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

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Abstract

We address the question to what extent a central bank can de-risk its balance sheet by unconventional monetary policy operations. To this end, we propose a novel risk measurement framework to empirically study the time-variation in central bank portfolio credit risks associated with such operations. The framework accommodates a large number of bank and sovereign counterparties, joint tail dependence, skewness, and time-varying dependence parameters. In an application to selected items from the consolidated Eurosystem's weekly balance sheet between 2009 and 2015, we find that unconventional monetary policy operations generated beneficial risk spill-overs across monetary policy operations, causing overall risk to be nonlinear in exposures. Some policy operations reduced rather than increased overall risk.

Keywords: Credit risk; risk measurement; central bank; lender-of-last-resort; unconventional monetary policy.

JEL classification: G21, C33.

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1 Introduction

For at least 150 years, going back to Baring (1797) and Bagehot (1873), central bankers have wondered to what extent they make rather than take their own balance sheet risks. 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 lender-of-last-resort (LOLR) 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 balance sheet risk; see e.g. Diamond and Dybvig (1983), Allen and Gale (2000), and Rochet and Vives (2004). Whether this possibility is empirically relevant, however, is unclear as reality rarely resembles the typical textbook case. In addition, empirical studies of central bank portfolio credit risks are rare, primarily because the required data are often confidential, proprietary and expensive, or publicly available but hard to find.

It is uncontroversial that lending freely in line with Bagehot (1873)-inspired principles as well as purchasing financial assets during a liquidity crisis can increase the credit risk of a central bank's balance sheet. How different lender- and investor-of-last-resort policies interact from a risk perspective, however, is currently less clear. Specifically, we ask: Can *increased* central bank liquidity provision or asset purchases during a liquidity crisis *reduce* bottom line central bank risks? This could happen if risk-taking in one part of the balance sheet (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 Eurosystem's financial buffers at all times sufficiently high to match the portfolio tail risks? Did past unconventional operations differ in terms of impact per unit of risk? Finally, can *other* central banks'

[1] Bagehot (1873) famously argued that any central bank liquidity support should be against good collateral, only to solvent banks, and at penalty rates when compared to normal times.

policy announcements spill over and affect the Eurosystem's credit risks?

During the euro area sovereign debt crisis 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 banks ensured the proper functioning of the financial system and, with it, the transmission of monetary policy. Such lending occurred mainly via main refinancing operations (MROs), multiple long-term refinancing operations (LTROs) with maturities of up to one year, two very-long-term refinancing operations (VLTROs) with a three-year maturity, as well as targeted LTROs (TLTROs), all backed by repeated expansions of the set of eligible collateral. In addition, the Eurosystem also acted as an investor-of-last-resort (IOLR) in stressed markets. For example, it purchased sovereign bonds in illiquid 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 lender- and investor-of-last-resort during the euro area sovereign debt crisis had a first-order impact on the size, composition, and, ultimately, the 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 banks. Particular concerns related to the materialization of credit risk and its effect on the central bank's reputation, credibility, 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 reports referred to the ECB unflatteringly as the ECBB: Europe's Central Bad Bank; see e.g. Brendel and Pauly (2011) and Böhme (2014). The Eurosystem's experience during the euro area sovereign debt crisis is, however, an ideal laboratory to study the impact of a central bank's unconventional policies on the risks inherent in its balance sheet.

The methodological part of this paper proposes a novel credit risk measurement framework that allows us to study the above questions. The framework is based on a tractable high-dimensional dependence (copula) function that can accommodate a large number of bank and sovereign counterparties simultaneously. The model is state-of-the-art in that it allows us to capture extreme joint tail dependence (fat tails), time-varying volatility and correlation parameters, as well as a potential asymmetry in the correlation dynamics. Our framework thus combines elements of earlier models put forward in Creal et al. (2011), Creal et al. (2014), and Lucas et al. (2014, 2017), which are here modified to accommodate a large number of counterparties and asymmetric correlation dynamics.

The central bank's risk management function is different from that of a commercial bank in at least three ways. First, unlike for commercial banks, 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 profit and loss statement 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 consequences for its ability to achieve its goals. Further, central bank profits are almost always distributed to sovereign treasuries, thus contributing to the public budget. In this sense, central bank profits have fiscal consequences; see e.g. Del Negro and Sims (2015). Because of this, and increasingly since the financial crisis, central banks as public institutions face scrutiny over their activities and financial risks.

Second, commercial banks, by engaging in maturity transformation, are by their very nature exposed to liquidity shocks. Central banks are uniquely able to provide liquidity-support in a liquidity crisis owing to the fact that they are never liquidity-constrained in the currency they issue; see e.g. Reis (2015), and Bindseil and Laeven (2017). Consequently, the default risk of the central bank in its domestic currency liabilities is zero at all times.

Finally, a small or medium-sized commercial bank is unlikely to be able to materially influence financial risks and risk correlations associated with the bank-sovereign nexus. Commercial banks are 'risk takers' in more than one sense – risk management is primarily about expediently choosing exposures at *given* risks. This is inherently less true for central banks, and as we show later particularly during a financial crisis.

The empirical part of this paper applies our high-dimensional credit risk framework to exposures associated with the Eurosystem's major conventional and unconventional monetary policy operations. Exposures are taken from the Eurosystem's balance sheet and measured at a weekly frequency between 2009 and 2015. Point-in-time risk measures are obtained from Moody's Analytics (for banks) or are inferred from CDS spreads (for sovereigns), also at a weekly frequency. All risk model parameters are estimated by the method of maximum likelihood. Standard portfolio risk measures, such as the expected loss and expected shortfall, are subsequently obtained through Monte Carlo simulation. We compare the model-implied portfolio credit risks shortly before and after key policy announcements to study the time differences associated with different monetary policy operations. A 'high-frequency' (weekly) assessment allows us to identify the effect of each policy on the relevant portfolio credit risks; see e.g. Rogers et al. (2014), Krishnamurthy et al. (2018), and Fratzscher and Rieth (2018) for similar event study approaches. To distinguish size from balance sheet composition effects we consider changes in portfolio credit risks both in absolute terms and in percentages of total assets.

We focus on four empirical findings. First, we find that LOLR- and IOLR-implied credit risks are usually negatively related in our sample. Taking risk in one part of the central bank's balance sheet (e.g., the announcement of SMP asset purchases) tended to de-risk other positions (e.g., collateralized lending 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, central bank risks can be nonlinear in exposures. In bad times, increasing size increases risk less than proportionally. Conversely, reducing balance sheet size may not reduce total risk by as much as one would expect by linear scaling. Risk spillovers between monetary policy operations are economically significant, and are similar in sign and magnitude around the time of the policy announcements.

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 invested some of the additional liquidity in government bonds, mitigating sovereign funding stress (see, e.g., Drechsler et al., 2016). The overall 99% ES increased, but only marginally so, by €0.8 bn. Total expected loss decreased, by €1.4 bn. We conclude that, in extreme situations, a central bank can de-risk its balance sheet by doing more, in line with Bagehot'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. For example, the asset purchases that were implemented in the week following the SMP's initial announcement on Sunday 09 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, also the extension of the SMP to include Spain and Italy in August 2011 did not reduce total balance sheet risk. In addition, this time the effect did not spill over to reduce the risk of the other monetary policy portfolios. This exception is probably 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.

Third, our risk estimates allow us to rank past unconventional monetary policies in terms of their ex-post 'risk efficiency'. Risk efficiency is the notion that an expected policy impact should be achieved with a minimum level of additional balance sheet risk. Put differently, policy impact should be maximal given a certain level of additional 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., a change in expected losses), it is possible to evaluate different policies ex-post by scaling the former by the latter. Doing so, we find that the OMT program dominates the SMP and VLTROs in terms of ex-post risk efficiency. The first allotment of VLTRO funds appears to have been 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.

Finally, we ask to what extent policy announcements of *other* central banks have influenced the Eurosystem's risks. For example, the Federal Reserve's announcement to 'taper off' asset purchases on 22 May 2013, or the announcement by the Swiss National Bank to unpeg the Swiss Franc from the Euro on 15 January 2015, could in principle have had a pronounced 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 this to be the case. Our expected loss and expected shortfall estimates barely move around these times.

Our findings can have important implications for the design of central banks' post-crisis operational frameworks. In addition, they can inform a debate on how to balance the need for a lender/investor-of-last-resort during liquidity crises with recent banking-sector regulations that seek to lower the frequency of such crises. As one key takeaway, a certain amount of excess liquidity 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 (by at least one order of magnitude in our crisis sample) than outright sovereign bond holdings per €1 bn of liquidity owing to a double recourse in the collateralized lending case. Implementing monetary policy via credit operations rather than asset holdings, whenever possible, therefore appears preferable from a risk efficiency perspective. 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 automatically increase a central bank's credit risks, and particularly so if the relevant haircuts are set in an appropriate way.

