05/2010			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	0.0	0.0	0.3	7.3	0.3	7.3
	[0.0 0.0]	[0.0 0.0]	[0.3 0.3]	[7.3 7.4]		
MRO	0.0	1.1	0.0	1.0	0.0	-0.1
	[0.0 0.0]	[0.9 1.2]	[0.0 0.0]	[0.8 1.0]		
LTRO<1y	0.0	0.6	0.0	0.5	-0.0	-0.1
	[0.0 0.0]	[0.5 0.7]	[0.0 0.0]	[0.5 0.6]		
LTRO1y	0.2	6.2	0.2	4.1	-0.0	-2.1
	[0.2 0.2]	[5.1 6.4]	[0.2 0.2]	[4.1 4.7]		
Total	0.2	7.9	0.5	13.0	0.3	5.1

SMP2	05/08/2011		12/08/2011			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	5.2	38.0	6.7	49.9	1.5	11.9
	[5.2 5.2]	[37.7 38.2]	[6.7 6.8]	[49.3 50.1]		
MRO	0.1	4.5	0.1	4.8	0.0	0.4
	[0.1 0.1]	[4.0 4.8]	[0.1 0.1]	[4.2 5.5]		
LTRO<1y	0.2	8.5	0.3	10.9	0.0	2.4
	[0.2 0.2]	[7.0 9.2]	[0.2 0.3]	[9.0 11.1]		
Total	5.5	51.0	7.1	65.6	1.5	14.7

VLTRO1	16/12/2011		30/12/2011			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	26.8	122.2	25.3	120.1	-1.5	-2.1
	[26.7 26.9]	[121.9 122.5]	[25.3 25.4]	[119.4 120.4]		
MRO	0.3	19.3	0.2	9.1	-0.1	-10.2
	[0.3 0.3]	[17.7 21.3]	[0.2 0.2]	[8.5 10.0]		
LTRO<1y	0.5	24.4	0.3	12.8	-0.2	-11.5
	[0.5 0.5]	[21.3 24.7]	[0.3 0.3]	[12.0 13.6]		
LTRO1y	0.1	3.9	0.0	1.0	-0.0	-2.9
	[0.1 0.1]	[3.5 4.1]	[0.0 0.0]	[0.9 1.0]		
VLTRO3y	0.0	0.0	0.5	27.6	0.5	27.6
	[0.0 0.0]	[0.0 0.0]	[0.4 0.5]	[26.0 28.8]		
Total	27.7	169.8	26.3	170.6	-1.4	0.8

The high (weekly) frequency of the risk estimates plotted in Figures F.1 and 4 allow us to identify the impact of certain key ECB policy announcements. Table 2 presents standard portfolio risk estimates shortly before and after six key policy announcements.

We obtain the following main findings. First, LOLR- and IOLR-implied credit risks are usually negatively related in our sample. Taking risk in one part of the central bank's balance

Table 2: Portfolio credit risks around six key policy announcements, II/II

Portfolio credit risks for different monetary policy operations around six policy announcements (continued): the allocation of the second VLTRO on 20 February 2012, the OMT announcement on 02 August 2012, and the announcement of the OMT's technical details on 06 September 2012. Square brackets [] contain 99% confidence intervals obtained from 200,000 simulation runs. Web Appendix G presents the analogous results in percent of the respective exposures.

VLTRO2	24/02/2012		09/03/2012			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	30.2	117.2	30.2	113.9	0.0	-3.3
	[30.1 30.2]	[116.1 118.3]	[30.2 30.3]	[112.2 114.5]		
MRO	0.2	6.7	0.0	0.7	-0.1	-6.0
	[0.1 0.2]	[6.5 7.2]	[0.0 0.0]	[0.7 0.8]		
LTRO<1y	0.1	5.2	0.1	2.3	-0.1	-2.9
	[0.1 0.1]	[4.6 5.4]	[0.1 0.1]	[2.0 2.4]		
LTRO1y	0.0	0.5	0.0	0.6	0.0	0.1
	[0.0 0.0]	[0.5 0.6]	[0.0 0.0]	[0.5 0.6]		
VLTRO3y	0.3	17.3	0.6	38.6	0.3	21.3
	[0.3 0.3]	[15.1 19.0]	[0.6 0.6]	[34.1 39.3]		
Total	30.8	147.0	31.0	156.1	0.2	9.1

OMT1	27/07/2012		03/08/2012			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	21.5	109.8	19.8	87.8	-1.7	-22.0
	[21.4 21.5]	[107.9 110.4]	[19.8 19.9]	[85.8 88.6]		
MRO	0.2	6.2	0.2	4.5	-0.0	-1.8
	[0.2 0.2]	[5.4 6.7]	[0.2 0.2]	[3.9 4.7]		
LTRO<1y	0.1	2.9	0.1	1.9	-0.0	-1.1
	[0.1 0.1]	[2.7 3.5]	[0.1 0.1]	[1.9 2.4]		
LTRO1y	0.0	0.4	0.0	0.3	-0.0	-0.1
	[0.0 0.0]	[0.4 0.4]	[0.0 0.0]	[0.3 0.3]		
VLTRO3y	1.0	47.0	0.8	30.5	-0.2	-16.5
	[0.9 1.0]	[38.3 47.7]	[0.8 0.8]	[29.4 33.8]		
Total	22.8	166.4	20.9	125.0	-1.9	-41.4

OMT2	31/08/2012		07/09/2012			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	15.8	62.4	14.5	51.5	-1.3	-10.8
	[15.7 15.8]	[61.0 63.0]	[14.4 14.5]	[51.1 52.5]		
MRO	0.2	3.1	0.1	2.0	-0.0	-1.1
	[0.2 0.2]	[2.4 2.9]	[0.1 0.1]	[1.8 2.1]		
LTRO<1y	0.0	1.3	0.0	1.0	-0.0	-0.3
	[0.0 0.1]	[1.1 1.4]	[0.0 0.0]	[0.9 1.1]		
LTRO1y	0.0	0.2	0.0	0.2	-0.0	-0.1
	[0.0 0.0]	[0.2 0.2]	[0.0 0.0]	[0.1 0.2]		
VLTRO3y	0.7	20.9	0.5	15.0	-0.1	-5.9
	[0.6 0.7]	[18.7 21.7]	[0.5 0.6]	[14.7 16.2]		
Total	16.6	87.8	15.2	69.7	-1.5	-18.1

sheet (e.g., the announcement of SMP asset purchases in May 2010) tended to de-risk other positions (e.g., collateralized lending from previous LTROs, by approximately €2.2 bn). Vice versa, the allotment of the two large-scale VLTRO credit operations each decreased the expected shortfall of the SMP asset portfolio (by €2.1 bn and €3.3 bn, respectively). This negative relationship strongly suggests that central bank risks can be nonlinear (concave) in exposures. The increase in balance sheet size increased overall credit risk less than proportionally, and by less than one would have expected at unchanged PD and risk dependence parameters. As a result, increasing balance sheet size during a financial crisis is unlikely to increase risk by as much as one would expect from linearly scaling up current portfolio risks with future exposures. Similarly, in the context of ultimately unwinding balance sheet positions, reducing the size of the balance sheet after the crisis may not reduce total risk by as much as one would expect from linear scaling. Arguably, the documented risk spillovers call for a measured approach towards reducing balance sheet size after the crisis has passed.

Second, a subset of unconventional monetary policies reduced (rather than added to) overall balance sheet risk. For example, the first OMT announcement de-risked the Eurosystem's balance sheet by €41.4 bn (99%-ES). The announcement of OMT technical details on 06 September 2012 was also associated with a strong further reduction of €18.1 bn in 99% ES. As another example, the allotment of the first VLTRO in December 2011 raised the 99% ES associated with VLTRO lending from zero to approximately €27.6 bn. However, it also sharply reduced the need for shorter-term MRO and LTRO funding, reducing exposures for these portfolios. In addition, financial sector point-in-time PDs declined as banks were awash in cash following the first VLTRO allotment. Finally, and importantly, the VLTRO allotment also de-risked the SMP asset portfolio, as banks funneled some of the additional liquidity into government bonds (Acharya and Steffen (2015), Drechsler et al. (2016)), alleviating stressed sovereigns' funding stress. As a result, the overall 99% ES increased, but only minimally so, by €0.8 bn. Expected losses declined by €1.4 bn. We conclude that, in extreme conditions, a central bank can de-risk its balance sheet by doing *more*.

Such risk reductions are not guaranteed, however. In particular the SMP2 announcement is an exception to the patterns described above; see Table 2. The extension of the program to include Spain and Italy in August 2011 did not reduce the credit risks inherent in the collateralized lending book. It also did not lead to a reduction in total risk. This exception is probably related to the pronounced controversy regarding the extension of the SMP at that time. The controversy as well as the related communication challenges may have caused market participants to doubt that the SMP would be large and active for long, thus lessening its economic and risk impact.

Third, portfolio risk estimates as reported in Figures 4 and 5 are a prerequisite for evaluating policy operations in terms of their "risk efficiency." Risk efficiency is the principle that a certain amount of expected policy impact should be achieved with a minimum level of balance sheet risk; see e.g. ECB (2015). Put differently, the impact of any policy operation should be maximal given a certain level of risk. Given an estimate of policy impact, such as, for example, a change in inflation swap rates or in bond yields around the time of a policy announcement, and given an estimate of additional risk, such as, for example, a change in expected shortfall, different policy operations can be evaluated by scaling the former by the latter. Web Appendix H reports our respective findings. To summarize, we find that the first round of SMP purchases in 2010 was more risk efficient than the second round following the SMP's extension to include Italy and Spain in 2011. The first VLTRO allotment was more risk efficient than its second allotment. The OMT program was particularly risk efficient ex-post.

Finally, monetary policy-related announcements of *other* central banks could in principle spill over and affect the Eurosystem's risks via an impact on its counterparties. For example, the Federal Reserve's announcement to 'taper off' asset purchases in May 2013, or the announcement by the Swiss National Bank to unpeg the Swiss Franc from the Euro in January 2015, could have had a discernible impact on the Eurosystem's portfolio credit risks via an impact on the euro area financial sector or its risk correlations with sovereigns. We do not find economically large effects when studying a small but relevant set of such announcements; see Web Appendix I for details.

5 Conclusion

We introduced a tractable framework to measure central bank balance sheet risks at a high frequency and applied it to all major Eurosystem unconventional monetary policy operations during the euro area sovereign debt crisis between 2010 and 2012. Our results suggest that central banks can influence their credit risks, particularly when they act as lenders- and investors-of-last-resort during turbulent times. They can use this to their advantage when implementing monetary policy in a risk-efficient way. For instance, though increasing the amount of central bank liquidity in the financial system for monetary policy purposes can be achieved via both credit operations and asset purchases, we find that collateralized credit operations imply substantially less credit risks per unit of liquidity provision, often by an order of magnitude. In short, our findings that central banks can influence their own credit risks in turbulent times give some, albeit not complete, support to Bagehot's famous conjecture that occasionally "only the brave plan is the safe plan."

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Web Appendix to Risk endogeneity at the lender/investor-of-last-resort*

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Contents

A Details on Eurosystem unconventional policies

The remainder of this section briefly reviews the SMP, the VLTROs, and the OMT programs. Each of these had a substantial impact on asset prices, point-in-time credit risks, and time-varying risk correlations; see ECB (2014) for a survey.

The SMP

The SMP was announced on 10 May 2010, with the objective to help restoring the monetary policy transmission mechanism by addressing the malfunctioning of certain government bond markets. The SMP consisted of interventions in the form of outright purchases which were aimed at improving the functioning of these bond markets by providing "depth and liquidity;" see González-Páramo (2011). Implicit in the notion of market malfunctioning is the notion that government bond yields can be unjustifiably high and volatile. For example, market-malfunctioning can reflect the over-pricing of risk due to illiquidity as well as contagion across countries; see Constâncio (2011).

SMP interventions occurred in government debt securities markets between 2010 and 2012 and initially focused on Greece, Ireland, and Portugal. The SMP was extended to include Spain and Italy on 08 August 2011. Approximately €214 billion (bn) of bonds were acquired between 2010 and early 2012; see ECB (2013a). The SMP's weekly cross-country breakdown of the purchase data is confidential at the time of writing. The Eurosystem, however, released the total cross-country SMP portfolio holdings as of the end of 2012 in its 2013 Annual Report. At that time, the Eurosystem held approximately €99.0bn in Italian government bonds, €30.8bn in Greek debt, €43.7bn in Spanish debt, €21.6bn in Portuguese debt, and €13.6bn in Irish bonds; see ECB (2013a). For impact assessments of SMP purchases on bond yields, CDS spreads, and liquidity risk premia see e.g. Eser and Schwaab (2016), Ghysels et al. (2017), and De Pooter et al. (2018).

The VLTROs

Two large-scale VLTROs were announced on 08 December 2011, and subsequently allotted to banks on 21 December 2011 and 29 February 2012. The first installment provided more than 500 banks with €489 bn at a low (1%) interest rate for the exceptionally long period of three years. The second installment in 2012 was even larger, and provided more than 800 euro area banks with €530 billion in three-year low-interest loans. By loading up on VLTRO funds stressed banks could make sure they had enough cash to pay off their own maturing debts, keep operating, and keep lending to the non-financial sector. Incidentally, banks used some of the money to also load up on domestic government bonds, temporarily bringing down sovereign yields. This eased the debt crisis, but may also have affected the bank-sovereign nexus (risk dependence) at the time; see e.g. Acharya and Steffen (2015).

