Monetary Policy and Long-Run Risk-Taking

Gilbert COLLETAZ
Grégory LEVIEUGE
Alexandra POPESCU
Monetary Policy and Long-Run Risk-Taking

Gilbert Colletaz† Grégory Levieuge†

Alexandra Popescu§

June 2016

Abstract

Since the outbreak of the global financial crisis, prolonged periods of accommodative monetary policy that lead to an increase in financial risk in the medium and long term have been labeled as the risk-taking channel of monetary policy. In this paper, we analyze the presence of this channel in the Eurozone using long-term causality measures. Considering various auxiliary variables, we find a significant long-term effect of monetary policy on risk, but no short-term effect. Reverse causality is rejected. Finally, we conclude that the risk-taking channel is difficult to separate from the traditional credit channel.

Keywords: monetary policy, risk-taking channel, financial risk

JEL classification: E52, E58, G21

* The authors would like to thank Eric Jondeau for the data on SRisk.
† Professor at the Univ. Orléans, LEO - UMR 7322, Rue de Blois – BP 26739, 45067 Orléans, France.
‡ Corresponding author. Professor at the Univ. Orléans, LEO - UMR 7322, Rue de Blois – BP 26739, 45067 Orléans, France. E-mail: gregory.levieuge(at)univ-orleans.fr
§ Assistant Professor at the University of Poitiers, CRIEF, 2, rue Jean Carbonnier, 86073 Poitiers, France.
1 Introduction

The accumulation of risk in the years leading to the crisis went without notice. An extremely favorable environment with low interest rates for a protracted period of time (2002 – 2006) and low inflation, accompanied by an abundance of global liquidity, led financial companies to behave in a riskier way. At the same time, banks relying on securitization eased their credit standards and even agreed to extend credit to the poorest households (Ioannidou et al., 2015; Jiménez et al., 2014; Maddaloni and Peydro, 2011). Contrary to what we might expect, risk premiums remained at very low levels and therefore the accumulation of risk went undetected until the summer of 2007, when both in the US and in Europe, the first signs of financial distress appeared.

The crisis represented the failure of both prudential regulation and monetary policy. However, the latter has been seen by some authors as one of the main factors of the crisis (Acharya and Richardson, 2009; Allen and Carletti, 2009; Diamond and Rajan, 2009) given that the central bank’s actions can negatively influence financial stability. The explanation comes from the fact that the monetary policy stance can have an impact on the level of risk in the financial sector. To explain the drivers of the recent crisis, Borio and Zhu (2012) gave the definition of a new monetary policy transmission mechanism – the risk-taking channel (RTC). They define it as “the impact of changes in policy rates on either risk perceptions or risk-tolerance and hence on the degree of risk in the portfolios, on the pricing of assets, and on the price and non-price terms of the extension of funding”.

This new concept drew the attention of researchers. Several empirical and theoretical studies took thenceforth interest in the relationship between monetary policy and risk. The majority of the empirical studies are performed on bank-level data and their results seem to converge towards the same idea: risk increases when interest rates are low. However, studies conducted at a macroeconomic level are less frequent and the results are not that clear in what concerns the existence of a risk-taking channel. Moreover, most of the conclusions drawn from these macroeconomic analyses are based on impulse response functions to a one-period monetary shock. This approach seems highly inadequate as one essential hypothesis of the risk-taking channel is precisely the duration of the accommodative monetary policy stance. According
to the RTC theory, interest rates have to be “too low”, but they should also stay at low levels for “too long” in order for the underlying mechanisms of this channel to start operating. The studies conducted thus far on this subject usually neglect this long-term perspective. Furthermore, none of the existing studies treats this subject from a causality point of view. Another criticism that one could make to this literature, is the use of risk measures that did not account for the risk accumulation before the crisis, casting thus some doubt on the results.

The objective of our paper is to study the presence of the risk-taking channel in the Eurozone. We adopt a macroeconomic perspective, contributing in this way to the debate on the existence of this channel at a macroeconomic level. To fulfill our objective, we rely on the long-term causality measures recently proposed by Dufour and Taamouti (2010), to analyze the link between the interest rate and financial risk. This approach allows us to examine the impact of the monetary policy stance on risk not only in the short run, but also at longer horizons. As underlined above, the duration of easy monetary policy conditions is an important feature of the RTC, making our choice of methodology particularly adequate to our research question. Moreover, to capture the slow risk accumulation, we employ a recent systemic risk measure, the SRisk (Engle et al., 2014), which gives true risk rather than perceived risk.

Given the present context of extremely accommodating monetary policy (both conventional and unconventional), this subject still proves relevant today. The risk of bubbles and of searching for yield is more than ever a matter of concern for policymakers. Our results show that accounting for the long term is important. In most of the configurations considered there is no causality according to the usual “short term” Geweke causality measures, whereas at longer horizons, monetary policy has a significant impact on risk. Another interesting result is that risk has no influence on the conduct of monetary policy. This confirms that, before the crisis, the European Central Bank did not account for financial risk. Finally, we also conclude from our analysis that the risk-taking channel works through similar mechanisms as two other existing channels: the balance sheet channel and the bank capital channel. It is therefore difficult to disentangle them.