Our study relates to at least four directions of current research. First, several studies investigate the central bank's role of LOLR and IOLR during a liquidity crisis. Important contributions include Bagehot (1873), Diamond and Dybvig (1983), Allen and Gale (2000), Rochet and Vives (2004), and Drechsler et al. (2016). Freixas et al. (2004) provide a survey; see also Bindseil (2014) for a textbook treatment.

Second, a nascent strand of literature applies stress-testing methods to central banks' assets and income. 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 sovereign 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.

Third, we effectively apply 'market risk' methods to solve a 'credit risk' problem. As a result, we connect a growing literature on non-Gaussian volatility and dependence modeling with another growing literature on portfolio credit risk and loan loss simulation. 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). We argue that 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 portfolio credit risk monitoring and impact assessments in real time. Such frameworks are urgently needed at financial institutions, including central banks.

Finally, 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.[2] 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 remainder of the paper is set up as follows. Section 2 presents our exposure and risk 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 and data

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

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

2.1 (Un)conventional monetary policy operations

The Eurosystem adjusts the money supply in the euro area mainly via so-called refinancing operations. Eurosystem refinancing operations between 2009 and 2015 included main refinancing operations (MROs), long-term refinancing operations (LTROs), very-long-term refinancing operations (VLTROs), and targeted long-term refinancing operations (TLTROs).

Before the onset of the global financial crisis in 2007, MROs and three-month LTROs were sufficient to steer short-term interest rates, to manage aggregate liquidity, and to signal the monetary policy stance in the euro area. Following the onset of the global financial crisis, however, the Eurosystem was forced to significantly extend the scale and maturity of its operations to include one-year LTROs and three-year VLTROs. TLTROs were set up in June 2014 mainly to further support (subsidize) bank lending to the non-financial sector. Between 2010 and 2012 the Eurosystem also conducted asset purchases within its SMP program.

Figure 1 plots selected items of the Eurosystem's weekly balance sheet between 2009 and 2015.[3] 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 riskiness during the course of the global financial crisis and euro area sovereign debt crisis. A peak in total assets was reached at the height of the debt crisis in mid-2012, at approximately €1.5 trn, following two VLTROs and SMP government bond 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 VLTRO funds 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. Banks from non-stressed countries such as Germany and France were less liquidity-constrained and therefore relied less heavily on Eurosystem funding

[3] 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 sovereign bond holdings from purchases within the Securities Markets Programme (SMP). Vertical axis is in trillion euro. Data is weekly between 2009 and 2015. The SMP1 horizontal line refers to the initial announcement of the SMP on 10 May 2010. SMP2 marks the cross-sectional extension of the program on 08 August 2011. VLTRO1 marks the allotment of the first three-year VLTRO on 20 December 2011. VLTRO2 marks the allotment of the second three-year VLTRO on 28 February 2012. OMT1 marks the initial announcement of the OMT on 02 August 2012. OMT2 marks the announcement of the OMT's technical details on 06 September 2012.

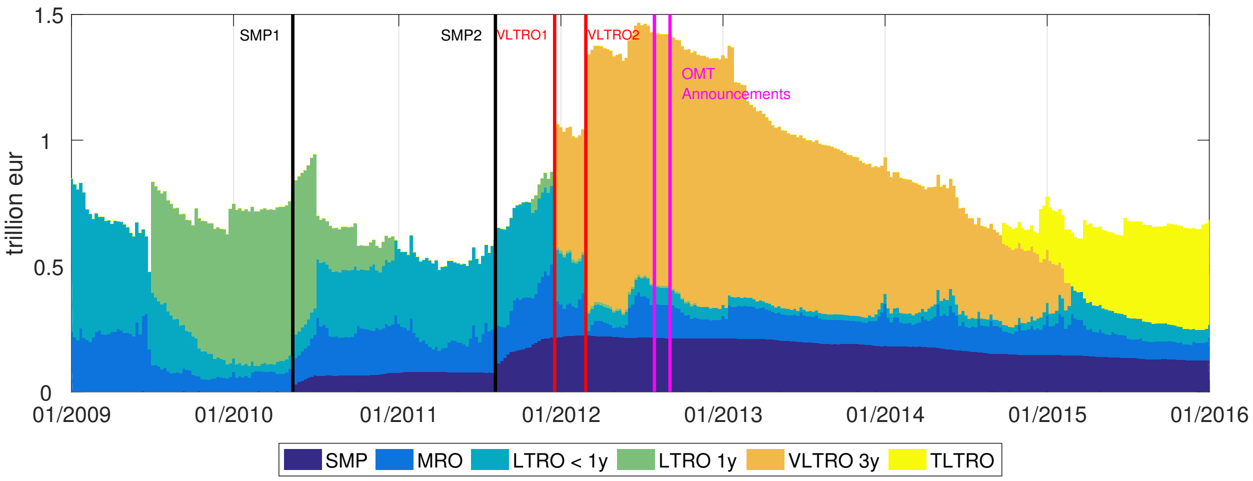
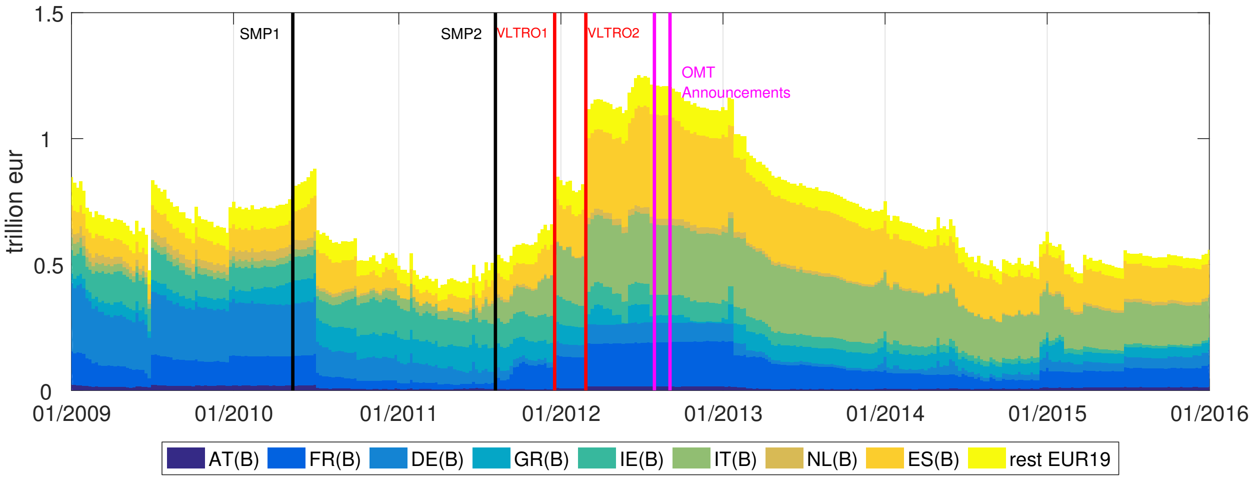


Figure 2: Eurosystem collateralized lending across countries

Exposures across different euro area countries from five liquidity-providing operations; see Figure 1. The vertical axis is in trillion euro. Vertical lines indicate the events described in Figure 1. Data is weekly between 2009 and 2015.



during the crisis.

The remainder of this subsection briefly reviews the three major unconventional monetary policy operations in chronological order: the SMP, the VLTROs, and the OMT. Each of these had a substantial impact on asset prices, point-in-time credit risks, and time-varying risk correlations; see, e.g., 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 purchases were not intended to affect the money supply. For this reason the purchases were sterilized at the time.