The OMT

On 26 July 2012, the president of the ECB pledged to do "whatever it takes" to preserve the euro, and that "it will be enough." The announcement of Outright Monetary Transactions (OMT), a new conditional asset purchase program, followed shortly afterwards on 02 August; see ECB (2012). The OMT technical details were announced on 06 September 2012. The details clarified that the OMT replaced the SMP, and that, within the OMT, the ECB could potentially undertake purchases ("outright transactions") in secondary euro area government bond markets provided certain conditions were met. OMT interventions were stipulated to be potentially limitless, to focus on short-maturity bonds, and to be conditional on the bond-issuing countries agreeing to and complying with certain domestic economic measures determined by euro area heads of state. In the years since its inception, the OMT never had to be used. Nevertheless, its announcement is widely credited for ending the acute phase of the sovereign debt crisis by restoring confidence; see e.g. Wessel (2013) and ECB (2014).

B CDS-implied sovereign EDFs

Firm-value based EDF measures are unavailable for euro area sovereigns. We therefore infer physical PDs from observed sovereign CDS spreads. This section provides details on how we construct CDS-implied-EDFs for euro area sovereigns.

We proceed in four steps. First, we invert the CDS pricing formula of O'Kane (2008) to obtain risk-neutral default intensities (hazard rates). We do this at each point in time for multiple CDS contracts referencing different maturities. Second, we convert the risk-neutral intensities into physical ones using the nonlinear mapping fitted by Heynderickx et al. (2016). The nonlinear mapping accounts for the fact that risk premia are a function of physical risk. Third, we fit a Nelson and Siegel (1987) curve to the term structure of physical default hazard rates. Two intuitive constraints ensure robust results. Finally, we obtain one-year ahead CDS-implied-EDFs as an integral over the [0,1]-year interval.

Step 1

We consider CDS spreads referencing euro area sovereign i at six different maturities: 1, 2, 3, 4, 5, and 10 years. CDS spreads are obtained from CMA via the ECB's Statistical Data Warehouse. The swap contracts are denominated in USD and are subject to a full-restructuring credit event clause. We convert the CDS spreads into risk-neutral default hazard rates λ_{it}^{Q} using the procedure described in O'Kane (2008). For this procedure to work we need to make some empirical choices. First, we fix a recovery rate at default at a stressed level of 40% for all countries. This is in line with our LGD modeling assumption in Section 3.4. Second, the term structure of discount rates is assumed to be flat at the one year EURIBOR rate. A numerical solver is then used to find the unique default intensity λ_{it}^{Q} that matches the expected present value of payments within the premium leg to the expected present value of payments within the default leg of the CDS contract.

Step 2

We next convert the risk neutral default intensities λ_{it}^{Q} into physical default intensities λ_{it}^{P}. We do so based on the functional form suggested and fitted in Heynderickx et al. (2016). This approach postulates two non-linear regimes between λ_{it}^{Q} and λ_{it}^{P},

$$\log\left(\frac{\lambda^{Q}}{\lambda^{P}}\right) = a_1 + b_1 \log\left(\lambda^{P}\right) \tag{B.1}$$

$$\log\left(\frac{\lambda^{Q}}{\lambda^{P}}\right) = a_2 \left(\lambda^{P}\right)^{b_2} \tag{B.2}$$

where we have dropped subscripts i and t for ease of reading. For small λ^{P} and λ^{Q}, (B.1) ensures that $\lambda^{P} \to 0$ as $\lambda^{Q} \to 0$. For large λ^{P} and λ^{Q}, (B.2) ensures that $\lambda^{P} = \lambda^{Q}$ in the limit of large λ^{Q}. The value of λ^{Q} at which the curves cross is a function of parameters a_1, b_1, a_2 and b_2. We use (B.1) for λ^{Q} to the left of the crossover point, and (B.2) to the right. The global parameters reported in Heynderickx et al. (2016) are $a_1 = 3.65, b_1 = -0.51, a_2 = 4.16$, and $b_2 = -0.26$, where λ^{Q} and λ^{P} are measured in inverse-years.

Step 3

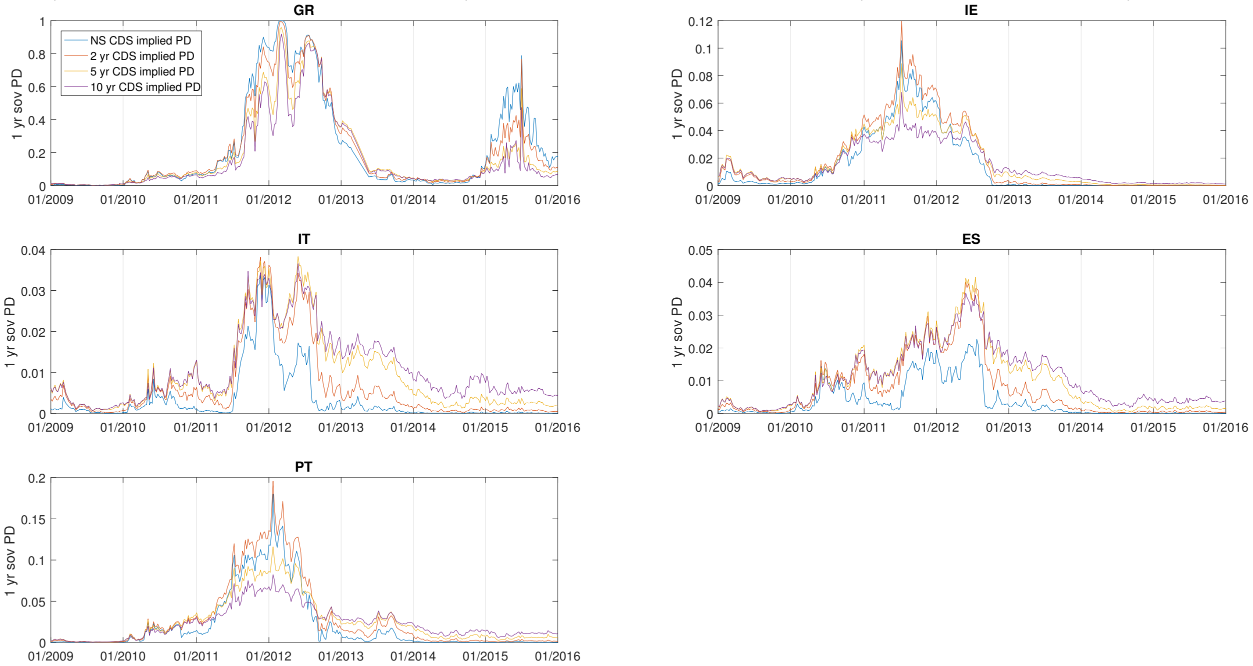
We fit a Nelson and Siegel (1987) curve to the term structure of physical hazard rates $\lambda_{\mathrm{NS};it}^{P}(\tau)$. This allows us to extract information from CDS spreads referencing a whole range of different maturities. By combining the information from multiple CDS spreads for the same reference entity on the same day we average out maturity-specific measurement errors that could be related to e.g. different levels of market (il)liquidity or other financial frictions. A new curve is fitted to obligor i at each time t,

$$\lambda_{\mathrm{NS}}^{P}(\tau) = \beta_0 + \beta_1 \tilde{\tau}^{-1}\left(1 - \exp\left(-\tilde{\tau}\right)\right) + \beta_2\left[\tilde{\tau}^{-1}\left(1 - \exp\left(-\tilde{\tau}\right)\right) - \exp\left(-\tilde{\tau}\right)\right], \tag{B.3}$$

where $\tilde{\tau} = \tau/T$ and where we dropped the i and t subscripts from τ. To ensure stable outcomes we impose two additional constraints, $\lambda_{\mathrm{NS}}^{P}(\tau)\big|_{\tau=0} \geq 0$ and $\frac{\partial \lambda_{\mathrm{NS}}^{P}(\tau)}{\partial \tau}\Big|_{\tau=0} = 0$. The

Figure B.1: CDS-implied-EDFs for five sovereigns

One-year-ahead CDS-implied-EDFs, plotted in blue. For comparison we show in red, yellow, and purple one-year-ahead EDFs if one were to only use CDS spreads of 2, 5 and 10 year tenors, respectively.



first constraint requires the instantaneous hazard rate to be non-negative at all times. This is intuitive. The second constraint requires the curve to be upwards-sloping at zero. This rules out negative default hazard rates at the short end of the term structure.

We use a standard solver to obtain parameter estimates for β_j for $j = 1, 2, 3$ in B.3 over a range of maturities T. The solver picks the set of $\{\beta_j, T\}$ that minimizes the least squares difference between λ^P_{it} and $\lambda^P_{\text{NS};it}$.

Step 4

Given the fitted curve, we can predict forward-looking physical default probabilities $\text{PD}^P_{it}(\tau)$. Such probabilities can be computed for any obligor i at time t for any given time horizon τ. For example, the one-year-ahead CDS-implied-EDF for i at time t is given by

$$\text{PD}^P_i(\tau = 1) = 1 - \exp\left(-\int_0^{\tau=1} \lambda^P_{\text{NS};it}(s)\text{d}s\right). \tag{B.4}$$

Figure B.1 plots the estimated one-year-ahead EDF for the five SMP countries. As a sanity check, we benchmark our estimates to three alternative EDFs. These alternative EDFs are extracted from only a single CDS contract at the 2, 5, and 10 year maturity, respectively, using a simpler procedure. Our baseline one-year-ahead EDF measure corresponds most closely to the 2-year EDF estimate. The term structure of default hazard rates is usually upward sloping. For example, the blue curve is below the other three curves in the Italian or Spanish EDF panels. Occasionally, however, the term structure of default hazard rates is inverted, such as e.g. for Greece during the peak of the crisis.

C The statistical model

C.1 Univariate modeling

Our univariate marginal modeling strategy is identical to the one used in Lucas et al. (2017). We restate it here for convenience.

To introduce time-variation into our empirical model specification we endow our model with observation-driven dynamics based on the score of the conditional predictive log-density. Score-driven time-varying parameter models are an active area of recent research, see for example Creal et al. (2011, 2013), Harvey (2013), Creal et al. (2014), Harvey and Luati (2014), Massacci (2016), Oh and Patton (2018), Lucas et al. (2018), and many more.[1] For an information theoretical motivation for the use of score-driven models, see Blasques et al. (2015), and for a forecasting perspective Koopman et al. (2016).

The parameters of the univariate dynamic Student's t models are estimated from log-changes in country i-specific banking sector EDFs. For sovereigns, we use log-changes in the CDS-implied-EDFs obtained as described in Web Appendix B. Parameter estimates are obtained by the method of maximum likelihood. The univariate models allow us to transform the observations into their probability integral transforms $\hat{u}_{it} \in [0, 1]$ based on parameter estimates for σ_{it} and ν_i. The univariate t density is given by

$$p(y_t; \sigma_t^2, \nu) = \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu/2)\sqrt{(\nu-2)\pi\sigma_t^2}} \cdot \left(1 + \frac{y_t^2}{(\nu-2)\sigma_t^2}\right)^{-\frac{\nu+1}{2}}, \tag{C.1}$$

where σ_t is chosen as $\sigma_t = \sigma(f_t) = \exp(f_t)$.

We include an asymmetry term also in the univariate volatility dynamics. We do so by defining a term that takes nonzero values whenever marginal risks increase, i.e., $y_t > 0$. The transition equation is given by

$$f_{t+1} = \tilde{\omega} + As_t + Bf_t + C(s_t - s_t^0)1\{y_t > 0\}, \tag{C.2}$$

[1] We refer to http://www.gasmodel.com for an extensive enumeration of recent work in this area.

where

$$
\begin{aligned}
s_t &= \mathcal{S}_t \nabla_t, \quad \nabla_t = \partial \log p(y_t | \mathcal{F}_{t-1}; f_t, \theta)/\partial f_t, \\
s_t^0 &= \mathcal{S}_t \nabla_t^0, \quad \nabla_t^0 = \nabla_t|_{y_t=0}, \\
\mathcal{S}_t &= \frac{\nu+3}{2\nu}, \\
\nabla_t &= \frac{(\nu+1)y_t^2}{(\nu-2)\sigma_t^2 + y_t^2} - 1.
\end{aligned}
$$

and where $\tilde{\omega}$, A, B, C, and ν are parameters to be estimated. Taken together, (C.1) and (C.2) can accommodate an asymmetric volatility response as well as skewness in the unconditional distribution of y_t.

C.2 The multivariate model

Our multivariate modeling strategy presented here is closely related to the approach developed in Creal et al. (2011) and extended in Lucas et al. (2014). We estimate the parameters of the multivariate dynamic t copula model using the pseudo-observations $\hat{u}_{it} \in [0, 1]$ from on the marginal univariate models as inputs. These pseudo-observations are later transformed to t distributed random variables $y_t = F^{-1}(\hat{u}_t; \nu)$.

Our model effectively applies 'market risk' methods to solve a 'credit risk' problem. Time-varying parameter models for volatility and dependence have been considered, for example, by Engle (2002), Demarta and McNeil (2005), Creal et al. (2011), Zhang et al. (2011), and Engle and Kelly (2012). At the same time, credit risk models and portfolio tail risk measures have been studied, for example, by Vasicek (1987), Lucas et al. (2001, 2003), Gordy (2000, 2003), Giesecke and Kim (2011), Koopman et al. (2012), and Giesecke et al. (2015). Our combined framework yields the best of these two worlds: portfolio credit risk measures (at, say, a one-year-ahead horizon) that are available at a market risk frequency (such as daily or weekly) for impact assessments in real time. Such frameworks are urgently needed at financial institutions, including central banks.