The rest of the paper is structured as follows. Section 2 summarizes the main theoretical and empirical results obtained in the literature on the risk-taking channel, underlying the flaws
of this literature and how we deal with them in this study. Section 3 shows some stylized facts for the Eurozone justifying our empirical analysis. In Section 4, we describe the methodology and in Section 5, we present our main results. We perform a robustness analysis in Section 6 and Section 7 concludes.

2 Related papers

Observing that the severe recent financial crisis occurred in the wake of a prolonged period of easy monetary conditions, Borio and Zhu (2012) have paved the way for research on what they have identified as a “risk-taking channel” of monetary policy. According to this channel, monetary policy would affect the risk perception and the risk tolerance of creditors, with forward consequences on financial and macroeconomic (in)stability.\(^1\) This section aims at reviewing the main theoretical and empirical developments related to the RTC. Furthermore, it presents the way in which our contribution deals with the limitations of the existing literature.

2.1 The theoretical foundations of the risk-taking channel

A comprehensive review of the literature indicates that this channel is a combination of four inextricable mechanisms. First of all, the RTC relies on the “search for yield” hypothesis supported by Rajan (2006) and Brunnermeier (2001), according to which financial institutions tend to engage in risky investments to earn excess returns in a low interest rate environment.\(^2\) This mechanism is reinforced when financial institutions have target rates of return established in nominal terms. Moreover, it is exacerbated by the bonus scheme and the herding behavior arising when managers are evaluated vis-à-vis their peers. The failure of financial supervision and regulation can also be incriminated.

Second, the effect of loose monetary policy on the risk perception and tolerance can be explained by firms’ balance sheet effects. A prolonged period of low interest rates stimulates firms’ income and cash flows, as well as the valuation of their assets. Due to higher collateral values,

\(^1\) Similar ideas were formulated by Fisher (1933), Hayek (1939) or Kindleberger (1978).

\(^2\) In this regard, Acharya and Naqvi (2012) propose a theoretical model whose main implication is that excessive liquidity induces risk-taking behavior on the part of managers, who misprice risk when interest rates are low, which in turn encourages the build-up of asset-price bubbles.
lenders tend to grant more risky loans and soften their lending standards. Borrowers with bad credit histories and more vague projects benefit from this higher risk tolerance. However, the quality of lenders’ balance sheet insidiously deteriorates with the decline in credit quality.\(^3\)

Third, the RTC relies on banks’ balance sheet effects. Indeed, banks’ willingness or ability to supply cheap credit and loose lending standards also depends on the structure of their own balance sheet. Precisely, the bank capital channel describes the procyclicality of bank practices and the way they amplify shocks. In a situation of asymmetric information between the banks and their creditors, the former have to bear an external financial premium that is related to the quality of their balance sheet. Banks ultimately pass their financing conditions on to firms’ credit standards and size of credit lines.\(^4\) Against this background, by increasing the net asset value of banks,\(^5\) a long period of low-level interest rates is likely to result in loose financing conditions. Moreover, as such a context results in a decreasing probability of bank run (Diamond and Rajan, 2006) and a reduction in adverse selection (Dell’Ariccia and Marquez, 2006), credit institutions can more easily issue debt in order to grant riskier loans.\(^6\)

Loose monetary policy not only insidiously deteriorates the assets side of banks’ balance sheet, it also negatively affects its liabilities. In this regard, Gertler et al. (2012) and Angeloni et al. (2015) find that an expansionary monetary policy induces banks to choose a more leveraged and less capitalized structure, which increases their risk exposure. From this point of view, a new generation of models with financial frictions proposed for example by Brunnermeier and Sannikov (2014), He and Krishnamurthy (2014) and Dewachter and Wouters (2014), can be related to the RTC. They demonstrate how low-risk environments are conducive to greater endogenous build-up of systemic risk.

Similarly, the literature on risk-shifting\(^7\) gives some insights that can be linked to the RTC. One example can be found in Farhi and Tirole (2012) who demonstrate that an accommodating

---

\(^3\) See the large literature on the financial accelerator, including Kiyotaki and Moore (1997), Bernanke et al. (1999) and Ciccarelli et al. (2013). See González-Aguado and Suarez (2015) for a demonstration on the link between balance sheet effects and the RTC.


\(^5\) See Adrian and Shin (2009) and Fostel and Geanakoplos (2008) among others.

\(^6\) See Altumbas et al. (2012) for empirical evidence.