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. However, the Eurosystem released its total cross-country SMP portfolio holdings at the end of 2012 in its 2013 Annual Report. At the end of 2012, the Eurosystem held approximately €99.0bn in Italian sovereign 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

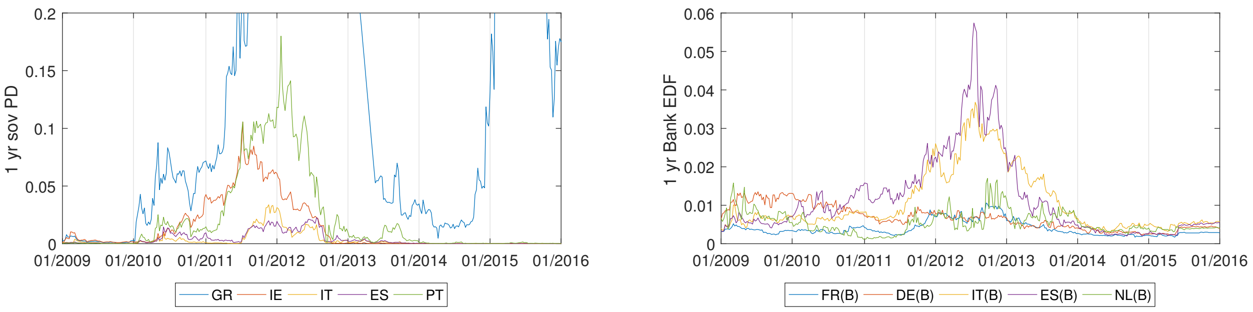
Two large-scale VLTROs were announced on 08 December 2011, and subsequently allotted to banks on 21 December 2011 and 29 February 2012. The first installment provided more than 500 banks with €489 bn at a low (1%) interest rate for the exceptionally long period of three years. The second installment 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, and at the same time keep operating and 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 sovereign 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).

Figure 3: Sovereign and banking sector EDFs

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



2.2 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 (PDs) to Eurosystem bank counterparties. EDFs are point-in-time forecasts of physical default hazard rates, and are based on a proprietary firm value model that takes firm equity values and balance sheet information as inputs; see Crosbie and Bohn (2003) for details. EDFs are standard credit risk measurements and are routinely used in the financial industry and credit risk literature; see for example Lando (2003), Duffie et al. (2007) and Duffie et al. (2009). We focus on the one-year-ahead horizon for data availability reasons and to align our estimates with the common annual reporting frequency.[4]

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. EDF indices based on averages

[4] Risk measures for different year-ahead horizons, when available, tend to be highly correlated. For example, the first principal component typically describes most of the total variation in a panel of CDS spreads across different maturities; see e.g. Longstaff et al. (2011). There is no instance of 1-year CDS rates falling significantly (by more than one standard deviation) and the 10-year rate increasing at the same time in our CDS spread data referencing the five SMP countries. As a result, we expect results based on one-year-ahead risk measures to be indicative of longer-term risk perceptions as well.

weighted by total bank assets are also available, but appear less reliable. The right panel of Figure 3 plots our 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.

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 A provides the details of our approach. To summarize, we first invert the CDS pricing formula of O'Kane (2008) to obtain risk-neutral default probabilities. We do this at each point in time for multiple CDS contracts at different maturities between 1 and 10 years. Second, we convert the risk-neutral probabilities into physical ones using the nonlinear mapping fitted by Heynderickx et al. (2016). Finally, we fit a Nelson Siegel curve to the term structure of CDS-implied-EDFs, and integrate the curve over the [0,1] year interval to obtain one-year-ahead CDS-implied-EDFs. The left panel of Figure 3 presents our sovereign risk measures for the five SMP countries.

3 Statistical model

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 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

$$\ell_t(k) = \sum_{i=1}^{N_t(k)} \ell_{it}(k) = \sum_{i=1}^{N_t(k)} \mathrm{EAD}_{it}(k) \cdot \mathrm{LGD}_{it} \cdot 1(\mathrm{default}_{it}), \tag{1}$$

where $k = 1, \ldots, K$ denotes monetary policy operations (e.g., LTRO lending or SMP asset holdings), $\ell_{it}(k)$ is the counterparty-specific one-year-ahead loss between week $t+1$ and $t+52$, $\mathrm{EAD}_{it}(k)$ is the exposure-at-default associated with counterparty i and policy operation k, $\mathrm{LGD}_{it} \in [0, 1]$ is the loss-given-default as a fraction of $\mathrm{EAD}_{it}(k)$, and $1(\mathrm{default}_{it})$ is an indicator function that takes the value of one if and only if counterparty i defaults. $N_t(k)$ is the total number of both bank and sovereign counterparties. 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, EAD_{it}, LGD_{it}, and the default indicator. Total losses from monetary policy operations are given by $\ell_t = \sum_{k=1}^{K} \ell_t(k)$. We focus on the one-year-ahead horizon as it coincides with typical reporting frequencies.

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

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

where $\mathbb{E}[\,\cdot\,]$ is the expectation over all sources of randomness in (1). 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 subscript t indicates that the time series of portfolio risk measures is available at a higher than annual frequency (e.g., weekly).

The remainder of this section reviews the modeling of the ingredients of (1) from right to left: dependent defaults, LGD, and EAD.

3.2 Copula model for dependent defaults

During and after the Great Financial Crisis the Gaussian 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 good risk models should include joint fat tails of individual risks, non-Gaussian copula dependence (to account for dependence in tail areas), time variation in parameters, and potential asymmetries in dependence; see e.g. McNeil et al. (2015, Ch. 7). Our model for dependent defaults follows closely from the frameworks developed in Creal et al. (2011) and Lucas et al. (2014, 2017). To tailor the model to the problem at hand, however, we need to modify it to accommodate a large number of 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 straightforward and reliable way.

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

$$p_{it} = \Pr[\tilde{y}_{it} < \tau_{it}] = F(\tau_{it}) \Leftrightarrow \tau_{it} = F^{-1}(p_{it}), \tag{2}$$

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, and F is the CDF of $\tilde{y}_{it}$. We stress that (2) is different from a typical Merton (1974) model in at least two ways. First, unlike Merton (1974), p_{it} is treated as an observed *input* in our model. 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 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 (2). The reduced form character of (2) 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

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

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 fat tails in the copula, 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 (3) without loss of generality since copula quantiles shift linearly with the mean.

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 (3), however, we introduce asymmetry in a novel way via the transition equation governing the correlation parameters in $\Omega_t^{(k)}$ as detailed in the next subsection. 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. By contrast, quantiles of skewed densities such as the Generalized Hyperbolic skewed-t density used in Lucas et al. (2014) 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.

3.3 Score-driven copula dynamics

The time-varying covariance matrix $\Omega_t^{(k)}$ introduced below (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 empirical applications based on dynamic (block-)equicorrelation matrices.

The smaller covariance matrix Σ_t is specified to depend on a vector of latent correlation factors f_t. Specifically, $\Omega_t^{(k)} = \Omega_t^{(k)}\left(\Sigma_t(f_t)\right)$, where $\Sigma_t\left(f_t\right) \in \mathbb{R}^{D\times D}$, and $D << N_t(k)$. Our empirical application below considers nine banking sector risk indices and five SMP countries, thus $D = 14 << N_t(k)$ at any t and k. The mapping of matrix elements $\Omega_t^{(k)}(i,j) = \Sigma_t\left(l(i), m(j)\right)$ is surjective but not injective (i.e. any element of Σ_t typically appears multiple 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) and Lucas et al. (2017). In any case, our results reported in Section 4 are robust to scaling up the within-country correlations.

Our approach for modeling $\Sigma_t(f_t)$ builds on the approach of Creal et al. (2011). In this framework, the Choleski decomposition of Σ_t is specified in terms its hyperspheric (polar) coordinates and the factors $f_t \in R^{(D-1)(D-2)/2\times 1}$ specify the relevant 'angles' of these coordinates. This setup ensures that Σ_t is always positive definite and symmetric.[5]

[5] The covariance matrix $\Omega_t^{(k)}$ obtained from Σ_t is symmetric but not guaranteed to be positive definite. A

The D-dimensional multivariate Student's t density implied by the mixture (3) is given by

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

where Σ_t is used instead of $\Omega_t^{(k)}$, $\Gamma(\cdot)$ is the gamma function, and ν is the degrees of freedom parameter. The dynamics of f_t are specified by the transition equation

$$f_{t+1} = \omega \cdot \text{vech}\left(\rho\left(\bar{\Sigma}\right)\right) + A \cdot S_t \nabla_t + B \cdot f_t, \tag{5}$$

where ω, A, and B are parameters and matrices to be estimated, $\text{vech}\Big(\rho\big(\bar{\Sigma}\big)\Big) \in R^{(D-1)(D-2)/2 \times 1}$ contains appropriately transformed unconditional correlations, the scaling matrix S_t is chosen as the inverse conditional Fisher information matrix $\text{E}_{t-1}\left[\nabla_t \nabla_t'\right]^{-1}$, and ∇_t is the score of (4) given by

$$\begin{aligned} \nabla_t &= \frac{\partial \text{vech}\big(\Sigma_t(f_t)\big)'}{\partial f_t} \cdot \frac{\partial \log p(y_t; \Sigma_t, \nu)}{\partial \text{vech}(\Sigma_t)} \\ &= \frac{1}{2} \Psi_t' \mathcal{D}_D' (\Sigma_t^{-1} \otimes \Sigma_t^{-1}) \left[\frac{(\nu + D)}{\nu - 2 + y_t' \Sigma_t^{-1} y_t} (y_t \otimes y_t) - \text{vec}(\Sigma_t)\right], \end{aligned} \tag{6}$$

where log denotes the natural logarithm, Ψ_t is the derivative $\partial \text{vech}(\Sigma_t)/\partial f_t'$, $\mathcal{D}_D$ is the duplication matrix as defined in Abadir and Magnus (2005), and $\otimes$ denotes Kronecker multiplication.