When modeling dependent defaults, we link default indicators using a Student's t copula function. In particular, we assume that one-year-ahead changes in log-asset values $\tilde{y}_{it}$ are generated by a high-dimensional multivariate Student's t density

$$\tilde{y}_{it} = \mu_{it} + \sqrt{\zeta_t} L_{it}^{(k)} z_t, \quad i = 1, \ldots, N_t(k), \tag{C.3}$$

where $z_t \sim \mathrm{N}(0, \mathrm{I}_{N_t(k)})$ is a vector of standard normal risk terms, $L_{it}^{(k)}$ is the ith row of $L_t^{(k)}$, $L_t^{(k)}$ is the Choleski factor of the Student's t covariance matrix $\Omega_t^{(k)} = L_t^{(k)} L_t^{(k)\prime}$, $\zeta_t \sim \mathrm{IG}(\frac{\nu}{2}, \frac{\nu}{2})$ is an inverse-gamma distributed scalar mixing variable that generates the joint fat tails, and ν is a degrees of freedom parameter that can be estimated. The covariance matrix $\Omega_t^{(k)}$ depends on k because different counterparties participate in different monetary policy operations. We can fix $\mu_{it} = 0$ in (C.3) without loss of generality since copula quantiles shift linearly with the mean.

The D-dimensional multivariate Student's t density implied by a normal-inverse gamma mixture construction such as (C.3) is given by

$$p(y_t; \Sigma_t, \nu) = \frac{\Gamma((\nu + D)/2)}{\Gamma(\nu/2)[(\nu - 2)\pi]^{D/2} |\Sigma_t|^{1/2}} \cdot \left(1 + \frac{y_t' \Sigma_t^{-1} y_t}{\nu - 2}\right)^{-\frac{\nu + D}{2}}, \tag{C.4}$$

where Σ_t is the covariance matrix of y_t and $\nu > 2$ is the degree of freedom parameter for the multivariate density. One could rewrite the model in terms of the scaling matrix $\tilde{\Sigma}_t$ as well. Doing so relaxes the parameter restriction on ν to $\nu > 0$.

Note that the variance is the identity matrix in our copula setting because the univariate models effectively de-volatized the log-changes in bank and sovereign EDFs. As a result, the covariance matrix Σ_t is also the correlation matrix.

The score-driven dynamics are incorporated in the covariance matrix in a similar fashion as in Creal et al. (2011), where $\Sigma_t = \Sigma(f_t)$. The dynamics are given by[2]

$$
\begin{aligned}
f_{t+1} &= \omega \cdot \mathrm{vech}\left(\rho\left(\bar{\Sigma}\right)\right) + A \cdot S_t \nabla_t + B \cdot f_t, && \text{(C.5)}\\
s_t &= \mathcal{S}_t \nabla_t, \quad \nabla_t = \partial \log p(y_t|\mathcal{F}_{t-1}; f_t, \theta)/\partial f_t, \\
\nabla_t &= \frac{1}{2}\Psi_t' \mathcal{D}_D' (\Sigma_t^{-1} \otimes \Sigma_t^{-1}) \Big[\frac{\nu + D}{\nu - 2 + y_t' \Sigma_t^{-1} y_t}(y_t \otimes y_t) - \mathrm{vec}(\Sigma_t)\Big], && \text{(C.6)}\\
\mathcal{S}_t &= \left(\frac{1}{4}\Psi_t' \mathcal{D}_D' (\mathcal{J}_t' \otimes \mathcal{J}_t')[gG - \mathrm{vec}(\mathrm{I})\mathrm{vec}(\mathrm{I})'](\mathcal{J}_t \otimes \mathcal{J}_t)\mathcal{D}_D \Psi_t\right)^{-1},
\end{aligned}
$$

where ω, A, and B are parameters and matrices to be estimated, $\mathrm{vech}\Big(\rho\big(\bar{\Sigma}\big)\Big) \in \mathbb{R}^{D(D-1)/2\times 1}$ contains appropriately transformed unconditional correlations to be targeted, the scaling matrix S_t is chosen as the inverse conditional Fisher information matrix $\mathrm{E}_{t-1}\left[\nabla_t \nabla_t'\right]^{-1}$, and ∇_t is the score of (C.4). Note that $\omega \cdot \mathrm{vech}(\rho(\bar{\Sigma})) = \bar{f}$ from (4) in the main text. Ψ_t is the derivative $\partial \mathrm{vech}(\Sigma_t)/\partial f_t'$, $\mathcal{D}_k$ is the duplication matrix in Abadir and Magnus (2005), and $\mathcal{J}_t$ is defined as the square root matrix such that $\Sigma_t^{-1} = \mathcal{J}_t' \mathcal{J}_t$. The scalar g is $(\nu+D)/(\nu+D+2)$. The $D^2 \times D^2$ matrix G is a particular matrix whose element $G[\cdot,\cdot]$ is given by

$$
G[(i-1)\cdot D + \ell, (j-1)\cdot D + m] = \delta_{ij}\delta_{\ell m} + \delta_{i\ell}\delta_{jm} + \delta_{im}\delta_{j\ell},
$$

for $i, j, \ell, m = 1, \cdots, D$. The Kronecker delta δ_{ij} is unity if $i = j$ or 0 otherwise.

The transition equation (C.5) adjusts f_t at every step using the scaled score $S_t \nabla_t$ of the conditional density at time t. This can be regarded as a steepest ascent improvement of the time-varying parameter using the local (at time t) likelihood fit of the model. The scaled score is a martingale difference sequence with mean zero, and acts as an innovation term. The coefficients in A and B can be restricted so that the process f_t is covariance stationary. The initial value f_1 is most conveniently initialized at the unconditional mean of the process.

There are a few alternative ways to map f_t into the covariance (correlation) matrix Σ_t, and the specific form of the derivative Ψ_t varies accordingly. We adopt a correlation structure

[2] We refer to http://www.gasmodel.com for computer code.

based on hyperspherical coordinates $\Sigma_t = X_t' X_t$ where $X_t(\phi_t)$ is an upper-triangular matrix,

$$X_t = \begin{pmatrix} 1 & c_{12t} & c_{13t} & \cdots & c_{1Dt} \\ 0 & s_{12t} & c_{23t}s_{13t} & \cdots & c_{2Dt}s_{1Dt} \\ 0 & 0 & s_{23t}s_{13t} & \cdots & c_{3Dt}s_{2Dt}s_{1Dt} \\ 0 & 0 & 0 & \cdots & c_{4Dt}s_{3Dt}s_{2Dt}s_{1Dt} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & c_{D-1,Dt}\prod_{\ell=1}^{D-2} s_{\ell Dt} \\ 0 & 0 & 0 & \cdots & \prod_{\ell=1}^{D-1} s_{\ell Dt} \end{pmatrix},$$

where $c_{ijt} = \cos(\phi_{ijt})$ and $s_{ijt} = \sin(\phi_{ijt})$. This setup ensures that Σ_t is a proper correlation matrix regardless of f_t. For example, in the 2-dimensional case, we have the root and correlation matrices given by

$$X_t = \begin{pmatrix} 1 & \cos(\phi_{12,t}) \\ 0 & \sin(\phi_{12,t}) \end{pmatrix}, \qquad \Sigma_t = X_t' X_t = \begin{pmatrix} 1 & \cos(\phi_{12,t}) \\ \cos(\phi_{12,t}) & 1 \end{pmatrix},$$

with the correlation given by $\cos(\phi_{12,t})$.

With this (hyperspherical) parameterization, the derivative matrix is given by

$$\Psi_t = \mathcal{B}_D[(\mathrm{I} \otimes X_t') + (X_t' \otimes \mathrm{I})\mathcal{C}_D]Z_t \mathcal{S}_\phi,$$

where $\mathcal{B}_k$ is the elimination matrix, $\mathcal{C}_k$ is the commutation matrix (Abadir and Magnus (2005)), and $Z_t = \partial \mathrm{vec}(X_t)/\partial \phi_t'$ consists of trigonometric functions that are available in closed form. $\mathcal{S}_\phi$ is a selection matrix containing 0s and 1s so that $\phi_t = \mathcal{S}_\phi f_t$.

C.3 High-dimensional & time-varying covariance matrices

The time-varying covariance matrix $\Omega_t^{(k)}$ introduced below (C.3) is typically of a high dimension. For example, more than 800 banks participated in the Eurosystem's second VLTRO program. The high dimensions and time-varying size of $\Omega_t^{(k)}$ imply that it is difficult to model directly. We address this issue by working with block equi-correlations within and across countries. This approach specifies $\Omega_t^{(k)}$ as a function of a much smaller covariance matrix Σ_t that is independent of k. We refer to e.g. Engle and Kelly (2012) and Lucas et al. (2017) for theory and applications based on dynamic (block-)equicorrelation models.

The smaller covariance matrix Σ_t is specified to depend on a vector of latent correlation factors f_t. Specifically, $\Omega_t^{(k)} = \Omega_t^{(k)}(\Sigma_t(f_t))$, where $\Sigma_t(f_t) \in \mathbb{R}^{D \times D}$, and $D \ll N_t(k)$. Our empirical application below considers nine banking sector risk indices and five SMP countries, thus $D = 14 \ll N_t(k)$ at any t and k; see Section 3.2. The mapping of matrix elements $\Omega_t^{(k)}(i,j) = \Sigma_t(l(i), m(j))$ is surjective but not injective (i.e. any element of Σ_t typically appears many times in $\Omega_t^{(k)}$). All bank correlation pairs across countries can be taken from Σ_t. The within-country correlation pairs — the off-diagonal elements in the diagonal blocks of $\Omega_t^{(k)}$ — cannot be read off Σ_t. We proceed by assuming that the within-country bank correlations are equal to the respective maximum (bank) row entry of Σ_t. As a result banks within each country are as correlated as the maximum estimated bank correlation pair across borders at that time t. We expect this approach to yield realistic within-country correlations given the single market for financial services and a substantial degree of cross-border banking sector integration in the euro area; see e.g. ECB (2013b). In any case, our results reported in Section 4 are robust to scaling up the within-country correlations.

The correlation matrix $\Omega_t^{(k)}$ obtained from Σ_t is symmetric but not guaranteed to be positive definite. In the rare case the Choleski decomposition of $\Omega_t^{(k)}$ fails we apply an eigenvalue (spectral) decomposition to the symmetric matrix and adjust negative eigenvalues to zero. The Choleski factor is then easily obtained. This is a standard procedure when correlation matrices are ill-conditioned. In our sample the thus regularized matrices are close approximations to the original $\Omega_t^{(k)}$s. The average (over t) Frobenius norm of the matrix differences is less than 10^{-5} per element for all k. We use the Choleski factor of $\Omega_t^{(k)}$ when generating draws from (C.3); it is not required at the parameter estimation stage.

The covariance $\Sigma_t(f_t)$ is fitted to weekly log-changes in observed bank and sovereign EDFs. Equation (C.3) refers to changes in unobserved log asset values, while $\Sigma_t(f_t)$ is estimated from changes in observed log EDFs. This is consistent since copula functions with continuous marginals remain invariant to increasing transformations of the data, see Proposition 5.6 in McNeil et al. (2005), and changes in log asset values are increasing in distances to default under mild assumptions, see e.g. Friewald (2009).

C.4 Asymmetric correlation dynamics

Lucas et al. (2014) find that default dependence across euro area sovereigns is asymmetric, and well-captured by a (Generalized Hyperbolic) skewed-t copula. Lucas et al. (2017) confirm this finding for banks. Rather than modeling any potential asymmetry in default dependence via (C.3) and (C.4), however, this section introduces asymmetry via the transition equation governing the correlation parameters in $\Omega_t^{(k)}$. This has the advantage that the quantiles of a standard t-density can be used in the estimation of the copula parameters. These quantiles are almost always tabulated and thus quickly available in standard software packages. The quantiles of skewed densities such as the Generalized Hyperbolic skewed-t density are not usually tabulated and need to be solved for numerically. Repeated numerical integration within a line search is time-consuming in high-dimensional applications, and in practice less reliable when τ_{it} is far in the tail.

Recall that the dynamics of the correlation factors f_t are specified by the transition equation (C.5). To accommodate a possibly asymmetric response in the correlation dynamics, we extend (C.6) slightly to read

$$\nabla_t = \frac{1}{2}\Psi_t'\mathcal{D}_D'(\Sigma_t^{-1}\otimes\Sigma_t^{-1})\Big[\frac{\nu+D}{\nu-2+y_t'\Sigma_t^{-1}y_t}(y_t\otimes y_t)-\text{vec}(\Sigma_t)+C\cdot(y_t^{+}\otimes y_t^{+})\Big], \tag{C.7}$$

where the ith element of y_t^+ equals $y_{it}^+ = \max(0, y_{it})$, and C is a scalar (or diagonal matrix) to be estimated.[3] Clearly, (C.7) reduces to (C.6) for $C = 0$. Values of $C \neq 0$, however, allow the correlation factors f_t to react differently to increasing versus decreasing marginal risks.[4]

The asymmetry in the conditional correlation dynamics carries over to skewness in the unconditional distribution of $\tilde{y}_{it}$, similar to features well-known from the familiar GARCH model with leverage; see e.g. Glosten et al. (1993). Inserting (C.7) into (C.5) and rearranging terms yields (4) in the main text.