\(^7\) See for example Hau and Lai (2016) for empirical evidence of risk-shifting from money to riskier equity markets when real interest rates decrease.
interest rate policy “sows the seeds for the next crisis” by facilitating the financing of unworthy projects. Dubecq et al. (2015) demonstrate that the misperception of risk is greater at lower levels of interest rates. Some evidence on the RTC is found by Dell’Ariccia et al. (2014) and Valencia (2014), at the halfway between the literature on the risk-shifting and on the bank capital channel. Last, the original contribution of Challe et al. (2013) demonstrates that the lower the interest rate, the higher the proportion of “imprudent” financial intermediaries, and thus the higher the systemic risk.

Fourth, a last strand of arguments relies on the moral hazard created by past policies. The “paradox of credibility view” assesses that improved communication, credibility and efficiency of central banks have reduced uncertainty. This has compressed risk premiums and encouraged risk-taking⁸ (Altunbas et al., 2009; Borio and Zhu, 2012; Montes and Peixoto, 2014). Consequently, Thakor (2015) asserts that a long period of favorable outcomes leads agents to assign high probabilities to the abilities of banks to manage risks. This causes banks and investors to underestimate the true risk. For Gennaioli et al. (2015), a series of good news leads to the neglect of risks up to a point where enough bad news accumulate and radically change the dominant beliefs. Moreover, past experiences of bail out produce an insurance effect, all the more for too-big-to-fail agents, that encourages risk-taking (Diamond and Rajan, 2009, 2012; Farhi and Tirole, 2012; Cao and Illing, 2015; Brandao Marques et al., 2013).

Note that in each of the four mechanisms described above, it is not only the monetary policy stance, but also its duration that encourages risk taking, as risk accumulation is a long process.

2.2 Empirical evidence

The empirical evidence mainly relies on micro-survey data. De Nicolo et al. (2010) was one of the first contributions, based on lending surveys, to find a negative relationship between real interest rates and the riskiness of banks’ assets. Altunbas et al. (2014) and Gambacorta (2009) show that low interest rates over an extended period of time significantly contribute to an increase in US and European banks’ expected default frequency (EDF). Similar results are

⁸ The “Greenspan conundrum” can be seen as an illustration. It designates the failure of long-term interest rates to increase despite the tightening of monetary policy in the first half of the 2000s in the US. One explanation relies on the context of the Great Moderation and on the underlying confidence in monetary policy, which made the risk premium decrease.
found by Gambacorta and Marques-Ibañez (2011) for a sample of 1000 banks from 15 developed countries. However, in retrospect, the EDF indicator cannot be considered as a satisfactory measure of the “true” risk. Instead, it can be viewed as an indicator of (inappropriately) perceived risk. Delis and Kouretas (2011) use the ratio of risk assets to total assets and the ratio of non-performing loans to total loans as measures of risk in a sample of 18000 observations on euro area banks over the period 2001-2008. Using static and dynamic panel data models estimated with a 2SLS-IV and GMM methods, in order to deal with potential endogeneity, they validate the RTC hypothesis. Furthermore, they observe that the impact of interest rates on assets’ riskiness depends on the equity capital of banks, in line with the banks’ balance sheet effects. An original measure of *ex-ante* bank risk-taking is used by Dell’Ariccia et al. (2013), who consider the rating of new loans based on the confidential individual loan-level data from the Federal Reserve’s Survey of Terms of Business Lending (STBL). The results of their panel regressions validate the RTC hypothesis in the US over the period 1997-2011.

Ioannidou et al. (2015) provide one of the most thorough empirical evidence. They focus on the Bolivian case while considering the US federal funds rate as the relevant measure of monetary policy stance, because of the peg to the US dollar and the highly dollarized financial system that was prevailing between 1999 and 2003. As the US federal funds rate was exogenous to the Bolivian economic conditions, they thus pretend to circumvent the usual endogeneity issue. Applying a time-varying duration model to a large set of about 30000 loan contracts and considering the time-to-default as their dependent variable, they find evidence that lower federal funds rate exacerbates banks’ risk-appetite, in particular for those banks that are more prone to agency problems. Using a similar approach, Jiménez et al. (2014) confirm these results from a sample of loan contracts granted by 350 financial institutions in Spain, from 1988 to 2006. They note that risk-taking especially occurs at banks with less capital at stake.

Thus, there exists evidence supporting the RTC at the microeconomic level. However, are its macroeconomic effects significant? There are fewer macroeconomic studies. Most of them rely on VAR models, with the policy rate as the indicator of the monetary policy stance. The RTC

---

9 This is the case for numerous risk measures used as dependent variables in this literature. See details in the next section and in Figure 2.