The transition equation (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

close approximation to $\Omega_t^{(k)}$, however, is always positive definite. In case the Choleski decomposition of $\Omega_t^{(k)}$ fails we apply an eigenvalue (spectral) decomposition to the symmetric matrix instead and subsequently set any negative eigenvalues to zero. A square-root of $\Omega_t^{(k)}$ is convenient when generating draws from (3), and is not required at the parameter estimation stage.

initial value f_1 is most conveniently initialized at the unconditional mean of the stationary process.

To accommodate a possibly asymmetric response in the correlation dynamics, we extend the score (6) slightly as

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

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. Clearly, (7) reduces to (6) for $C = 0$. Values of $C \neq 0$, however, allow the correlations to react differently to increasing versus decreasing marginal risks. 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).

The covariance $\Sigma_t(f_t)$ is fitted to weekly log-changes in observed bank and sovereign EDFs. Web Appendix B discusses our univariate modeling strategy for changes in marginal risks. The scaling function S_t in (5) is available in closed form; see Web Appendix C for details.

3.4 Loss-given-default

Portfolio risk levels depend substantially on the assumptions made in 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, owing to conservative ex-ante risk protection frameworks and haircuts.

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, out-of-fashion mortgage-backed-securities had been posted as collateral. These 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

$$\text{LGD}_{it} = 0.02 + 0.58 \cdot 1\left\{\tilde{y}_{jt} < \tau_{jt} \text{ for at least one SMP country } j\right\}.$$

i.e., $\text{LGD}_{it} = 0.02$ if bank counterparty i defaults but no SMP counterparty $j \neq i$ defaults. The LGD increases to 60% if bank i defaults and a (any) SMP sovereign defaults as well (in the same simulation) and a sovereign debt crisis were to ensue as a result. The 2% value for bank workout LGDs is not unrealistically low, as explained above. The 60% stressed LGD is chosen in line with international evidence on sovereign bond haircuts; see e.g. Cruces and Trebesch (2013, Table 1).

In case of a sovereign counterparty, e.g., for government bonds acquired within the SMP, only a single recourse applies. We set the LGD to 60% should such a default be observed,

$$\text{LGD}_{jt} = 0.60 \cdot 1\left\{\tilde{y}_{jt} < \tau_{jt} \text{ for SMP country } j\right\}.$$

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.

3.5 Exposures-at-default

Exposures-at-default $\text{EAD}_{it}(k)$ 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. To keep things simple and interpretable, however, we assume that $\text{EAD}_{it}(k) = \text{EXP}_{it}(k)$.

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.[6] 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

$$\text{EXP}_{i,jkt} = \frac{a_{i,jkt}}{\sum_{i=1}^{N_t(j,k)} a_{i,jkt}} \cdot \text{CountryExp}_{jkt}^{\text{observed}},$$

in this way dividing up the observed aggregate bank lending volume per country and policy

[6] 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).

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 is approximately consistent with the cross-section of total bank liabilities in the euro area between 2009 and 2015 using the Hill (1975) estimator.

3.6 Parameter estimation

Observation-driven multivariate time series models such as (2)–(5) are attractive because the log-likelihood is known in closed form. Parameter estimation is standard as a result. This is a key advantage over alternative parameter-driven risk frameworks, as e.g. considered in Koopman et al. (2011, 2012), and Azizpour et al. (2017), for which the log-likelihood is not available in closed form and parameter estimation is non-standard. For a given set of observations $y_1, \ldots, y_T$, 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

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

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 the observed 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 as described in Section 3.3. The maximization in (8) can be carried out using a conveniently chosen quasi-Newton optimization method. The sub-covariance matrix $\Omega^{(k)}$ for program k can be obtained directly from the general matrix $\Omega(\Sigma_t(f_t))$.

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. As is standard, we transform the outcomes using the probability integral transform and subsequently estimate the copula parameters. Lucas et al. (2014) discuss similar one-step and two-step estimation approaches in a related setting and find that they lead to similar estimates. Second, we assume that matrices A, B, and C in the factor transition equation (5) are scalars, such that $\theta = \{\omega, A, B, C, \nu\} \in \mathbb{R}^5$ is a vector of relatively low dimension.

4 Empirical results

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

4.1 Model specification and parameter estimates

For model selection, we are most interested in whether the novel leverage term in (5) is preferred by the data. Table 1 reports parameter estimates for two different specifications of the copula model (2)–(7). The model parameters are estimated from $9+5 = 14$ multivariate time series of daily log changes in banking sector 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 B.

Allowing for an asymmetric response of the correlation factors is preferred by the data based on the log-likelihood fit.The increase in log-likelihood is significant at the 5% level. Web Appendix D shows that model choice can have a small-to-moderate effect on our expected shortfall estimates. Mean loss estimates are less sensitive. The degree-of-freedom parameter $\nu \approx 12$ allows for a moderate (but certainly non-Gaussian) degree of joint tail

Table 1: Parameter estimates

Parameter estimates for the copula model (4)–(7) fitted to daily log changes in banking sector and sovereign EDFs. Univariate Student's t models with leverage are used to model the marginal volatilities; see Web Appendix B. Standard errors, in parentheses, are constructed from the numerical second derivatives of the log-likelihood function.

	Copula dynamics	
	symmetric	asymmetric
	($C = 0$)	($C \neq 0$)
ω	0.977	0.988
	(0.005)	(0.007)
A	0.007	0.008
	(0.003)	(0.002)
B	0.953	0.969
	(0.034)	(0.013)
C	-	-0.555
	-	(0.206)
ν	11.964	11.970
	(0.991)	(0.982)
logLik	1629.49	1631.83
AICc	-3251.0	-3253.6

dependence in the copula.[7] Parameter $C < 0$ implies that correlations *increase* more quickly in bad times than they decrease in good times.[8] Experimenting with block-specific C parameters did not lead to significantly improved log-likelihoods. We select the asymmetric 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 hypotheses given the data at hand.

4.2 Expected losses

A large literature studies the beneficial impact of Eurosystem unconventional monetary policies during the euro area sovereign debt crisis on financial markets and macroeconomic outcomes; see e.g. Eser and Schwaab (2016), Krishnamurthy et al. (2018), and Fratzscher and Rieth (2018), among many others. By contrast, the potential downsides of unconventional policies, e.g. in terms of increased balance sheet risk, have received less attention.

[7] The degree-of-freedom parameters ν for the marginal univariate models are substantially lower, and vary between approximately three and eight; see Web Appendix B.

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

Figure 4: Expected losses for collateralized lending and SMP portfolios

Top panel: one-year-ahead expected losses from liquidity providing operations at a weekly frequency. Bottom panel: one-year-ahead expected losses 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.