C.5 Exposures-At-Default (EAD)

We do not have access to all counterparty-specific exposures (loan amounts) over time in our sample. Instead, we have access to the weekly aggregate exposures at the (country(j), operation(k)) level. In addition, we know the number of banks $N_t(j,k)$ that have accessed monetary policy operation k in week t and country j.[5] We therefore proceed under the assumption that exposures $a_{i,kt}$ for $i = 1, \ldots, N_t(j,k)$ within country j are Pareto-distributed, in line with e.g. Janicki and Prescott (2006). We thus draw counterparty-specific exposures according to $P(a_{i,jkt}) \propto (a_{i,jkt})^{-1/\xi}$ for a given value of ξ as $\text{EXP}_{i,jkt} = \left(a_{i,jkt} / \sum_{i=1}^{N_t(j,k)} a_{i,jkt} \right) \times \text{CountryExp}_{jkt}^{\text{observed}}$, in this way dividing up the observed aggregate bank lending volume per country and policy operation over $N_t(j,k)$ banks. We chose $1/\xi = 2$ in line with Janicki and Prescott (2006) to construct the relative shares. We checked that this choice is approximately in line with the cross-section of total bank liabilities in the euro area in our sample, and that it has little influence on our portfolio risk estimates.

[3] The score could alternatively be adjusted by $C \cdot (y_t^- \otimes y_t^-)$, where $y_{it}^- = \min(0, y_{it})$. We prefer formulation (C.7) as it is more intuitive in a joint risk setting.

[4] The extended score (C.7) does not have a conditional expectation of zero. This is not an issue for estimation if the intercept terms in the transition equation (C.5) are estimated in an unconstrained way. If the unconditional correlations are targeted, however, then $(y_t^+ \otimes y_t^+)$ should be demeaned.

[5] The identities of the $N_t(j,k)$ Eurosystem counterparties are confidential. For a detailed study of who borrows from the Eurosystem as a lender-of-last-resort see Drechsler et al. (2016).

C.6 Risk simulation procedure

We use the following steps to estimate EL and ES99% at time t for a certain monetary policy portfolio $k = 1, \dots, 6$.

1. Given the parameters of the model, we obtain an estimate of f_t. Using f_t, we compute $\Sigma_t = \Sigma(f_t)$ and construct $\Omega_t^{(k)}$ as explained in Section C.3.
2. Repeat the following many (200,000) times to obtain a set of draws of portfolio losses:
   (a) Generate a draw from the copula using the matrix $\Omega_t^{(k)}$ using Equation (C.3) and subsequently transforming the draws $\tilde{y}_{it}$ to uniforms u_{it} via the univariate Student's t distribution (cdf).
   (b) Using the copula draws u_{it} for $i = 1, \dots, N_t(k)$, check if u_{it} is smaller than the default probability $p_{it} = \mathrm{E}_t[1(\mathrm{default}_{i,t+1:t+52})]$; if it is smaller, then institution (or sovereign) i defaults at some (unmodeled) time between $t+1$ and $t+52$.
   (c) LGDs for the defaulted firms and sovereigns are computed as explained in Section 3.4. Exposures-at-default are obtained as explained in Web Appendix C.5. Use (1) to obtain one draw of portfolio loss $\ell_t(k)$.
3. The EL is the average taken over all draws obtained in Step 2. The ES99% is the average taken over the worst 1% of draws.

C.7 Parameter estimation

Observation-driven multivariate time series models such as (C.5) are attractive because the log-likelihood is known in closed form. Parameter estimation is standard as a result. For a given set of observations $y_1, \dots, y_T$, the vector of unknown copula parameters $\theta = \{\omega, A, B, C, \nu\}$ can be estimated by maximizing the log-likelihood function with respect to θ, that is

$$\hat{\theta} = \arg\max_{\theta} \sum_{t=1}^{T} \log p(y_t | f_t; \theta), \tag{C.8}$$

where $p(y_t|f_t;\theta) = p(y_t;\, \Omega(\Sigma_t(f_t))\,, \nu\,)$ is the multivariate Student's t density for the vector y_t containing weekly log-changes in bank and sovereign one-year-ahead EDF measures for all counterparties observed at time t. The evaluation of $\log p(y_t|f_t;\theta)$ is easily incorporated in the filtering process for f_t; see (C.5).

For the empirical application, we reduce the computational burden of parameter estimation in two ways. First, we proceed in two steps and estimate the parameters of D marginal models with time varying volatility for each series of log EDF changes. We transform the outcomes using the probability integral transform and subsequently estimate the copula parameters. This approach is standard in the literature; see e.g. Fan and Patton (2014). Second, we assume that matrices A, B, and C in the factor transition equation (C.5) are scalars, such that $\theta = \{\omega, A, B, C, \nu\} \in \mathbb{R}^5$ is a vector of relatively low dimension.

D Diagnostic checks

D.1 Data descriptive statistics

Table D.1 provides summary statistics for weekly de-meaned changes in $D = 14$ time series. All time series have significant non-Gaussian features under standard tests and significance levels. In particular, we note the non-zero skewness and large values of kurtosis for almost all time series in the sample. All series are covariance stationary according to standard unit root (ADF) tests. The pronounced non-Gaussian data features suggest a non-Gaussian empirical model.

D.2 Parameter estimates for D univariate models

Table D.2 reports the parameter estimates that correspond to the D univariate models discussed in Section C.1. The parameter estimates are in line with the pronounced non-Gaussian features of the data as documented above. The estimates of the degree-of-freedom

Table D.1: Data descriptive statistics

The table reports descriptive statistics for weekly log changes in $D = 14$ banking sector and sovereign EDFs between 03 October 2008 and 11 March 2016 ($T = 389$), in 100 basis points. P-values for skewness and kurtosis are based on d'Agostino (1970)'s tests and indicate a strong departure from normality for all series.

	Median	Std. Dev.	Skewness	Skewness p-value	Kurtosis	Kurtosis p-value	Min	Max
GR(sov)	-0.02	0.19	0.32	0.01	5.29	0.00	-0.65	0.75
IE(sov)	0.00	0.27	0.09	0.49	5.07	0.00	-0.93	0.92
IT(sov)	-0.01	0.34	0.09	0.45	4.25	0.00	-1.11	1.12
PT(sov)	0.00	0.30	-0.03	0.79	3.96	0.00	-0.93	0.97
ES(sov)	0.00	0.34	-0.14	0.26	4.99	0.00	-1.16	1.12
AT	-0.01	0.11	0.08	0.52	4.55	0.00	-0.34	0.34
FR	0.00	0.10	0.38	0.00	4.29	0.00	-0.32	0.31
DE	-0.01	0.09	0.28	0.02	6.39	0.00	-0.36	0.35
GR	-0.01	0.18	-1.14	0.00	14.41	0.00	-1.31	0.83
IE	-0.01	0.10	0.09	0.46	6.02	0.00	-0.41	0.41
IT	-0.01	0.09	0.26	0.04	3.72	0.01	-0.26	0.30
NL	0.00	0.11	0.20	0.10	5.85	0.00	-0.44	0.40
ES	0.00	0.09	-0.04	0.72	4.12	0.00	-0.32	0.29
EUR19	0.00	0.07	0.44	0.00	4.36	0.00	-0.23	0.28

Table D.2: Univariate parameter estimates

The table reports parameter estimates for $D = 14$ univariate time series models. The sample consists of weekly changes in log-EDFs between 03 October 2008 and 11 March 2016 ($T = 389$). The top five rows refer to sovereign (sov) CDS-implied EDFs. The bottom nine rows correspond to banking sector EDFs. The Student t volatility models are estimates separately by the method of maximum likelihood. Standard errors are in parentheses and are based on the numerical second derivative of the respective log-likelihood function.

	$\tilde{\omega}$	A	B	C	ν
GR(sov)	-0.139	0.106	0.927	0.041	3.332
	(0.070)	(0.041)	(0.038)	(0.039)	(0.631)
IE(sov)	-0.062	0.101	0.957	0.017	3.191
	(0.040)	(0.028)	(0.024)	(0.034)	(0.684)
IT(sov)	-0.291	0.090	0.757	0.097	3.808
	(0.167)	(0.057)	(0.154)	(0.059)	(0.892)
PT(sov)	-0.245	0.043	0.811	0.061	4.204
	(0.158)	(0.041)	(0.126)	(0.057)	(1.192)
ES(sov)	-0.024	0.078	0.975	-0.008	3.894
	(0.028)	(0.024)	(0.019)	(0.031)	(0.822)
AT	-0.145	0.025	0.949	0.075	3.496
	(0.056)	(0.026)	(0.022)	(0.038)	(0.729)
FR	-0.098	0.094	0.939	0.139	6.209
	(0.044)	(0.027)	(0.021)	(0.040)	(1.878)
DE	-0.195	0.083	0.897	0.096	2.942
	(0.125)	(0.031)	(0.062)	(0.054)	(0.502)
GR	-0.156	0.170	0.900	-0.067	3.633
	(0.103)	(0.046)	(0.055)	(0.048)	(0.731)
IE	-0.198	0.294	0.936	0.102	2.662
	(0.063)	(0.049)	(0.019)	(0.055)	(0.344)
IT	-0.148	0.063	0.930	0.063	8.473
	(0.072)	(0.027)	(0.032)	(0.030)	(3.315)
NL	-0.103	0.029	0.963	0.044	3.252
	(0.051)	(0.022)	(0.020)	(0.027)	(0.513)
ES	-0.288	0.022	0.899	0.097	5.635
	(0.137)	(0.036)	(0.054)	(0.041)	(1.570)
EUR19	-0.119	0.071	0.942	0.099	6.800
	(0.070)	(0.032)	(0.031)	(0.041)	(2.151)

parameter ν vary between approximately three and eight. These are thus much lower than the degree-of-freedom parameter that is estimated for the copula; see Section 4.1. The asymmetry parameters C are significant in most but not all univariate specifications. Most volatility processes are quite persistent with autoregressive parameters B varying between 0.75 and 0.97. A robust score-driven approach to modeling time-varying volatility and dependence is particularly attractive in a non-Gaussian context when the data are fat tailed and skewed; see e.g. Harvey (2013) and Blasques et al. (2015).

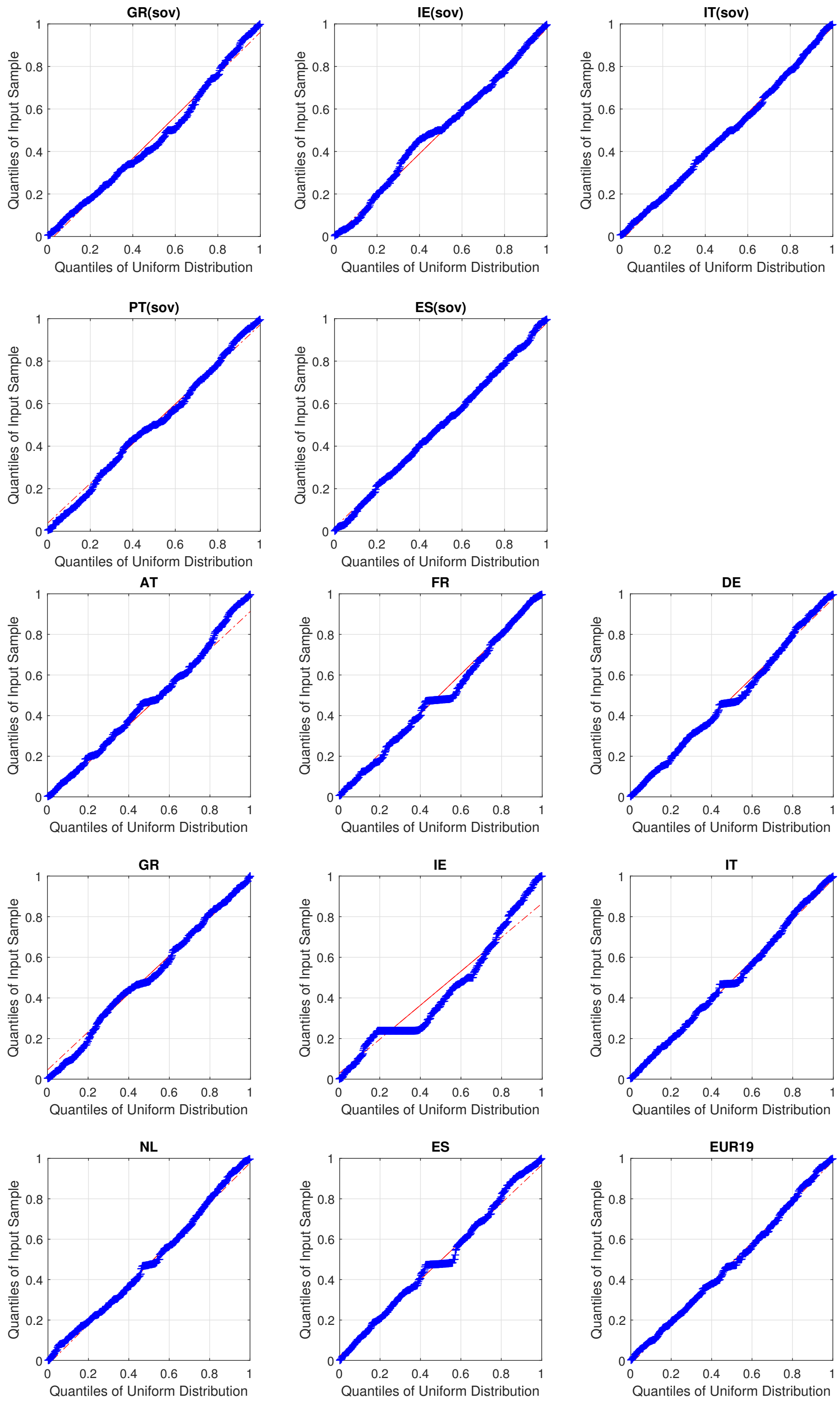
The numerical maximization of the log-likelihood function is not always entirely unproblematic given the moderate $T = 389$ dimension and the nonlinearities present in the univariate model (C.1) – (C.2). Specifically, the maximizer may converge to a boundary value of the parameter space, or may end up stuck in a local maximum, for reasonable starting values of the parameters $\theta \in \mathbb{R}^5$. To overcome such problems we estimate each univariate model 100 times with different random starting values. The random starting values are centered around previously converged parameter estimates for the other countries. We then study the maximum likelihood estimate in detail. Specifically, we plot the log-likelihood evaluated at the maximum sliced in each dimension, and test the non-singularity (invertibility) of the numerical second derivative to rule out saddle points as suggested by e.g. Rothenberg (1971). The standard errors in Table D.2 are obtained from the numerical second derivatives and suggest that the marginal model parameters can be estimated fairly precisely from our moderately-sized sample once convergence to the global maximum has taken place. We proceed in an analogous way for the five copula model parameters as discussed in Section 4.1.