10 This is a question worth asking. For instance, while they find micro evidence of a RTC in Portugal, Bonfim and Soares (2014) admit that its macro-financial impact is rather limited.
is then gauged with regard to the impulse response functions (IRFs) of a measure of risk to a monetary policy shock. These studies differ only in terms of risk measure. Bekaert et al. (2013) use the VIX index that they decompose into two components: a proxy for risk aversion and one for uncertainty. On the basis of IRFs, they conclude that, in the US, a lax monetary policy decreases both risk aversion and uncertainty, with the former effect being stronger. Angeloni et al. (2015) successively use, as the dependent variable, the difference between M3 and M2 (to capture “funding risk”), the stock of private debt (for “lending risk”) and the volatility of the Datastream US bank equity index (to deal with the “total bank risk”). They conclude that monetary policy robustly influences these risks in the banking sector by changing the banks’ funding structure, as well as the riskiness of their assets. Even more, Bruno and Shin (2015) find that the US monetary policy has an impact on the leverage of international banks. Finally, Buch et al. (2014) use a factor-augmented autoregressive model (FAVAR) in which they exploit information provided by the Federal Reserve’s STBL on the riskiness of banks’ new loans. Their study concerns thus the US and is conducted over the period 1997-2008. On the basis of IRFs, they find that in particular small banks significantly increase new loans to high-risk borrowers after an expansionary monetary policy shock. Nevertheless, evidence is less clear for large and for foreign banks.

The contribution of Maddaloni and Peydro (2011) does not rely on a VAR approach. They use standard panel data approaches to investigate whether accommodative monetary conditions soften bank lending standards. The latter come from the Bank Lending Survey (BLS) for the euro area countries and the Senior Loan Officer survey for the US. Lax monetary policy is measured by (negative) Taylor rule residuals. They find robust evidence that low interest rates soften lending standards to households and firms.

The aforementioned articles have common limits. In particular, they do not duly consider the duration of the monetary policy easing. For instance, surprisingly, Buch et al. (2014) consider the duration of lax policy just as an independent hypothesis to be tested, although the “too low for too long” assertion is essential in the functioning of the RTC. In Maddaloni and Peydro (2011), the persistence of accommodative monetary conditions is roughly measured by the “number of periods of relatively low monetary policy rates”, alone and as an interaction
variable with the Taylor rule residuals. Moreover, evaluating the “too low for too long” effect of monetary policy by a short-run response to a one-period shock in interest rates is inadequate.

It is far from the theoretical foundations of the RTC, which describe mechanisms that have effects after an “incubation period”. Last but not least, the existing works do not measure causality from monetary policy to risk.

In contrast, in our paper, we search for evidence supporting the RTC in terms of causality from monetary policy to risks, at the macroeconomic level in the euro area. Furthermore, consistently with the definition of the RTC, our approach allows taking long-run causalities into consideration. This is critical, as low interest rates may reduce total credit risk in the short run (by reducing the probability of default), although risk increases in the medium and long run. Our approach allows analyzing the reverse causality too, namely whether the monetary authorities have leaned against the wind or not. Last, the use of the SRisk indicator (Engle et al., 2015), which in retrospect has proved to be one of the most reliable risk measure, constitutes another originality of our contribution.

3 Stylized Facts for the Eurozone

We present in this section some stylized facts from the euro area. More precisely, we highlight two problems that need to be considered before engaging in our risk-taking channel analysis. First, as noted earlier, this channel is supposed to function when maintaining the policy rate at low levels for an extended period of time. One question may arise concerning the stance of monetary policy in the Eurozone from the beginning of 2000 and up to the first signs of crisis: Was monetary policy too accommodating for too long in the Eurozone? To answer this question, we plot in Figure 1 (i) the evolution of inflation and (ii) the output gap, as well as (iii) the dynamics of the short-term interest rate with respect to the rate implied by the classic Taylor rule (Taylor, 1993) and (iv) the short-term interest rate gap with respect to its HP filter.

Over this period, the inflation rate was rather stable, fluctuating around 2%, the ECB’s established upper limit for inflation. Only at the end of 2007, inflation rocketed to reach its highest level since the beginning of 2000. The evolution of the output gap, computed on the
basis of a HP filter for the monthly industrial production index, can be divided into three sub-periods. The first one, between 2000 and 2001, corresponds to the peak, crash and contraction of the European economy triggered by the Dot-com Bubble. Between 2002 and 2006, the second sub-period, the output gap was almost exclusively negative, meaning that the economy did not run at full capacity. However, this can be interpreted as a signal that inflation would not rise in the following periods, because production and labor costs would maintain their levels. At the end of 2006 and up until the outbreak of the crisis, the output gap became positive, signaling an overheating of the economy.

Figure 1: The evolution of inflation, output gap and interest rates

Note: The upper left panel of the figure presents inflation in the euro area computed based on the harmonized consumer price index. The horizontal line corresponds to the upper inflation threshold established for the euro area. The upper right panel represents the output gap, computed as the industrialized production index minus its long-term trend given by the HP filter. The lower left panel plots the short-term interest rate (solid line) and the Taylor rate (dashed line). The Taylor rule is computed as: \( i_t = r^* + 1.5\pi_{t,12} + 0.5(y_t - \bar{y}) \), where \( i_t \) is the short-term interest rate, \( r^* \) is the long-term real interest rate and \( y_t - \bar{y} \) gives the output gap. The lower right panel represents the interest rate gap computed as the difference between the short-term interest rate and its trend, given by a HP filter. The time span is 2000M1 – 2008M4. Source: Datastream and authors’ calculations.