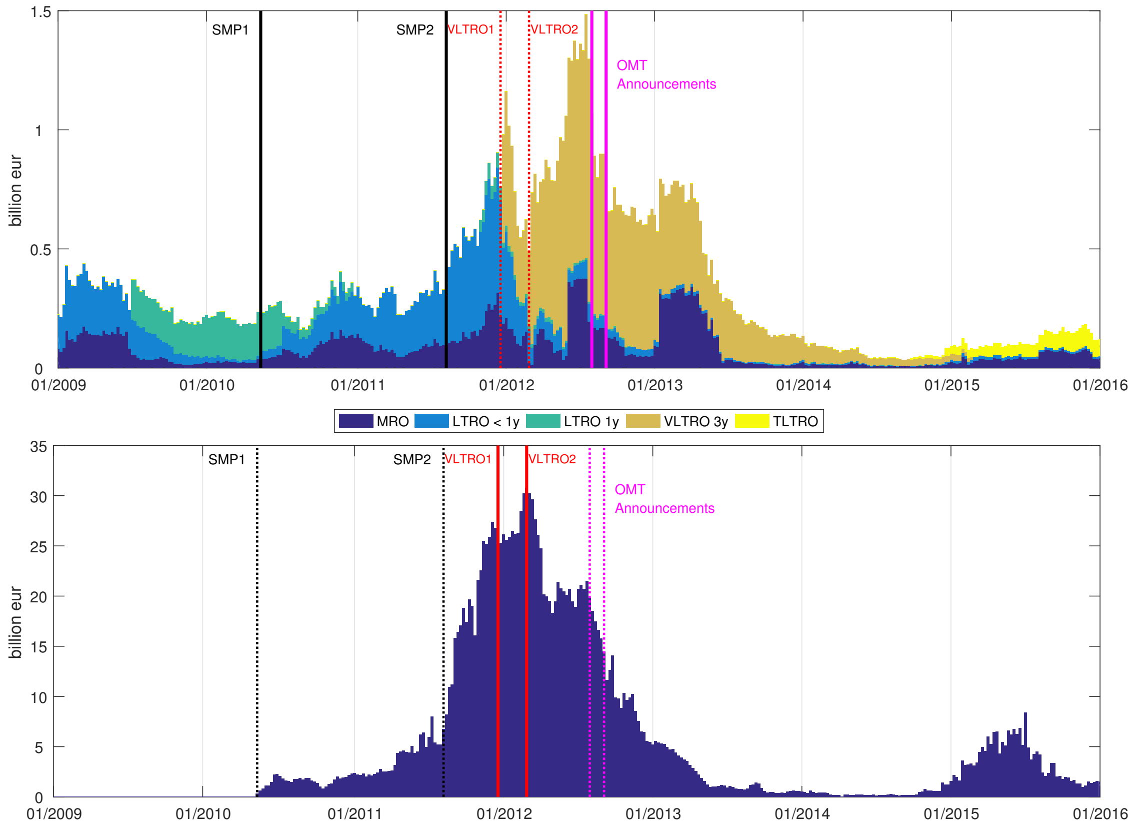


Figure 4 plots estimated one-year-ahead expected losses from Eurosystem collateralized lending operations (top panel) and SMP asset purchases (bottom panel). Expected losses are additive across operations, and therefore stacked vertically in the top panel of Figure 4. The mean of the loss density is calculated by simulation, using 200,000 draws at each time t. 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 expected losses in Figure 4 reflect, first, 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. The pronounced difference in risk is explained by the double recourse in the case of collateralized lending. In addition, Figure 4 hints at the presence of beneficial spillovers across monetary policy operations. For example, the OMT announcements appear to have had a pronounced impact on the expected losses associated with the collateralized lending and SMP asset portfolios.

4.3 Financial buffers and portfolio tail risk

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

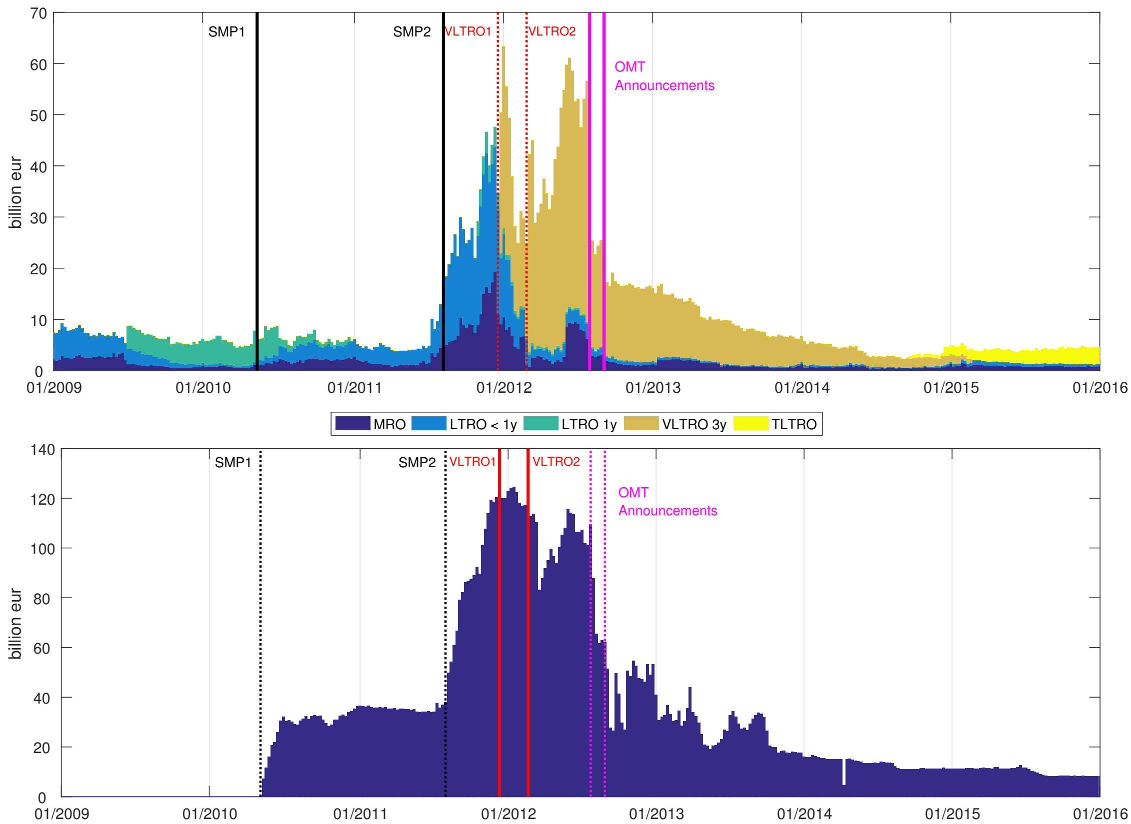
The top and bottom panel of Figure 5 plot the 99% ES associated with five collateralized lending operations and SMP assets. The ES estimates exhibit pronounced time series variation, peaking in 2012 at approximately €60 bn for the collateralized lending operations and at approximately €120 bn for the SMP portfolio. All portfolio tail risks collapse sharply following the OMT announcements.

When our EL and ES estimates are scaled by the corresponding policy's exposure, the SMP assets are substantially more risky per €1 bn of exposures than the collateralized lending operations. Risk per unit of exposure often differs by more than an order of magnitude. We refer to Web Appendix E for details.

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 financial

Figure 5: ES 99% for collateralized lending and SMP portfolios

Top panel: 99% expected shortfall 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 2.1. Data is weekly between 2009 and 2015.



(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 (2013b, p. 44). The overall financial buffers therefore stood at €552 bn. Comparing these balance sheet items with our ES estimates in Figure 5 we conclude that the Eurosystem's buffers were at all times sufficient to withstand an ES99%-sized credit loss, even at the peak of the euro area sovereign debt crisis.

Table 2: Portfolio credit risks around key policy announcements

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, the allocation of the first VLTRO on 20 December 2011 and of the second VLTRO on 20 February 2012, OMT announcement on 02 August 2012, and the announcement of the OMT's technical details on 06 September 2012.

SMP1	07/05/2010		14/05/2010			
	EL	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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

4.4 Risk spillovers across monetary policy operations

The riskiness of the Eurosystem's balance sheet depends on the financial health of its counterparties, which in turn depends on central bank liquidity provision to and asset purchases from those same counterparties. This two-way interdependence can give rise to a pronounced nonlinearity in the central bank balance sheet risks, e.g. as the economy switches from a 'bad'

Table 2: Portfolio credit risks around key policy announcements; ctd.

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, the allocation of the first VLTRO on 20 December 2011 and of the second VLTRO on 20 February 2012, OMT announcement on 02 August 2012, and the announcement of the OMT's technical details on 06 September 2012.

VLTRO2	24/02/2012		09/03/2012			
	EL	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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

equilibrium to a 'good' one.

The high (weekly) frequency of the risk estimates plotted in Figures 4 and 5 allow us to identify the impact of certain key ECB announcements on those risks. Table 2 presents our risk estimates (EL and 99% ES) shortly before and after six key policy announcements. Web Appendix E presents the analogous results in per cent of the corresponding exposures.[9]

We focus on two main results. 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 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. Increasing size increased overall risk less than proportionally, and by less than one would have expected holding PDs and risk dependence fixed at pre-announcement levels. This suggests that increasing balance sheet size during a liquidity 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 a financial crisis.

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, and de-risked the SMP asset portfolio (as banks invested some of the VLTRO additional liquidity in government

[9]SMP-related exposures only build up gradually over time. We return to this issue in Section 4.5.

bonds; see e.g. Acharya and Steffen (2015) and Drechsler et al. (2016)). As a result, the overall 99% ES increased, but only marginally 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. I.e., 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 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.

4.5 Risk efficiency

Portfolio risk estimates 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 losses or in expected shortfall as reported in Figures 4 and 5, different policy operations can be evaluated by scaling the former by the latter. This is similar to the definition of a Sharpe (1966) return-to-risk ratio.