D.3 Uniformity of the u_{it}

Figure D.1 reports QQ-plots for the probability integral transforms u_{it} resulting from our D marginal models. The u_{it} correspond to five sovereign CDS-implied-EDF and nine bank EDF time series, and should be uniformly distributed if the marginal model is appropriate.

Figure D.1: QQ plot of u_{it} against uniform quantiles

Top panel: QQ plots of u_{it} vs. uniform quantiles for five sovereign CDS-implied-EDFs. Bottom panel: QQ plots of u_{it} vs. uniform quantiles for nine bank EDF series.



Overall, the Student's distributional assumption made in the marginal modeling stage appears appropriate. Slight deviations from uniformity in the center of the distribution for some banking sector EDFs are related to interpolating patches of missing values in the early part of the sample (2008–2009). This interpolation results in a small plateau around the median. This does not affect our risk simulations, which mainly build on tail draws rather than on the center of the distribution. The only series with substantial deviations from uniformity is the Irish banking sector, which displays many more zero values than the other series with relatively less observations in the first part of the upper tail. In the upper 10% tail area, however, uniformity appears re-established, which is important for our tail risk quantile simulations.

D.4 Testing for remaining serial correlation

Figures D.2 and D.3 report the autocorrelation coefficients for the marginal models' residuals and squared residuals, respectively. The autocorrelation estimates allow us to screen for any remaining un-modeled serial correlation. Figures D.2 suggests that there is no important serial correlation left in the first moment of the data. This is intuitive, as the EDFs are derived from financial market prices. More importantly, Figure D.3 suggests that there is no important serial correlation remaining also in the residuals' second moments, suggesting that our volatility models with fat tails and leverage are appropriate for the data at hand.

Figure D.2: Residual autocorrelations

Autocorrelation coefficients for D residual time series for lags $1, \ldots, 9$. The Portmanteau critical value bands are at the 5% confidence level.

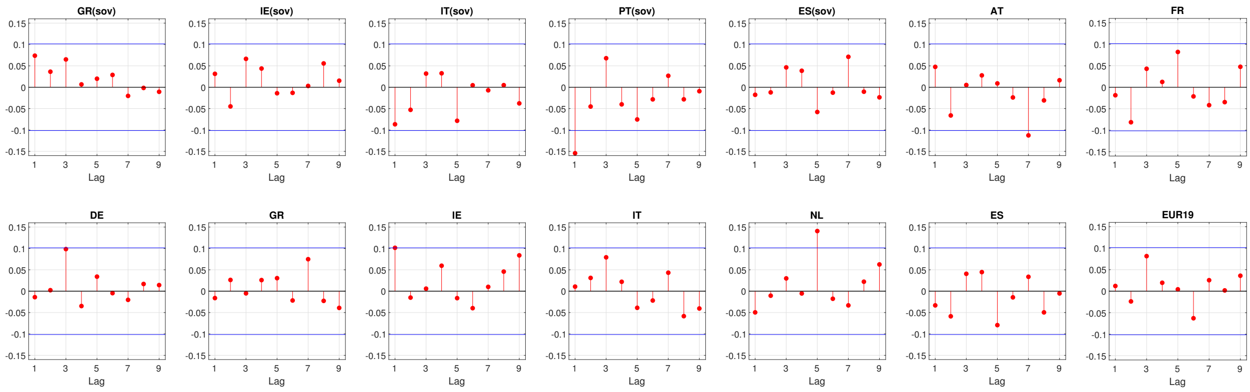
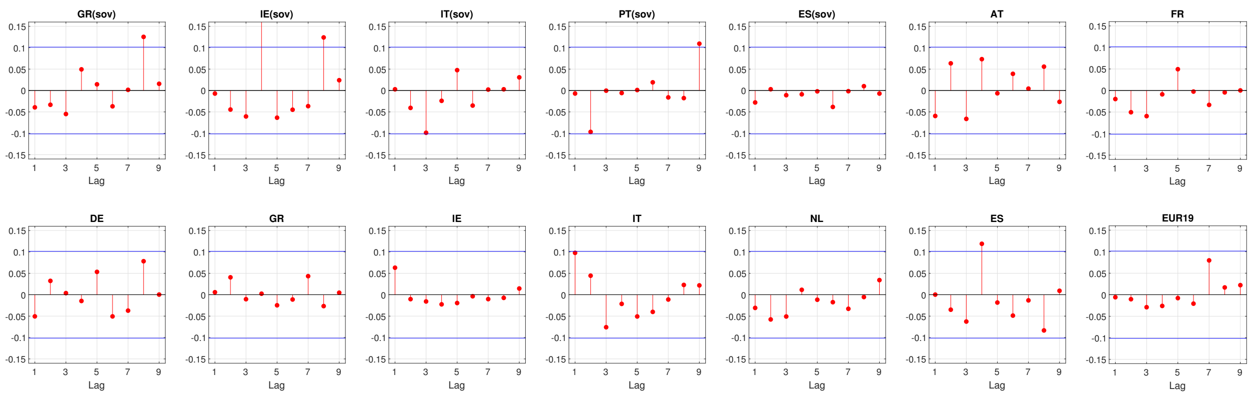


Figure D.3: Autocorrelation in squared residuals

Autocorrelation coefficients for D squared residuals for lags $1, \ldots, 9$. The Portmanteau critical value bands are at the 5% confidence level.



E Robustness results

E.1 Comparison with a Gaussian benchmark

This section reports alternative EL and ES99% estimates that are based on the simpler Gaussian copula model as discussed in Section 4.1. These alternative estimates allow us to asses how sensitive the measured risks are to the fatness of the joint tail in the dependence function.

Figures E.1 and E.2 plot EL and ES99% based on the Gaussian model, but are otherwise analogous to Figure 4 in the main text and Figure F.1 in Web Appendix F. Figures E.3 and E.4 provide a one-to-one comparison of the measured risks at the portfolio level.

In general, and not surprisingly, not accounting for joint tail risk leads to lower measured risks. The differences are the least pronounced for the EL of the SMP portfolio. The risk of the SMP portfolio is determined mainly by its three to five elevated marginal risks. The differences between risk estimates are the most pronounced for the ES99% estimates of the collateralized lending portfolios. Here, marginal risks are relatively lower, diversification occurs over many more counterparties, and large losses materialize only in case of *joint* bank and sovereign credit events.

Figure E.1: EL based on Gaussian copula model

Top panel: one-year-ahead EL from liquidity providing operations at a weekly frequency. Bottom panel: one-year-ahead EL from SMP assets. Vertical lines indicate the announcement of the SMP on 10 May 2010 and its cross-sectional extension on 08 August 2011, the allotment of two VLTROs on 21 December 2011 and 28 February 2012, and two announcements regarding the Outright Monetary Transactions (OMT) in August and September 2012. The vertical axis is in billion euro. Data is weekly between 2009 and 2015.

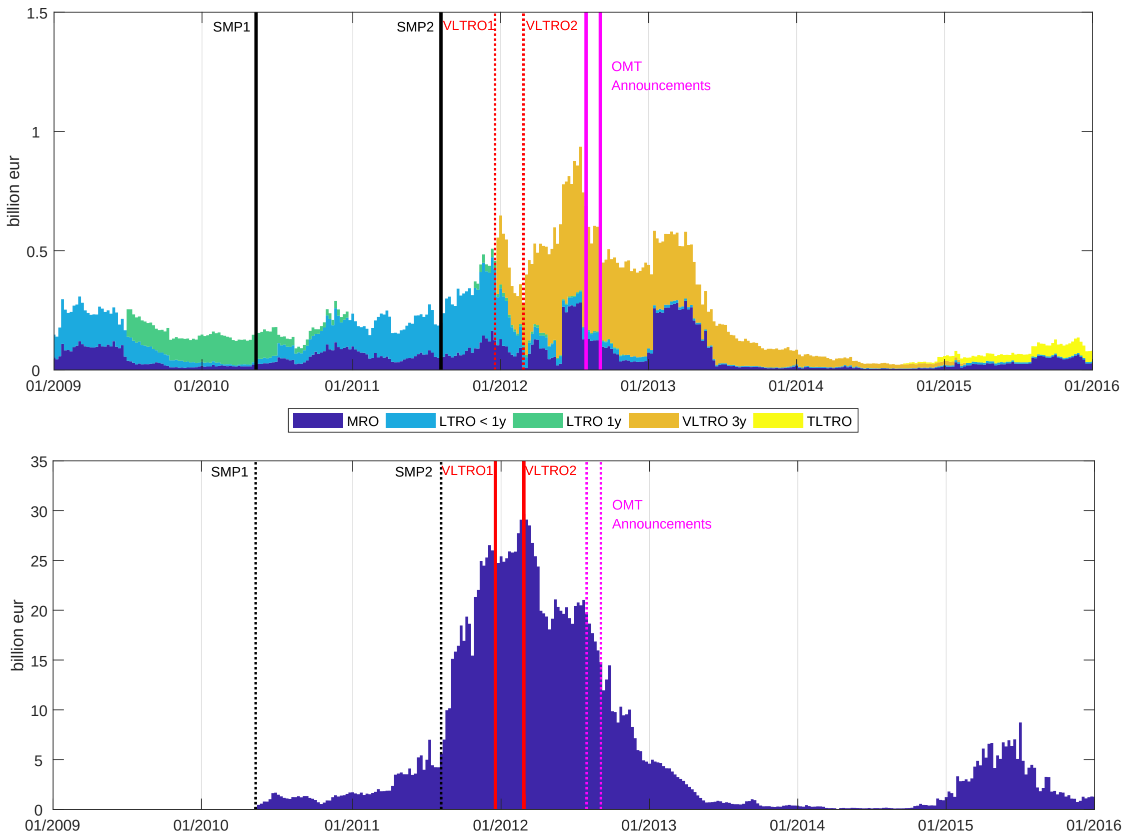


Figure E.2: ES99% based on Gaussian copula model

Top panel: ES99% in €bn for five Eurosystem collateralized lending operations. Bottom panel: 99% ES for SMP asset portfolio. Six vertical lines mark the events described in Section 2. Data is weekly between 2009 and 2015.

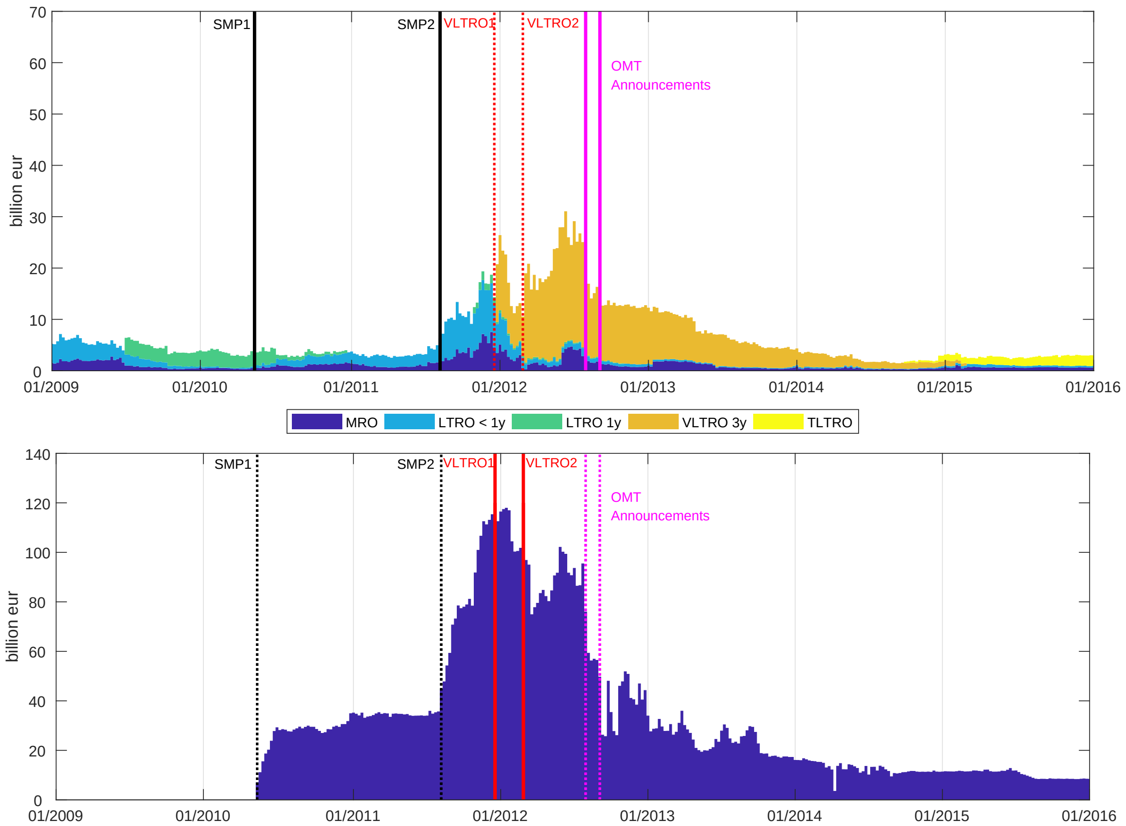


Figure E.3: Comparison EL: t vs. Gaussian copula

The panels report Student's t and Gaussian copula model-based EL estimates for six portfolios: SMP asset holdings and MRO lending (top row), LTRO$<1y$ and LTRO$1y$ lending (middle row), and VLTRO and TLTRO lending (bottom row). The respective EL estimates are not stacked. Data is weekly between 2009 and 2015.