We might think in this case that the low level of the interest rate was justified by the stable inflation and the negative output gap during the middle sub-period. Indeed, the lower left
panel of Figure 1 shows that the short-term rate (solid line) was mostly consistent with the evolution of both inflation and output. In 2000, the burst of the Dot-Com Bubble generated a gradual decrease in the short term interest rate, from 5% in 2000M11 to approximately 2.15% in 2003M6. However, when the economy started to recover, interest rates remained low for a protracted period, between 2003 and 2006. This period corresponds exactly to the one when the central bank was blamed for being too accommodating, keeping the interest rates too low for too long. This can better be seen by comparing the short-term interest rate to the Taylor rule rate (dashed line). The latter is almost everywhere – between April 2003 and September 2005 – superior to the level of the actual short-term rate. This would indeed indicate that monetary policy was too easy for approximately 30 months. To further confirm our intuition, the lower right panel of Figure 1 plots the difference between the short-term interest rate and its HP trend. We consider the gap and not the level of this money market rate because a key point of the risk-taking channel is the unusually accommodative monetary policy stance. This gap is negative from the end of 2002 and until the second half of 2006, consequently, the monetary policy stance could be considered expansionary during this time span.

The second problem concerns risk measures. Finding such indicators is not straightforward as most of the existing measures did not account for the latent accumulation of risk during the period of easy monetary policy. It is precisely one of the criticisms made to the regulatory framework which failed to provide a good risk indicator before the burst of the financial crisis. Figure 2 presents the evolution of several commonly used risk measures, over the period 2000 – 2008: the expected default frequency of banks and of non-financial corporations, the implied volatility index for the Eurozone, the risk premium, the term spread and banks’ credit default swap. Before the outbreak of the crisis, creditors misperceived risk as they were faced with seemingly high-valued collateral or with apparently sound balance sheets. Therefore, when low interests rates are low for a long period of time, risk measures and especially risk premiums, do not reflect risk anymore. This can clearly be seen in Figure 2, as all of the six measures underline the misperception of risk as described by the theory of the risk-taking channel. According to these indicators, during the time span 2002 – 2006, when monetary policy was supposed to be expansionary, risk was following a descending trend. With the benefit of
hindsight, we know that risk was actually increasing at that time. Using these measures as a risk indicator in empirical analyses will therefore not correspond to the true evolution of risk and will lead to inaccurate results. However, while true risk increased during the period of monetary policy expansion, risk aversion and risk perception declined. These measures could thus be more appropriate if they were used as a proxy for risk perception, rather than risk itself.

Figure 2: The risk measures considered in the literature

Note: This figure presents several risk measures over the period 2000 – 2008, at a monthly frequency. Data concerns the euro area. EDF Bank and EDF NFC represent the expected default frequencies for banks and non-financial corporations, respectively. VSTOXX is the implied volatility index for the euro zone, computed on option prices. The risk premium is computed as the bank lending rate minus the short term interest rate, whereas the term spread is the difference between the long and the short term interest rates. Bank CDS stands for credit default swaps. Due to a lack of availability, data for CDS starts only in 2004. Source: Datastream.

For capturing true risk, we rely on the recent literature on systemic risk measurement and choose the SRisk (Engle et al., 2015) for our analysis. Initially proposed by Brownlees and Engle (2016), this indicator is used in the literature to measure the systemic risk of financial firms. Engle et al. (2015) transposed it to the European case in order to determine systematically important financial institutions. To compute the SRisk, they use data on the market capitalization of firms, their financial leverage, but also data related to the sensitivity of the
equity return to market shocks. Consequently, this measure accounts not only for the size of
the institution and its individual risk, but also for the correlations between the market and the
firm’s returns. It hence takes into account the two main components of systemic risk – size and
interconnectedness. The $SRisk$ we use in our analysis represents an aggregate of systemic risk
at the European level and is computed for four types of financial firms: banking institutions,
insurance companies, financial services and real estate firms. In accordance with what we have
learned after the outbreak of the crisis about risk accumulation, this indicator started increasing
in 2002, after a short period of stability (Figure 3). The SRisk is therefore particularly suitable
for our analysis of the risk-taking channel, as it gives a truer view of how risk accumulation
evolved during the period of easy monetary policy.