Scaling policy impact by additional risk is not unproblematic for at least three reasons. First, ex-ante risk efficiency deliberations are probably 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 after the announcement. Second, scaling impact by additional risk may create the impression that both are equally important. 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. 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 3 presents the efficiency ratios of purchase programs and credit operations separately for this reason.

Table 3 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, including 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 3. Additional risk could, similarly, be assessed in different ways. We consider the EL and the 99% ES for this purpose. The efficiency ratios in the final column of Table 3 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).

We focus on three findings. First, the OMT program dominates the VLTROs and the SMP in terms of ex-post risk efficiency. 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

Table 3: Risk efficiency ratios

Economic benefit, additional central bank balance sheet risk, and efficiency ratio 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. Double entries are omitted for clarity below the first panel. Ratios are in basis points per €bn for changes in inflation swap rates, and in percentage points per €bn for changes in GIIPS bond yields.

Program	Econ. benefit		Add. risk		Ratio
SMP1	d(infl. swap)	0.01	d(EL)	0.3	4.9
07 May to		0.01	d(ES)	5.1	0.3
14 May 10	-d(5y yields)	2.66		0.3	8.9
		2.66		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			0.7
					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			-0.1
					-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			-0.6
					-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			0.0
					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			5.0
					0.1

sheet. By contrast, the risk efficiency ratios associated with the SMP and VLTROs are not consistently negative.[10]

Second, the initial announcement of the SMP in 2010 appears to have been more risk efficient than its later cross-sectional extension in 2011. This is intuitive, as the second

[10] 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. Scaling by maximum in-sample exposures could also be adopted for the VLTROs and OMT program. In this case, however, the efficiency ratios would remain unchanged as the VLTRO exposures materialize with their allotment in the same week, and no OMT interventions have taken place so far.

installment of the SMP focused on deeper and relatively less stressed debt markets. As a result, 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.[11]

Finally, the first allotment of VLTRO decreased GIIPS bond yields and increased inflation without (initially) increasing the Eurosystem's expected loss. By contrast, the second allotment was associated with both an increase in expected loss and 99% expected shortfall. As a result, the first allotment appears to have been more risk efficient than its second installment.

4.6 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: the Federal Reserve's announcement of "QE3" combined with forward guidance on short term interest rates on 13 September 2012, the"taper tantrum" following Fed communication on 22 May 2013, and the Swiss National Bank's announcement to stop defending the peg of the Swiss franc to the euro on 15 January 2015. The first event is accommodative, while the second and third event are contractionary. Each of these had a major impact on domestic asset prices and volatilities at the time, and could in principle have impacted the Eurosystem's risks.

Table 4 reports our risk estimates before and after these announcements. We focus on the Friday close before and after the announcement. Overall, other central banks' policy

[11] We also note the temporary increase in SMP-related expected losses around a Greek referendum in mid-2015 (see bottom panel of Figure 4), 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.

Table 4: 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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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

announcements appear to have had only a minor impact on the Eurosystem's risks. Changes in expected losses are typically below €1 bn. A potential exception is the Fed's 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. The effect could also be attributable, however, to a lagged response to the ECB's second OMT announcement one week earlier.

5 Conclusion

We introduced a tractable non-Gaussian framework to infer central bank balance sheet risks at a high (weekly) frequency. We applied our framework to a subset of Eurosystem monetary policy operations during the euro area sovereign debt crisis. 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, and particularly try to obtain policy objectives 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. It therefore seems preferable from a risk efficiency perspective to implement this part of monetary policy via credit operations rather than asset holdings, provided this is possible. Our results also suggest that such a policy implementation does not necessarily have to result in substantially increased central bank credit risks conditional on haircuts and eligibility criteria being set appropriately.

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Web Appendix to

“Risk endogeneity at the lender/investor-of-last-resort”

Web Appendix A: CDS-implied sovereign EDFs

Firm-value based EDF measures are unavailable for euro area sovereigns. We therefore seek to 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. 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},

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

$$\log\left(\frac{\lambda^Q}{\lambda^P}\right) = a_2 \left(\lambda^P\right)^{b_1} \tag{A.2}$$

where we have dropped subscripts i and t for ease of reading. For small λ^P and λ^Q, A.1 ensures that $\lambda^P \to 0$ as $\lambda^Q \to 0$. For large λ^P and λ^Q, A.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 A.1 for λ^Q to the left of the crossover point, and A.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,

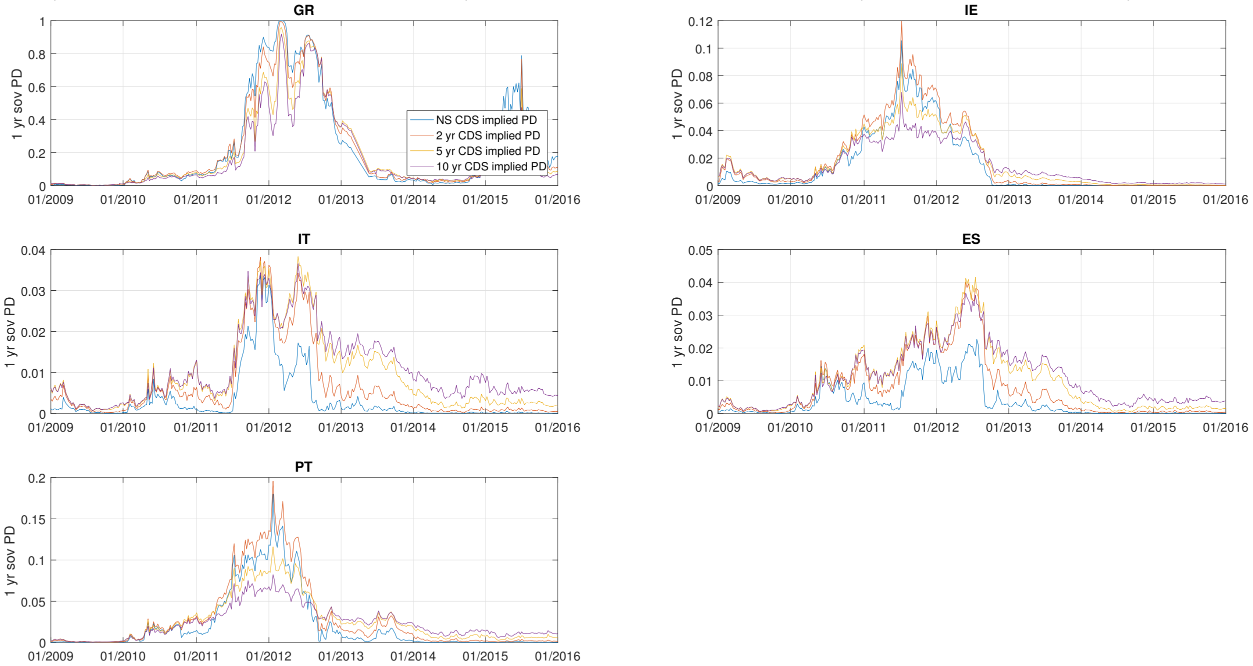
$$\lambda_{\mathrm{NS}}^{P}(\tau) = \beta_0 + \beta_1 \tilde{\tau}^{-1}\left(1 - \exp\left(-\tilde{\tau}\right)\right) + \beta_2\left[\tilde{\tau}^{-1}\left(1 - \exp\left(-\tilde{\tau}\right)\right) - \exp\left(-\tilde{\tau}\right)\right], \tag{A.3}$$

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 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 A.3 over a range of maturities T. The solver picks the set of $\{\beta_j, T\}$ that minimizes the least squares difference

Figure A.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.



between λ_{it}^P and $\lambda_{\mathrm{NS};it}^P$.

Step 4

Given the fitted curve, we can predict forward-looking physical default probabilities $\mathrm{PD}_{it}^P(\tau)$. 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

$$\mathrm{PD}_i^P(\tau = 1) = 1 - \exp\left(-\int_0^{\tau=1} \lambda_{\mathrm{NS};it}^P(s)\mathrm{d}s\right). \tag{A.4}$$

Figure A.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.

Web Appendix B: Univariate models

Our univariate marginal modeling strategy is identical to the one used in Lucas et al. (2017). We first restate it here for convenience. Then we discuss the relevant parameter estimates.

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 detailed in Web Appendix A. 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

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

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

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

where

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

The transition equation (B.1) accommodates both an asymmetric volatility response as well as skewness in the unconditional distribution of y_t.

Table B.1 reports the univariate models' parameter estimates. Most volatility processes are fairly persistent with autoregressive parameters B varying between 0.75 and 0.97. The leverage

Table B.1: Univariate Parameter estimates

The table reports parameter estimates for 14 univariate time series models. The sample consists of weekly changes in log-EDFs from January 2009 to December 2015. The top five rows refer to sovereign (sov) CDS-implied EDFs. The bottom nine rows correspond to banking sector EDFs. The Students 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.