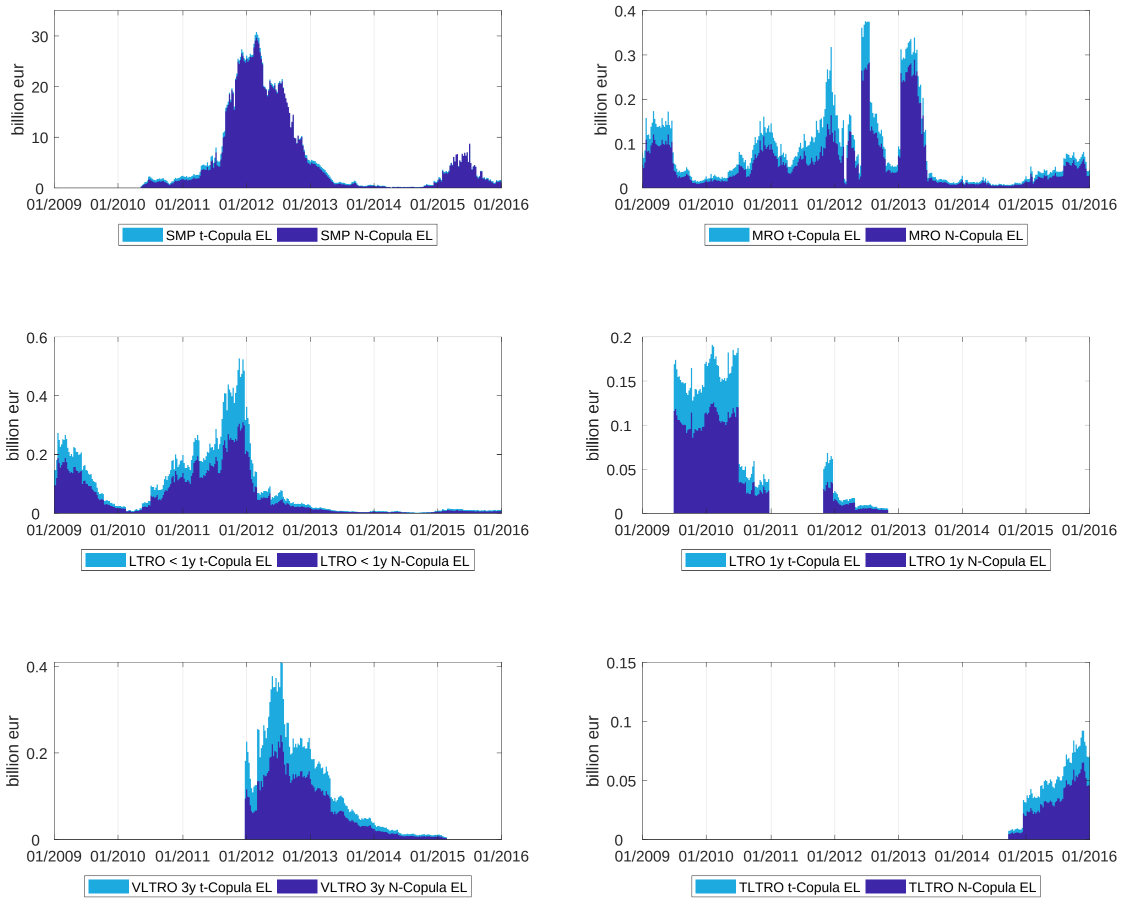
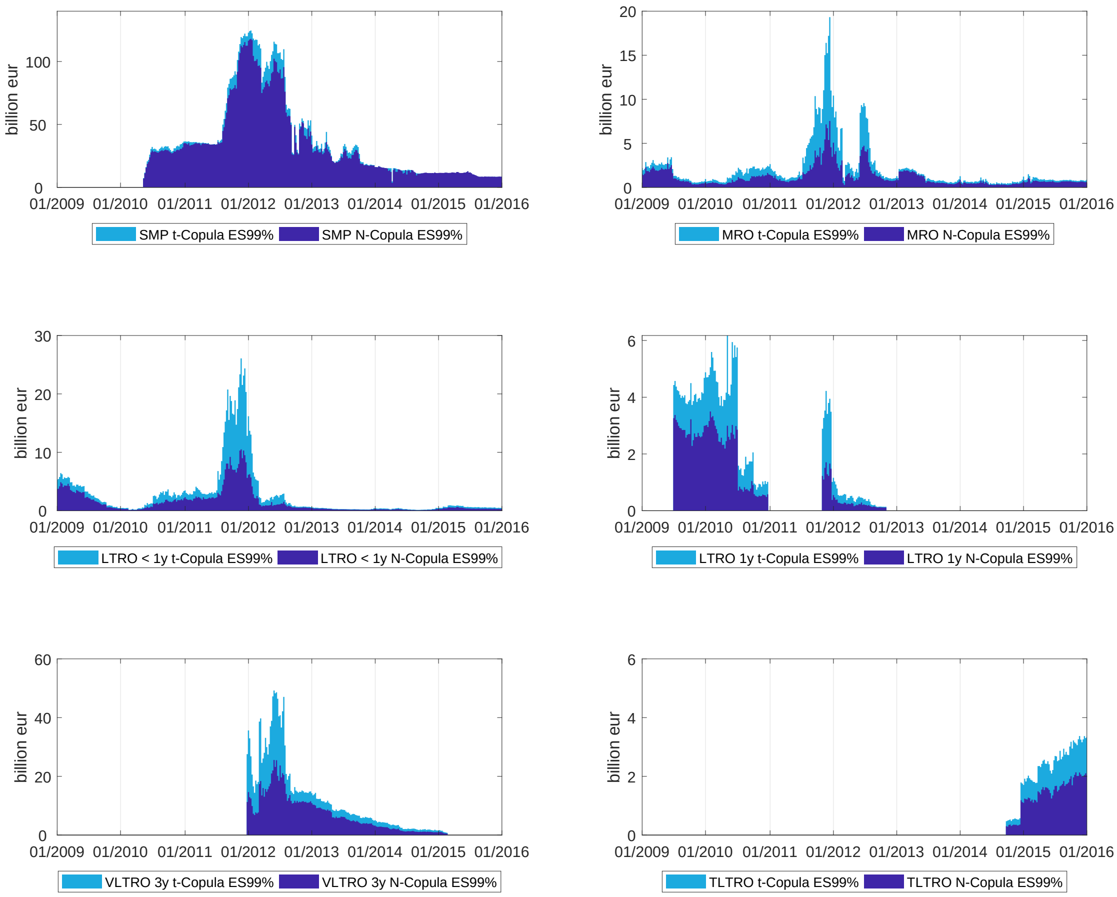


Figure E.4: Comparison ES99%: t vs. Gaussian copula

The panels report Student's t and Gaussian copula model-based ES99% estimates for six portfolios: SMP asset holdings and MRO lending (top row), LTRO$< 1y$ and LTRO$1y$ lending (middle row), and VLTRO and TLTRO lending (bottom row). The respective ES99% estimates are not stacked. Data is weekly between 2009 and 2015.



E.2 Alternative LGD assumptions

This section studies the sensitivity of our risk estimates to an alternative parametrization of the LGD equations (5) and (6).

Figures E.5 and E.6 plot our alternative EL and ES99% estimates. Both figures are based on less conservative LGDs, but are otherwise analogous to Figure 4 in the main text and Figure F.1 in Web Appendix F.

Specifically, for a bank counterparty i, we now model LGD stochastically as

$$\mathrm{LGD}_{i,t+1:t+52} = 0.01 + 0.29 \cdot 1\left\{\tilde{y}_{jt} < \tau_{jt} \text{ for at least one SMP country } j\right\}. \tag{E.1}$$

i.e., $\mathrm{LGD}_{i,t+1:t+52} = 0.01$ if bank counterparty i defaults but no SMP counterparty defaults. The LGD increases to 30% if bank i defaults and a SMP sovereign defaults as well (in the same simulation). Similarly, in case of a sovereign counterparty, we now set the LGD to 30% should such a default be observed,

$$\mathrm{LGD}_{j,t+1:t+52} = 0.30 \cdot 1\left\{\tilde{y}_{jt} < \tau_{jt} \text{ for SMP country } j\right\}. \tag{E.2}$$

While the copula model presented in Web Appendix C is decidedly nonlinear, the implied EL and ES99% estimates *are* linear in LGD. This is most apparent from (1). Figures E.5 and E.6 are numerically exactly half of the portfolio credit risks reported in Figures 4 and F.1.

Figure E.5: EL based on alternative LGD assumptions

Top panel: one-year-ahead EL from liquidity providing operations at a weekly frequency. Bottom panel: one-year-ahead EL from SMP assets. Vertical lines indicate the announcement of the SMP on 10 May 2010 and its cross-sectional extension on 08 August 2011, the allotment of two VLTROs on 21 December 2011 and 28 February 2012, and two announcements regarding the Outright Monetary Transactions (OMT) in August and September 2012. The vertical axis is in billion euro. Data is weekly between 2009 and 2015.