Figure 3: SRisk in Europe (in bln euros)

![SRisk Graph](image)

Note: This figure presents the SRisk over the period 2000M1 – 2008M4. Source: Engle et al. (2015)

All in all, it seems that the underlying assumptions of the risk-taking channel are fulfilled
and studying its existence in the Eurozone is a relevant research question. Now that we have
identified adequate measures for the monetary policy stance and for both true and perceived
risk, we introduce them into a VAR to study the risk-taking channel. Based on this model,
we compute long-run causality measures which are informative of the connections between
monetary policy and risk at long horizons.
4 Methodology

In order to study causality beyond horizon one, Dufour and Renault (1998) define *long-run causality* as: *x* causes *y* at horizon *h* if the past of a variable *x* improves the prediction of *y* for period *t* + *h*, where *t* is the present. This concept is useful when studying relations in a VAR with more than 2 variables. In this configuration, causality between two variables, from *x* to *y* for example, may appear at higher horizons, even if at horizon one, *x* does not cause *y*. This happens because causality can transit through some auxiliary variable(s), *z*. This methodology is particularly suitable to our research question, as monetary policy needs to be accommodative for a longer period before influencing risk. The time dimension is therefore crucial to this study.

Computing long-run causality measures implies defining and estimating a VAR model with at least three variables, determining the forecast errors for different horizons *h* and computing their covariance matrix. The methodology used to estimate these measures and to compute corresponding confidence intervals can be summarized by the following five steps.

**Step 1. Specification of the model.** We define a VAR(3) model with 3 types of variables: *x*, *y* and *z*. The system defined in this way corresponds to the *unconstrained model*. In our analysis, *x* represents the proxy for the monetary policy stance, *y* is a measure quantifying risk in the financial sector and *z* includes all auxiliary variables through which monetary policy may transit before influencing risk. Let *k* be the number of variables in the VAR, with *k* = *kx* + *ky* + *kz*. *x* and *y* are variables, so their dimension is one (*kx* = *ky* = 1), while *kz*, the number of auxiliary variables, may be greater or equal to one. Let *W* = (*x′*, *y′*, *z′*)′. The VAR model takes the following form:

\[ W_t = \sum_{j=1}^{p} \Phi_j W_{t-j} + \varepsilon_t, \]

where \( \Phi_j \) represent the coefficient matrices and \( \varepsilon_t \) are independent and identically distributed with \( E(\varepsilon_t) = 0, E(\varepsilon_t \varepsilon_t') = \Sigma_{\varepsilon} \), a nonsingular covariance matrix and \( E(\varepsilon_t \varepsilon_s') = 0 \), for all \( t \neq s \).

The identification of the optimal lag, *p*, is made with the Akaike information criterion (AIC) (Ivanov and Kilian, 2005; Kilian, 2001). To compute causality measures, we also need to define the *constrained models*, meaning a model where only *x* and *z* are included and a model with
only $y$ and $z$. With the former specification, we aim at studying causality from $y$ to $x$, whereas the latter is used to measure causality from $x$ to $y$. Given that causality measures are based on determinants of the covariance matrices of the constrained and unconstrained forecast errors, for comparison reasons, we use the same lag order, $p$, for the three defined models.

Step 2. Model estimation. Depending on the combination of variables, $x$, $y$ and $z$, the obtained model is either stationary, stationary in first difference or cointegrated. To avoid employing different types of estimation methodologies, we follow Sims et al. (1990) and estimate the model in levels by applying the ordinary least squares estimators for $\Phi_t$ and for the covariance matrix of the residuals, $\Sigma_\epsilon$. Sims et al. (1990) prove that even when there are some unit roots in the VAR system or there is possible cointegration between variables, the estimation of the system in first difference or in a vector error correction form (VECM) is unnecessary as OLS estimators for the model in levels remain consistent. Moreover, using a VECM would prevent us from computing long-run causality between variables, as this would lead to several technical problems that could only be solved by making ad-hoc hypotheses and that would imply an increase in the sources of potential bias. An additional advantage of estimating the model in levels is the ease of interpretation of results. The same estimation procedure is applied for the two constrained models in order to determine parameters and covariance matrices of residuals.

Step 3. Estimation of the forecast errors’ covariance matrix at horizon $h$. Causality measures are computed based on the moving average representation and more precisely, on the covariance matrix of the forecast error of $W_{t+h}$, obtained from the unconstrained and the constrained models. Our aim is first to determine the forecast errors at horizon $h$, and then to estimate their covariance matrix. For that, the Wold representation theorem is used to transform the VAR($p$) in a VMA($\infty$):

$$W_t = \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i},$$

where $\Psi_i$ represent the response of the endogenous variables, at each horizon $i$, to a shock to $11$ In the analysis subsection, we will consider several associations of these variables. Mainly, the auxiliary variables, $z$ will represent different quantities. For robustness purposes, we will also consider several proxies for the monetary policy stance and risk indicators (variables $x$ and $y$, respectively).