	ω	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)

parameters C are significant in some but not all specifications. The estimates of the degree-of-freedom 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.

The sample size T is 7 (years) $\times$ 52 (weeks) $=$ 364. Given the moderate T dimension and the nonlinearities present in the univariate model (B.1) – (B.2), the numerical maximization of the log-likelihood function is not always unproblematic. Specifically, the maximizer may converge to a boundary value of the parameter space, or may end up in a local maximum, for some reasonable starting value of the parameters in $\theta \in \mathbb{R}^5$. To overcome such numerical problems we estimate each univariate model 100 times with different random starting values, and then further study the maximum likelihood estimate. Specifically, we plot the log-likelihood at the maximum sliced in each dimension and study the non-singularity (invertibility) of the numerical second derivative as suggested by e.g. Rothenberg (1971). The standard errors in Table B.1 suggest that the marginal model parameters can be estimated fairly precisely from our moderately-sized sample. We proceed in an analogous way for the copula model parameters.

Web Appendix C: Score and scaling function for the multivariate t-copula

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 $y_t = F^{-1}(\hat{u}_t;\nu)$. The D-dimension multivariate t density is given by

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

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 equivalent to the correlation matrix R_t.

The score-driven dynamics are incorporated in the covariance matrix in a similar fashion as in Creal et al. (2011), where $\Sigma_t = \Sigma(f_t)$. We also include an asymmetry/leverage term in the copula, defined for the adverse case that risks go up, i.e. that $y_t > 0$. The dynamic system is given by

$$\begin{aligned}
f_{t+1} &= \omega \cdot \text{vech}\left(\rho\left(\bar{\Sigma}\right)\right) + A \cdot S_t\nabla_t + B \cdot f_t,\\
s_t &= \mathcal{S}_t\nabla_t,\\
\nabla_t &= \frac{1}{2}\Psi_t' D_D'(\Sigma_t^{-1}\otimes\Sigma_t^{-1})\Big[\frac{(\nu+k)}{\nu-2+y_t'\Sigma_t^{-1}y_t}(y_t\otimes y_t) - \text{vec}(\Sigma_t)\\
&+ C\cdot\text{vec}\Big(\big(1(y_t\ .>0)\odot y_t\big)\cdot\big(1(y_t\ .>0)\odot y_t\big)'\Big)\Big],\\
\mathcal{S}_t &= \left(\frac{1}{4}\Psi_t'\mathcal{D}_k'(\mathcal{J}_t'\otimes\mathcal{J}_t')[gG - \text{vec}(\mathrm{I})\text{vec}(\mathrm{I})'](\mathcal{J}_t\otimes\mathcal{J}_t)\mathcal{D}_k\Psi_t\right)^{-1},
\end{aligned}$$

where Ψ_t is the derivative $\partial\text{vech}(\Sigma_t)/\partial f_t'$, $\mathcal{D}_k$ is the duplication matrix 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 $(\nu+k)/(\nu+k+2)$.

The $k^2 \times k^2$ matrix G is a particular matrix whose element $G[\cdot,\cdot]$ is given by

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

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

There are a few alternative ways to map f_t into the covariance matrix Σ_t, and the specific form of the derivative Ψ_t varies accordingly. We adopt a correlation structure based on hyperspherical coordinates $R_t = X_t' X_t$ where $X_t(\phi_t)$ is an upper-triangular matrix,

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

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

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

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

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

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

where $\mathcal{B}_k$ is the elimination matrix, $\mathcal{C}_k$ is the commutation matrix (Abadir and Magnus (2005)), and $Z_t = \partial \mathrm{vec}(X_t)/\partial \phi_t'$ is available in closed form.

Web Appendix D: Portfolio risk with and without the leverage term

Figures D.1 and D.2 help assess the economic significance of the leverage term in the copula specification (7). The leverage term matters moderately for the ES estimate. EL estimates are less affected. Rather than subtle changes in the dependence structure, portfolio credit risks are most sensitive to changes in the marginal PDs p_{it}, as inferred from banking sector-specific and sovereign EDFs.

Figure D.1: ES 99% with and without leverage term

The top panel plots the 99% ES with a non-zero leverage term, as used in the main text. The bottom panel plots the 99% ES from collateralized lending operations, with the leverage term restricted to zero and all remaining parameters re-estimated. Vertical axes are in billion euro. Data is weekly between 2009 and 2015.

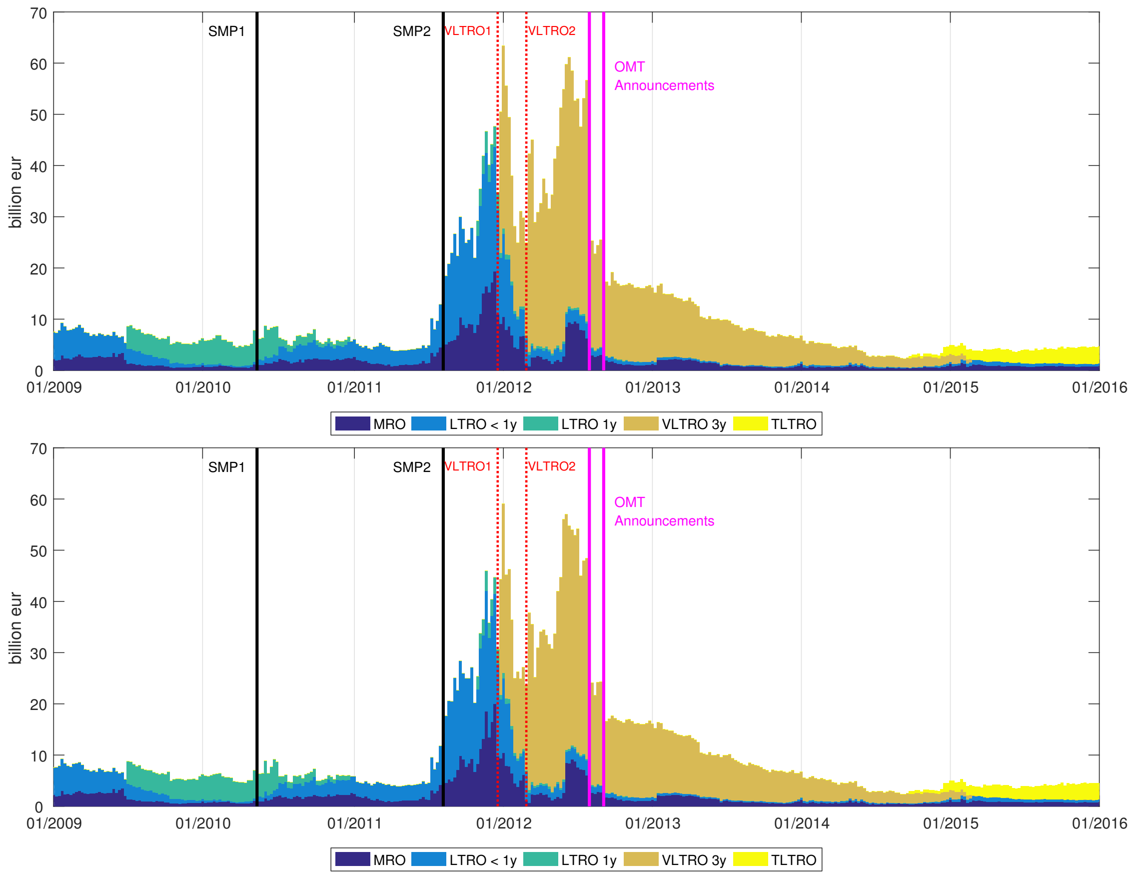
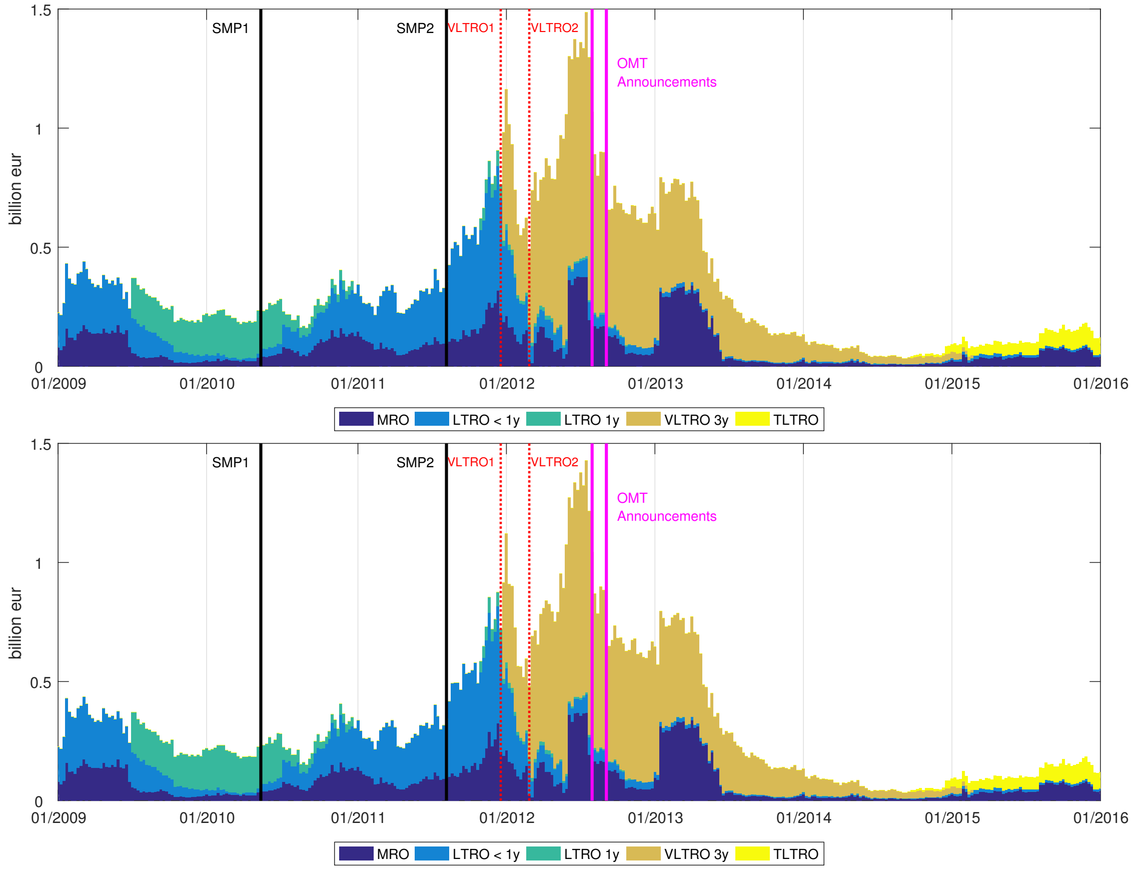