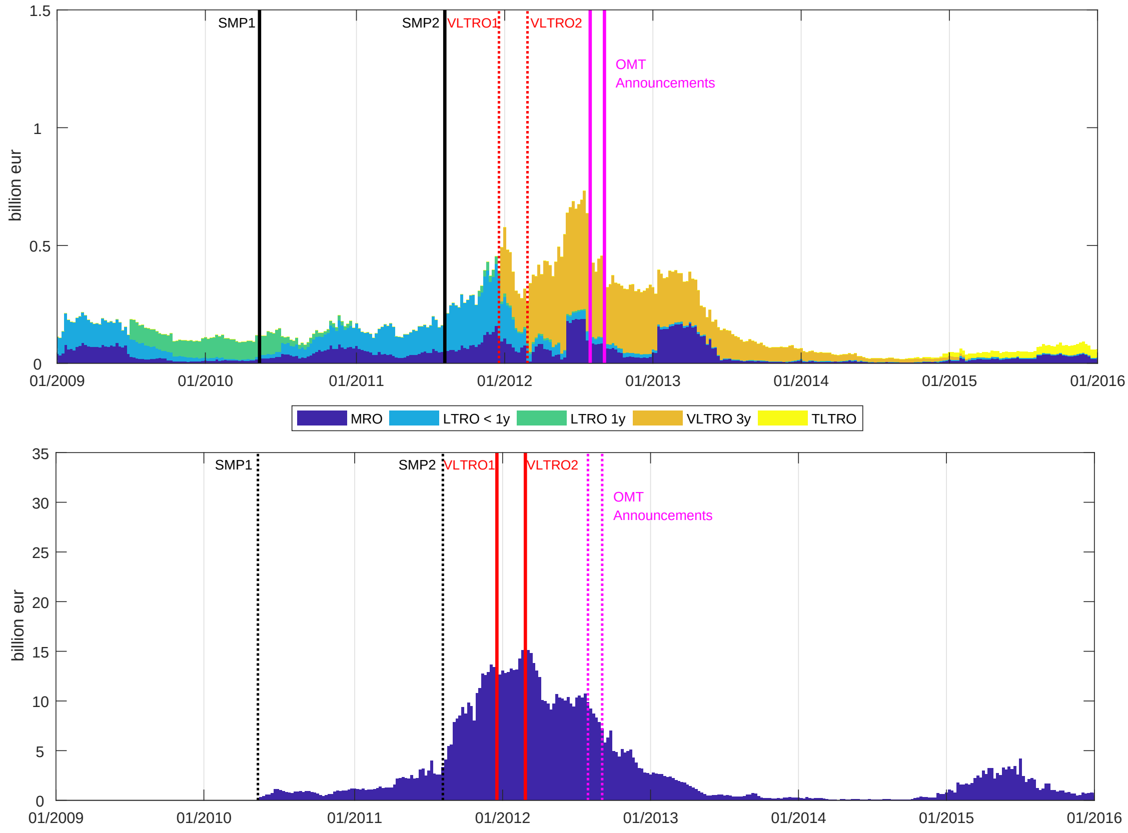
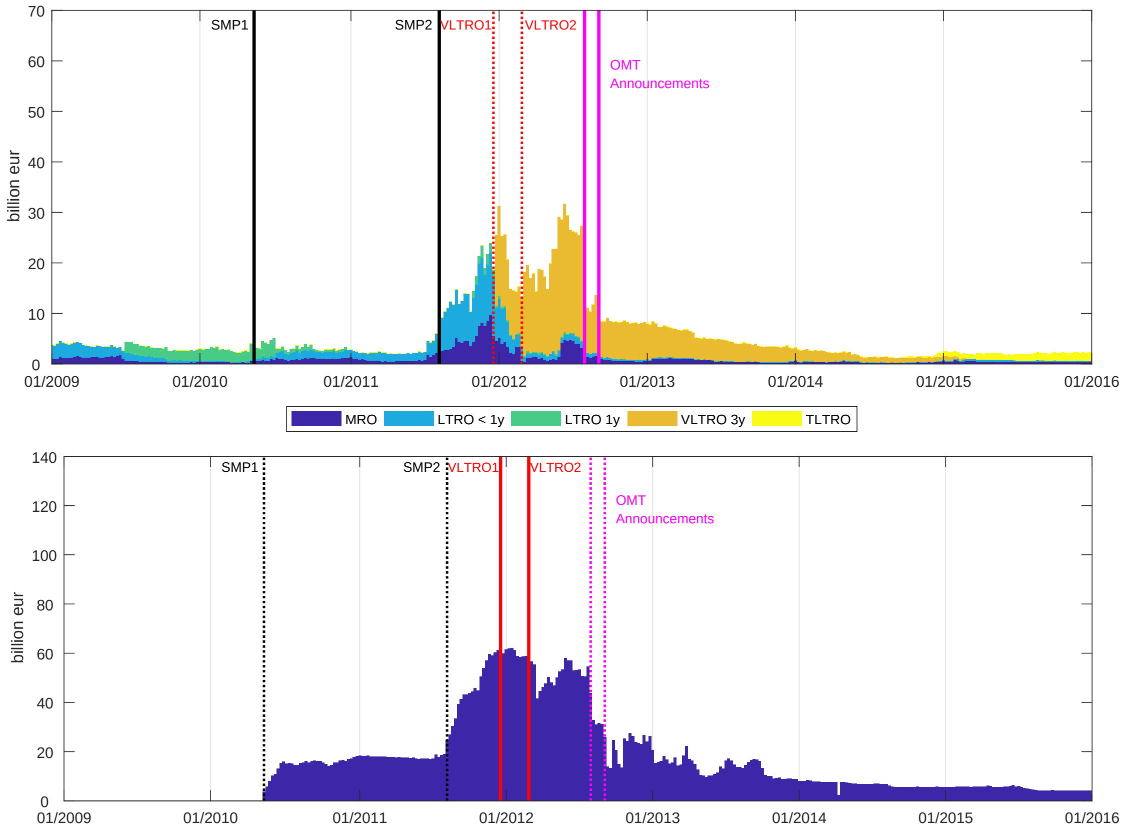


Figure E.6: ES99% based on alternative LGD assumptions

Top panel: ES99% in €bn for five Eurosystem collateralized lending operations. Bottom panel: 99% ES for SMP asset portfolio. Six vertical lines mark the events described in Section 2. Data is weekly between 2009 and 2015.



F Expected loss: total and scaled by exposures

Figures 4 and 5 in the main text plot the ES99% for five collateralized lending portfolios as well as for SMP assets in absolute value as well as in percent of their nominal (par) value, respectively. For completeness, Figures F.1 and F.2 in this section present the analogous figures for the EL.

Figure F.1 plots estimated one-year-ahead EL from Eurosystem collateralized lending operations (top panel) and SMP asset purchases (bottom panel). EL estimates are additive across operations, and therefore stacked vertically in the top panel of Figure F.1. The figure reflects a clear deterioration of financial conditions since the beginning of the euro area sovereign debt crisis in the spring of 2010, and second, a clear turning of the tide around mid-2012. Expected losses for both collateralized lending and SMP exposures peak in mid-2012 at around approximately €1.5 bn and €30 bn, respectively. This is a pronounced difference in risk levels, particularly when considering the much smaller size of the SMP portfolio vis-à-vis all collateralized lending; see Figure 1. The difference is explained by the double recourse in the case of collateralized lending.

Figure F.2 plots the EL for five collateralized lending portfolios in percent of total lending exposures, stacked vertically (top panel), and the EL for SMP assets in percent of their nominal (par) value. The collateralized lending book is substantially less risky per unit of exposure than the outright SMP holdings, by up to two orders of magnitude.

Figure F.1: EL for collateralized lending and SMP portfolios

Top panel: one-year-ahead EL from liquidity providing operations at a weekly frequency. Bottom panel: one-year-ahead EL from SMP assets. Vertical lines indicate the announcement of the SMP on 10 May 2010 and its cross-sectional extension on 08 August 2011, the allotment of two VLTROs on 21 December 2011 and 28 February 2012, and two announcements regarding the Outright Monetary Transactions (OMT) in August and September 2012. The vertical axis is in billion euro. Data is weekly between 2009 and 2015.

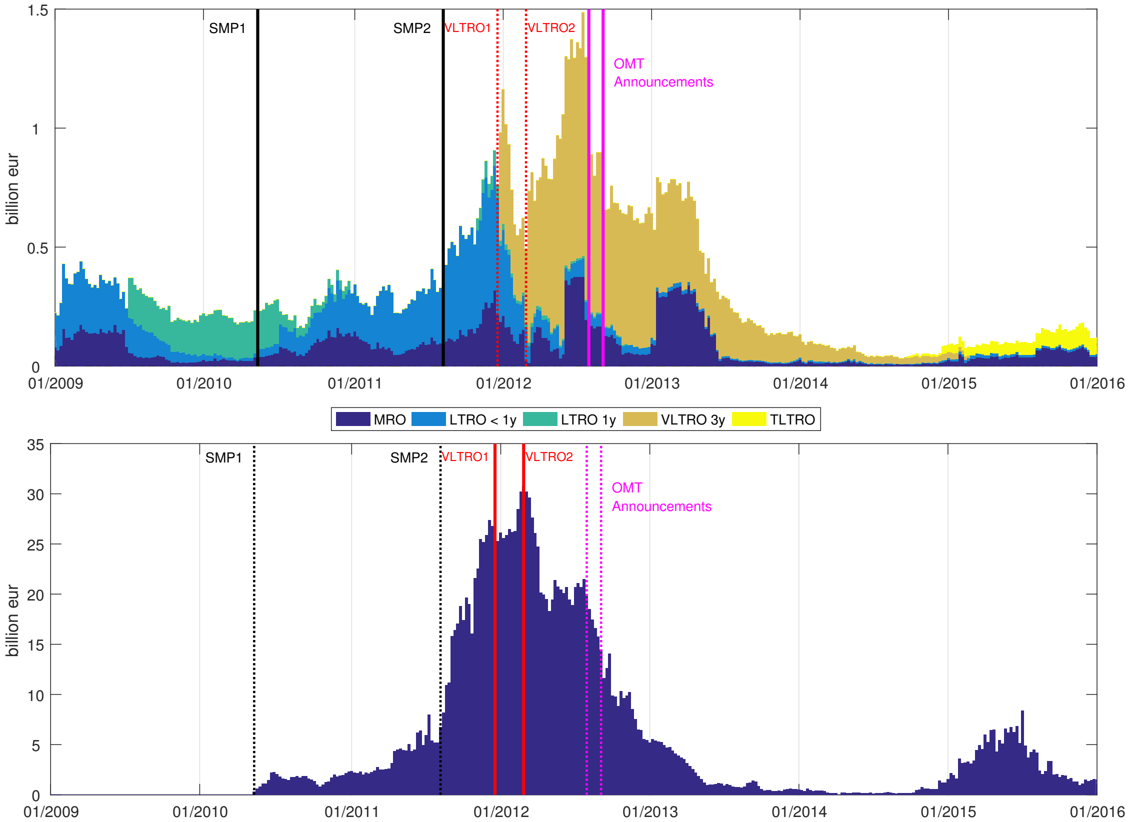
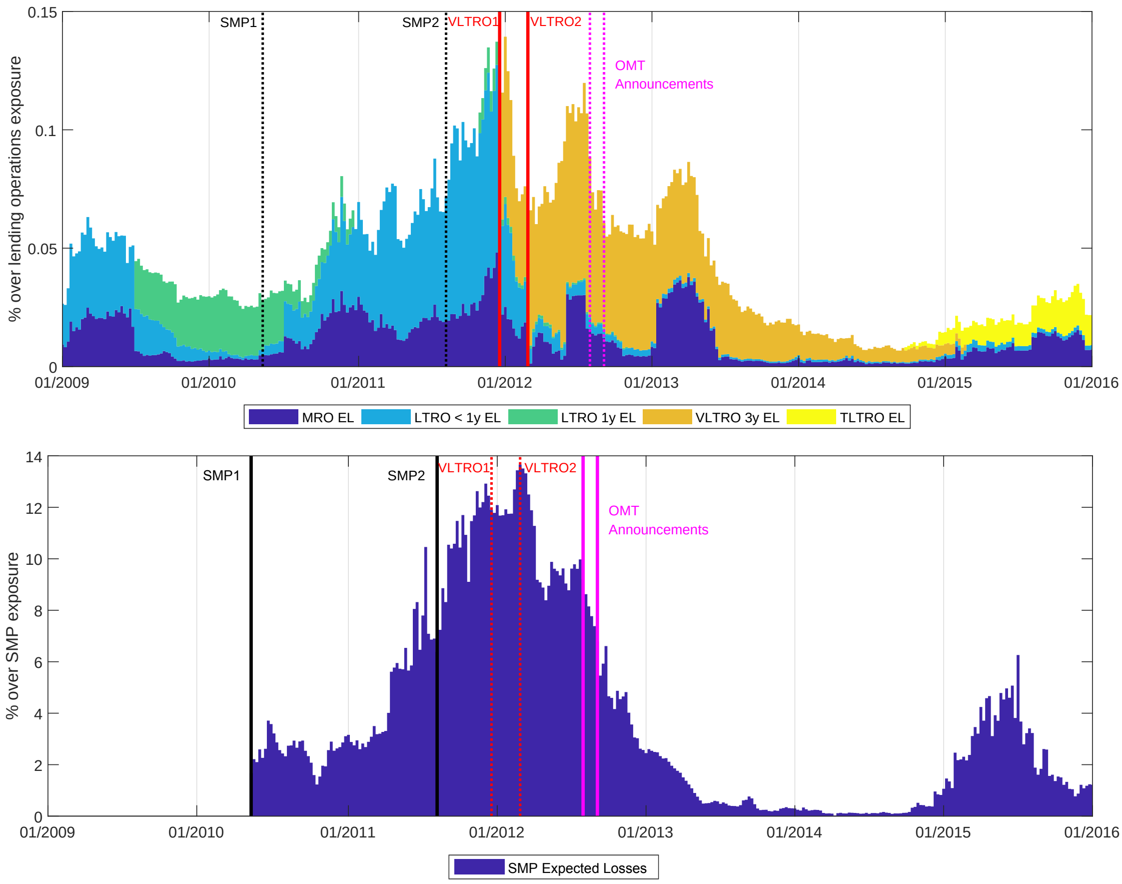


Figure F.2: EL in percent of exposures

Top panel: EL for five collateralized lending portfolios in percent of total collateralized exposures, stacked vertically. Bottom panel: EL for SMP assets in percent of its nominal (par) value. The vertical lines mark the events described in Section 2. Data is weekly between 2009 and 2015.



G Time differences in risk scaled by exposures

Table G.1 corresponds to Table 2, reporting portfolio credit risks around six key policy announcements in percent of their respective exposures at the time. The changes in portfolio credit risks around key policy dates, as reported in Table 2 in the main text, can be decomposed into a risk (PD and correlation) component and an exposure component. In line with Figures 5 and F.2, the risk component is the main driver. For example, the ES 99% collapses from approximately 51% of SMP exposures the Friday close before the first OMT announcement (27 July 2012) to approximately 24% of SMP exposures following the second OMT announcement (07 September 2012).

Table G.1: Portfolio credit risks around key policy announcements, in percent of exposures

Portfolio credit risks for different monetary policy operations around six policy announcements. EL and ES99% are expressed in percent of the respective policy's exposure at the time. Total values are scaled by the sum of all active exposures at the time. Monte Carlo standard error bands are omitted for compactness.