$12$ We refer here, for example, to the fact that the unconstrained model could present one cointegration relation, that can very well disappear when one of the variables is removed from the analysis (constrained model). Other example would concern the bootstrap of confidence intervals that would become even more complex (see Step 5 further on).
the system. These matrices can be recursively computed using $\Phi_j$: \[ \Psi_i = \Phi^{(i)} \quad \text{and} \quad \Phi^{(i+1)}_j = \Phi^{(i)}_{j+1} + \Phi^{(i)}_1 \Phi_j, \quad \Phi^{(1)}_j = \Phi_j, \quad \Phi^{(0)}_1 = I_k, \] (3)

where $I_k$ represents the identity matrix of size $k$ and $i \geq 1$. The forecast error at horizon $h$ is given by:

\[
W_{t+h} - E_t(W_{t+h}) = \sum_{i=0}^{h-1} \Psi_i \varepsilon_{t+h-i}.
\]

(4)

An estimator of the variance covariance matrix of these forecast errors for the unconstrained model is:

\[
\hat{\Sigma}(h) = \sum_{i=0}^{h-1} \hat{\Psi}_i \hat{\Sigma}_\varepsilon \hat{\Psi}_i',
\]

(5)

where $\hat{\Sigma}_\varepsilon$ is the estimated covariance matrix from Step 2 and where $\hat{\Psi}_i$ are computed base on the relations in equation (3) in which we replace $\Phi_j$ by $\hat{\Phi}_j$. As defined in Step 1, the disturbances, $\varepsilon_t$, are not serially correlated, but may be contemporaneously correlated. If this is the case, the forecast errors’ covariance matrix can also be obtained by applying a Cholesky decomposition.

Let $P$ be a lower triangular matrix such that $PP' = \Sigma_\varepsilon$ and let $u_t = P^{-1} \varepsilon_t$, where $u_t$ are orthogonal residuals with $\Sigma_u$ equal to $I$, the identity matrix. Equation (4) becomes:

\[
W_{t+h} - E_t(W_{t+h}) = \sum_{i=0}^{h-1} \Psi_i P u_{t+h-i} = \sum_{i=0}^{h-1} \gamma_i u_{t+h-i},
\]

(6)

where $\gamma_i = \Psi_i P$. Given that $u_t$ are orthogonal, the covariance matrix of the forecast errors is given by:

\[
\hat{\Sigma}(h) = \sum_{i=0}^{h-1} \hat{\gamma}_i \hat{\gamma}_i'.
\]

(7)

An alternative solution to this estimation technique is obtained by writing the system in its companion form. More precisely, any VAR of order $p$ can be written as a VAR(1). In our case,
(1) becomes:
\[
\begin{pmatrix}
W_t \\
W_{t-1} \\
\vdots \\
W_{t-p+1}
\end{pmatrix} =
\begin{pmatrix}
\Phi_1 & \Phi_2 & \cdots & \Phi_p \\
I_k & 0 & \cdots & 0 \\
0 & \ddots & \ddots & 0 \\
0 & 0 & I_k & 0
\end{pmatrix}
\begin{pmatrix}
W_{t-1} \\
W_{t-2} \\
\vdots \\
W_{t-p}
\end{pmatrix} +
\begin{pmatrix}
\varepsilon_t \\
0 \\
\vdots \\
0
\end{pmatrix}.
\]

(8)

or, in a compact form:
\[
\tilde{W}_t = A\tilde{W}_{t-1} + \tilde{\varepsilon}_t.
\]

(9)

Repeatedly substituting for $\tilde{W}$ leads to an equation where $\tilde{W}_t$ depends on current and past shocks in the following way:
\[
\tilde{W}_t = \tilde{\varepsilon}_t + A\tilde{\varepsilon}_{t-1} + A^2\tilde{\varepsilon}_{t-2} + \ldots + A^h\tilde{\varepsilon}_{t-h} + A^{h+1}\tilde{W}_{t-h-1}.
\]

(10)

The first $k$ rows of each matrix $A^i$, with $i = 1, \ldots, h$, give the impulse response of the variables at horizons 1 to $h$. These elements will be used in equations (2)-(5) instead of $\Psi_i$. Moreover, when orthogonal residuals are used, equation (10) is written as:
\[
\tilde{W}_t = \tilde{u}_t + AP\tilde{u}_{t-1} + A^2P\tilde{u}_{t-2} + \ldots + A^hP\tilde{u}_{t-h} + A^{h+1}P\tilde{W}_{t-h-1}.
\]

(11)

where $\tilde{u}$ is the orthogonal residual obtained from a Cholesky decomposition, $\tilde{u}_t = P^{-1}\tilde{\varepsilon}_t$ and $PP' = \Sigma_{\tilde{\varepsilon}}$. Step 3 is repeated for both constrained models defined above.