Figure D.2: EL with and without leverage term

The top panel plots the EL with a non-zero leverage term, as used in the main text. The bottom panel plots the EL from collateralized lending operations, with the leverage term restricted to zero and all remaining parameters re-estimated. Vertical axes are in billion euro. Data is weekly between 2009 and 2015.



Web Appendix E: Risks in % of size around policy announcements

Figures E.1 and E.2 report the ES 99% and EL for collateralized lending and SMP assets, respectively. The risk estimates are now plotted in per cent of the respective exposures. Table E.1 reports portfolio credit risk estimates around six key policy announcements, also in per cent of exposures.

Table E.1 and Figure E.2 are in line with the notion that balance sheet risks also depend on asset composition. For example, the expected loss and shortfall estimates for SMP assets per €1 bn of bonds decreased around the extension of the program to include Italian and Spanish bonds (SMP2). These bonds were perceived by market participants at the time to be relatively less credit-risky than the Irish, Portuguese, and Greek bonds purchased earlier.

A certain amount of excess liquidity for monetary policy purposes can be achieved via both credit operations and asset purchases. Table E.1 suggests that collateralized credit operations imply substantially less credit risks than outright sovereign bond holdings per €1 bn of excess liquidity. This is intuitive, owing to a double recourse in the collateralized lending case. Implementing monetary policy via credit operations rather than asset holdings, whenever possible, therefore appears preferable from a risk efficiency perspective.

Figure E.1: ES 99% and EL for collateralized lending in per cent of exposures

ES 99% and EL for five collateralized lending portfolios, each in per cent of the respective total exposure. The vertical lines mark the events described in Section 2.1. Data is weekly between 2009 and 2015.

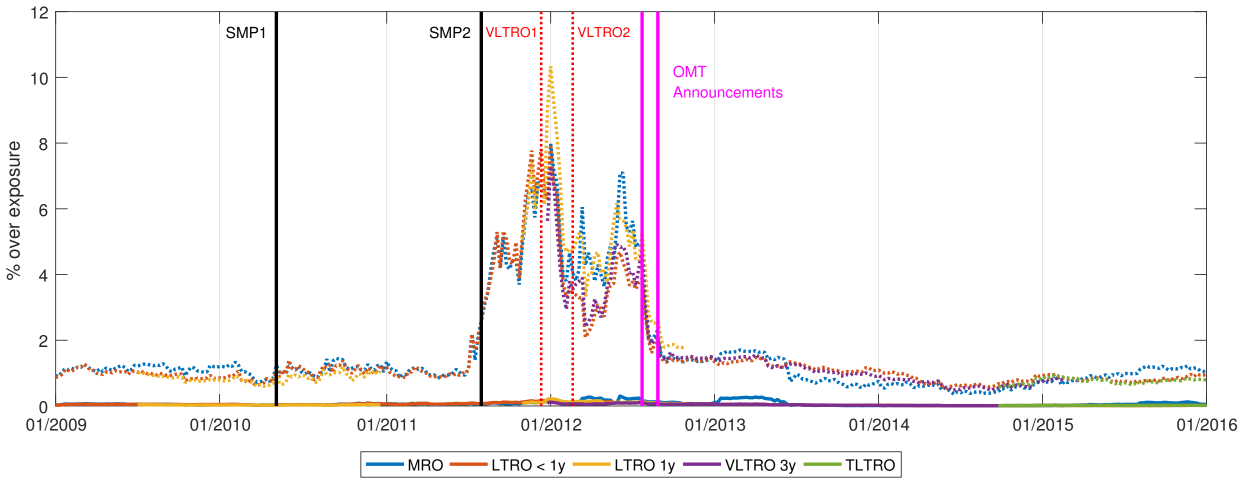


Figure E.2: ES 99% and EL for SMP assets in per cent of exposures

ES 99% and EL for SMP assets in per cent of nominal (par) value. The vertical lines mark the events described in Section 2.1. Data is weekly between 2009 and 2015.

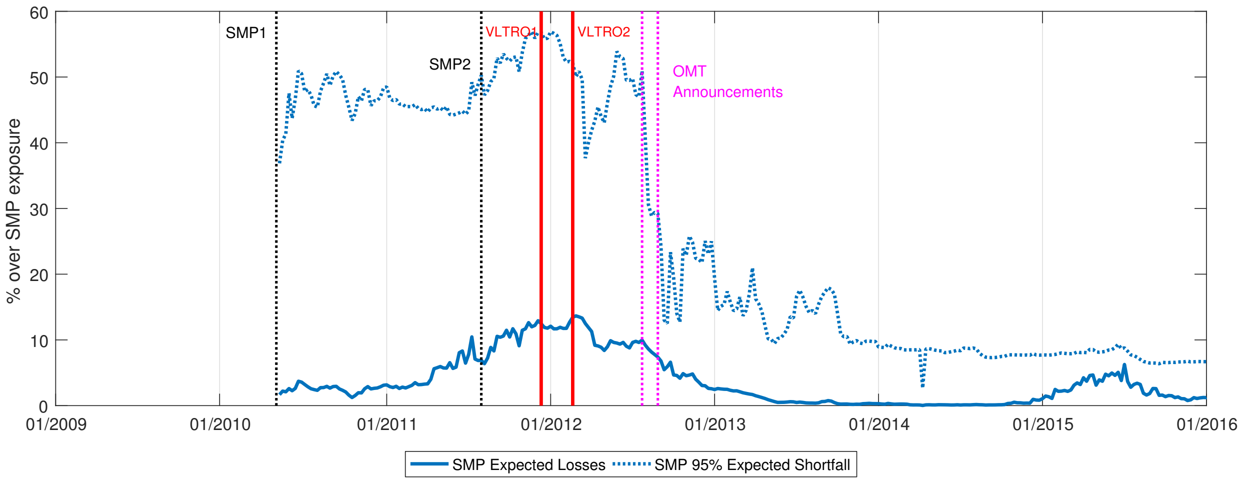


Table E.1: Portfolio credit risks around key policy announcements, in per cent of exposures

Portfolio credit risks for different monetary policy operations around six policy announcements. EL and ES are expressed in per cent of exposures at the time.

SMP1	07/05/2010		14/05/2010			
	EL	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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	ES(99%)	EL	ES(99%)	ΔEL	ΔES(99%)
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