SMP1	07/05/2010		14/05/2010			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	-	-	1.7	36.9	1.7	36.9
MRO	0.0	1.2	0.0	1.0	-0.0	-0.2
LTRO<1y	0.0	1.1	0.0	0.9	-0.0	-0.2
LTRO1y	0.0	1.0	0.0	0.7	-0.0	-0.3
Total	0.0	1.0	0.1	1.6	0.0	0.6

SMP2	05/08/2011		12/08/2011			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	6.9	50.3	6.4	47.3	-0.5	-3.0
MRO	0.1	2.6	0.1	3.1	0.0	0.5
LTRO<1y	0.1	2.5	0.1	3.2	0.0	0.6
Total	1.0	8.8	1.2	10.9	0.2	2.1

VLTRO1	16/12/2011		30/12/2011			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	12.5	56.8	11.8	55.9	-0.7	-0.9
MRO	0.1	6.6	0.1	6.3	0.0	-0.3
LTRO<1y	0.2	7.8	0.2	6.3	-0.0	-1.5
LTRO1y	0.1	6.9	0.2	9.1	0.1	2.1
VLTRO3y	-	-	0.1	5.6	0.1	5.6
Total	3.2	19.4	2.5	16.0	-0.7	-3.4

VLTRO2	24/02/2012		09/03/2012			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	13.4	52.1	13.5	50.8	0.1	-1.3
MRO	0.1	4.0	0.1	4.2	-0.0	0.1
LTRO<1y	0.1	3.4	0.1	3.3	0.0	-0.1
LTRO1y	0.1	4.7	0.1	5.3	0.0	0.6
VLTRO3y	0.1	3.5	0.1	3.8	-0.0	0.2
Total	3.0	14.1	2.3	11.6	-0.6	-2.5

OMT1	27/07/2012		03/08/2012			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	10.0	50.9	9.2	40.8	-0.8	-10.1
MRO	0.1	4.8	0.1	3.4	-0.0	-1.4
LTRO<1y	0.1	3.9	0.1	2.7	-0.0	-1.1
LTRO1y	0.1	5.3	0.1	4.2	-0.0	-1.1
VLTRO3y	0.1	4.7	0.1	3.1	-0.0	-1.7
Total	1.6	11.6	1.5	8.8	-0.1	-2.9

OMT2	31/08/2012		07/09/2012			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	7.4	29.2	6.8	24.2	-0.6	-5.1
MRO	0.1	2.3	0.1	1.6	-0.0	-0.7
LTRO<1y	0.1	1.9	0.1	1.5	-0.0	-0.4
LTRO1y	0.1	2.7	0.1	2.0	-0.0	-0.7
VLTRO3y	0.1	2.1	0.1	1.5	-0.0	-0.6
Total	1.2	6.2	1.1	4.9	-0.1	-1.3

H Risk efficiency

Portfolio risk estimates as reported in Figures 4 and F.1 are a prerequisite for evaluating policy operations in terms of their "risk efficiency." Risk efficiency is the principle that a certain amount of expected policy impact should be achieved with a minimum level of balance sheet risk; see e.g. ECB (2015). Put differently, the impact of any policy operation should be maximal given a certain level of risk. Given an estimate of policy impact, such as, for example, a change in inflation swap rates or in bond yields around the time of a policy announcement, and given an estimate of additional risk, such as, for example, a change in EL or in ES99%, different policy operations can be evaluated by scaling the former by the latter. This is similar to the definition of Sharpe (1966)'s return-to-risk ratio.

Scaling policy impact by additional risk is not unproblematic for at least three reasons. First, scaling impact by additional risk may create the impression that both are equally important for the central bank. This is not the case. Recall that, unlike for commercial banks, risk and profitability are not first-order measures of success for a central bank. Second, ex-ante risk efficiency deliberations may be too uncertain to be of practical use. Ex-ante estimates of impact (and additional risk) are highly uncertain, particularly if the policy operation is unprecedented and risks change following the announcement. Finally, asset purchase programs and credit operations are hard to compare in terms of ex-post risk efficiency. In the case of purchase programs, the policy impact includes the market's expectation about future purchases, while the associated credit risks only accumulate slowly over time. By contrast, the policy impact and credit risk of additional lending operations are more closely aligned. Table H.1 presents the efficiency ratios of purchase programs and credit operations separately for this reason.

Table H.1 reports four alternative 'risk efficiency ratios' for six major policy announcements during the euro area sovereign debt crisis; see Section 2. The policy impact could be assessed in different ways. For example, impact could be proxied by the change in long-term inflation swap rates. This reflects the intuition that all monetary policy operations, includ-

Table H.1: Risk efficiency ratios

Economic benefit, additional balance sheet risk, and the ratio of the two around six policy announcements. Benefit is proxied by the change in market prices for five-year five-year-out euro area inflation swap rates, or alternatively by the decrease in five-year benchmark bond yields for GIIPS countries (Greece, Ireland, Italy, Portugal, and Spain). Benefit entries are in percentage points. Additional balance sheet risk is measured in €bn. The ratios in the final column are expressed in basis points per €1 bn (for changes in inflation swap rates), and in percentage points per €1 bn (for changes in GIIPS bond yields) for visibility. Ratios can be negative if benefits are negative at increasing risks (lose–lose), or if benefits are positive at decreasing risks (win–win).

Program	Econ. benefit		/	Add. risk		= Ratio
SMP1	d(infl. swap)	0.01		d(EL)	0.3	4.9
07 May to				d(ES)	5.1	0.3
14 May 10	-d(5y yields)	2.66		d(EL)	0.3	8.9
				d(ES)	5.1	0.5
SMP2	d(infl. swap)	0.09		d(EL)	1.5	5.7
05 Aug to				d(ES)	14.7	0.6
12 Aug 11	-d(5y yields)	1.08		d(EL)	1.5	0.7
				d(ES)	14.7	0.1
OMT1	d(infl. swap)	0.09		d(EL)	-1.9	-4.9
27 Jul to				d(ES)	-41.4	-0.2
03 Aug 12	-d(5y yields)	0.21		d(EL)	-1.9	-0.1
				d(ES)	-41.4	-0.0
OMT2	d(infl. swap)	0.06		d(EL)	-1.5	-4.2
31 Aug to				d(ES)	-18.1	-0.3
07 Sep 12	-d(5y yields)	0.88		d(EL)	-1.5	-0.6
				d(ES)	-18.1	-0.0

Program	Econ. benefit		Add. risk		Ratio
VLTRO1	d(infl. swap)	0.10	d(EL)	-1.4	-7.3
16 Dec to			d(ES)	0.8	12.8
30 Dec 11	-d(5y yields)	0.02	d(EL)	-1.4	0.0
			d(ES)	0.8	0.0
VLTRO2	d(infl. swap)	-0.11	d(EL)	0.3	-56.3
24 Feb to			d(ES)	19.8	-1.2
09 Mar 12	-d(5y yields)	1.00	d(EL)	0.3	5.0
			d(ES)	19.8	0.1

ing unconventional ones, are ultimately tied to the ECB's single mandate of ensuring price stability, and that inflation was below target during the crisis. Alternatively, policy impact could be proxied by how much five-year benchmark bond yields decreased in stressed GIIPS countries (Greece, Ireland, Italy, Portugal, and Spain). This reflects the intuition that each policy operation was implemented during an escalating sovereign debt crisis. Both impacts are reported in Table H.1.

We report three findings. First, the OMT program was particularly risk efficient ex-post. Surprisingly, our risk efficiency ratio estimates can be negative. For instance, the two OMT-related announcements shifted long-term inflation expectations from deflationary tendencies toward the ECB's target of close to but below two percent (beneficial) and decreased the five-year sovereign benchmark bond yields of stressed euro area countries (also beneficial), while *removing* risk from the central bank's balance sheet. By contrast, the risk efficiency ratios associated with the SMP and VLTROs are not consistently negative.[6]

Second, the initial announcement of the SMP in 2010 has been more risk efficient than its later cross-sectional extension in 2011. This is intuitive, as the second installment of the SMP focused on deeper and relatively less stressed debt markets. Consequently, more bonds had to be purchased to have the same effect on liquidity risk premia. Since one key aim of the SMP was to add "depth and liquidity" to stressed government bond markets, it is natural to focus on its impact on GIIPS bond yields rather than a change in inflation swap rates. Overall, despite its benefits documented elsewhere (see, e.g., Eser and Schwaab, 2016), the SMP does not appear to have been a particularly risk-efficient policy ex post, particularly when compared to the two OMT announcements.[7]

Finally, the first allotment of VLTRO decreased GIIPS bond yields and increased inflation without increasing the Eurosystem's EL. By contrast, the second allotment was associated with both an increase in EL and ES99%, and a decrease in inflation swap rates. In this sense the first allotment was more risk efficient than the second installment.

[6]Scaling the SMP's impact by the risk of total SMP exposures at the end of the program, instead of the exposures just one week after its announcement, would make the SMP appear even less risk-efficient compared to the other two programs. Similarly, taking into account the additional duration risk implied by the SMP purchases would make the SMP appear less risk-efficient. Scaling by maximum in-sample exposures could in principle also be adopted for the VLTROs and OMT program. In these cases, however, the efficiency ratios would remain unchanged: The VLTRO exposures materialize with their allotment in the same week, and no OMT interventions have taken place so far.

[7]We also note the temporary increase in SMP-related EL around a Greek referendum in mid-2015 (see bottom panel of Figure F.1), approximately five years after the bonds were acquired. While the economic benefits of the asset purchases accrued mostly on impact, the associated risks remain on the central bank's balance sheet until the bonds mature.

I International risk spillovers

This section studies to what extent monetary policy announcements of *other* central banks can spill over to affect the Eurosystem's risks. To this purpose we focus on three important policy announcements:

1. the Federal Reserve's announcement of "QE3" combined with forward guidance on short term interest rates on 13 September 2012,

2. the"taper tantrum" following Fed communication on 22 May 2013, and

3. the Swiss National Bank's announcement to stop defending the peg of the Swiss franc to the euro on 15 January 2015.

Each of these had a discernable impact on domestic asset prices at the time, and could have had a discernible impact on the Eurosystem's portfolio credit risks.

Table I.1 reports our risk estimates before and after these announcements. Overall, other central banks' policy announcements did not have a large discernable impact on the Eurosystem's risks. Our EL and ES99% estimates move little around the respective dates. Changes in EL are typically below €1 bn from one Friday close to the next. A potential exception is the Fed's accommodative joint QE3 and forward guidance announcement in September 2012. At first glance, this announcement appears to have had a strong beneficial impact on the Eurosystem's EL and 99% ES. More likely, however, this impact could also be a lagged response to the ECB's second OMT announcement one week earlier.

Table I.1: Portfolio credit risks around other central banks' announcements

Portfolio credit risks for different monetary policy operations around three policy announcements: *i*) the Federal Reserve's QE3 and forward guidance announcement on 13 September 2012; *ii*) the Federal Reserve's announcement of their withdrawal from the bond market on 22 May 2013, which resulted in the so-called "taper tantrum"; and *iii*) the announcement by the Swiss National Bank to unpeg the Swiss Franc from the Euro on 15 January 2015.

Fed QE3 & FG,	07/09/2012		14/09/2012			
(following OMT2)	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	14.5	51.5	11.6	27.7	-2.8	-23.8
	[14.4 14.5]	[51.1 52.2]	[11.6 11.7]	[27.0 28.1]		
MRO	0.1	2.0	0.1	1.9	-0.0	-0.1
	[0.1 0.1]	[1.8 2.2]	[0.1 0.1]	[1.7 1.9]		
LTRO<1y	0.0	1.0	0.0	0.8	-0.0	-0.3
	[0.0 0.0]	[1.0 1.1]	[0.0 0.0]	[0.7 0.8]		
LTRO1y	0.0	0.2	0.0	0.1	-0.0	-0.0
	[0.0 0.0]	[0.1 0.2]	[0.0 0.0]	[0.1 0.1]		
VLTRO3y	0.5	15.0	0.5	14.5	-0.0	-0.6
	[0.5 0.5]	[14.8 16.1]	[0.5 0.5]	[13.9 15.2]		
Total	15.2	69.7	12.3	45.0	-2.9	-24.8

Fed 'taper	17/05/2013		24/05/2013			
tantrum'	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	1.2	19.2	1.0	20.6	-0.3	1.4
	[1.2 1.3]	[18.9 19.5]	[1.0 1.0]	[20.3 21.1]		
MRO	0.2	1.5	0.2	1.5	0.0	0.1
	[0.2 0.2]	[1.4 1.5]	[0.2 0.2]	[1.5 1.6]		
LTRO<1y	0.0	0.3	0.0	0.3	0.0	0.0
	[0.0 0.0]	[0.3 0.3]	[0.0 0.0]	[0.3 0.3]		
VLTRO3y	0.2	8.2	0.2	8.7	0.0	0.5
	[0.2 0.2]	[8.1 8.3]	[0.2 0.2]	[8.4 8.7]		
Total	1.6	29.2	1.4	31.2	-0.2	2.0

SNB peg	09/01/2015		16/01/2015			
	EL	ES99%	EL	ES99%	ΔEL	ΔES99%
SMP	2.2	11.3	2.0	11.3	-0.2	-0.0
	[2.1 2.2]	[11.3 11.5]	[2.0 2.0]	[11.3 11.4]		
MRO	0.0	0.8	0.0	0.8	-0.0	0.0
	[0.0 0.0]	[0.8 0.9]	[0.0 0.0]	[0.8 0.8]		
LTRO<1y	0.0	0.5	0.0	0.5	-0.0	-0.0
	[0.0 0.0]	[0.5 0.5]	[0.0 0.0]	[0.5 0.5]		
VLTRO3y	0.0	1.7	0.0	1.5	-0.0	-0.2
	[0.0 0.0]	[1.6 1.7]	[0.0 0.0]	[1.4 1.5]		
TLTRO	0.0	1.9	0.0	1.8	-0.0	-0.1
	[0.0 0.0]	[1.8 1.9]	[0.0 0.0]	[1.8 1.9]		
Total	2.3	16.3	2.1	15.9	-0.2	-0.4

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