**Step 4. Computing causality measures.** Long run causality measures are interpreted in the same way as the measures of short run causality defined by Geweke (1982): $y$ causes $x$ at horizon $h \geq 1$ if the past of variable $y$, in addition to the past of $x$ and $z$, is helpful in forecasting $x_{t+h}$. Causality measures for horizon $h$ are based on the covariance matrices of the forecast errors from the unconstrained and the constrained models. Having estimated these elements in Step 3, we can proceed with the computation of long run causality measures. As defined by Dufour and Taamouti (2010), causality from $y$ to $x$ is given by:
\[
\hat{C}(y \rightarrow^h x|F) = \ln \frac{\text{det}[J_0\hat{\Sigma}_0(h),J_0']}{\text{det}[J_1\hat{\Sigma}(h),J_1']},
\]

(12)
where $J_0 = [I_{kx} \ 0]$ and $J_1 = [I_{kx} \ 0 \ 0]$ and where $F$ defines the information set. $\Sigma(h)$ is the covariance matrix in the unconstrained model, whereas $\Sigma_0(h)$ is the covariance matrix from the constrained model, that is where $y$ has been withdrawn from the system. $J_0$ and $J_1$ actually serve to identify the block of the covariance matrices that corresponds to $x$. The numerator is based on the constrained model and the denominator on the unconstrained one. As the constrained model has less explanatory variables (only $x$ and $z$) than the unconstrained one, the covariance of the forecast errors at horizon $h$ from the former model should be higher than (equal to) the covariance corresponding to the latter if $y$ causes (does not cause) $x$. Consequently, the measure is by construction either equal to zero, if there is no causality from $y$ to $x$, or greater than zero if $y$ causes $x$ at horizon $h$. The measure for causality from $x$ to $y$ can be defined in a similar manner:

$$\hat{C}(x \overset{h}{\rightarrow} y|F) = ln \left[ \frac{det[J_0^* \Sigma_0^*(h) J_0^*]}{det[J_1^* \Sigma(h) J_1^*]} \right],$$

with $\Sigma_0^*$ the covariance matrix of the forecast errors at horizon $h$ obtained from the constrained model with $y$ and $z$ as variables. This time $J_0^* = [I_{ky} \ 0]$ and $J_1^* = [0 \ I_{ky} \ 0]$ are used to recuperate the blocks corresponding to the variable $y$ in the covariance matrices $\Sigma_0^*$ and $\Sigma(h)$. Instantaneous causality at horizon $h$ is quantified by the following formula:

$$\hat{C}(x \overset{h}{\leftrightarrow} y|F) = ln \left[ \frac{det[J_1 \Sigma(h) J_1^*]}{det[G \Sigma(h) G]} \right],$$

with $G = \begin{bmatrix} I_{kx} & 0 & 0 \\ 0 & I_{ky} & 0 \end{bmatrix}$. As in the case of short run measures of causality, no direction can be established for this type of connection. Finally, the sum of the three long run causality measures (12), (13) and (14), gives the dependence measure at horizon $h$:

$$\hat{C}(x \overset{h}{\rightarrow} y|F) = \hat{C}(y \overset{h}{\rightarrow} x|F) + \hat{C}(x \overset{h}{\rightarrow} y|F) + \hat{C}(x \overset{h}{\leftrightarrow} y|F).$$

Under certain regularity assumptions that can be found in Lewis and Reinsel (1985) or Dufour and Taamouti (2010), the above estimators are weakly consistent.
Step 5. Confidence intervals. The last step of our methodology consists in building confidence intervals for our causality measures. We proceed by bootstrap-after-bootstrap as proposed by Kilian (1998),\textsuperscript{14} which allows us to correct for small-sample bias and skewness. Not applying this correction may lead to changes in the interval width and location, even if the bias is small. Additionally, this method can successfully be applied not only to stationary VARs, but also to random walk processes and cointegrated processes estimated in levels, as might be our case.

In the first round of bootstrap, the purpose is to compute the bias in the VAR coefficients. For this, we generate, based on the residuals obtained in Step 2, new bootstrap data for the dependent variable of the unconstrained model:

\[
W_t^* = \sum_{j=1}^{p} \hat{\Phi}_j W_{t-j}^* + \varepsilon_t^*,
\]

where \(\varepsilon_t^*\) is a random draw with replacement from \(\{\hat{\varepsilon}_t\}_{t=p+1}^T\), with \(T\) the sample size. OLS estimates are used to determine bootstrap coefficients, \(\hat{\Phi}^*\). We repeat this procedure \(B\) times, where \(B\), the number of bootstrap samples, is chosen such that \(\frac{1}{2} \alpha (B+1)\) is an integer (Davidson and MacKinnon, 2004), with \(1 - \alpha\) the confidence level.\textsuperscript{15} The bias of the VAR coefficients is given by \(\text{Bias}^* = \mathbb{E}[\hat{\Phi}^* - \hat{\Phi}]\), where \(\mathbb{E}\) represents the expectation term. The bias estimate is \(\widehat{\text{Bias}}^* = \frac{1}{B} \sum_{j=1}^{B} \hat{\Phi}^*(j) - \hat{\Phi}\). At this stage, one should determine whether the VAR model is stationary or not. This can be done based on the absolute value of the largest root of the companion matrix associated with \(\hat{\Phi}\). If this value is larger than one, no correction is needed for coefficients. If the value is less than one, bias-corrected coefficients, \(\hat{\Phi} - \widehat{\text{Bias}}^*\), should be used from this point on.

The second round of bootstrap concerns the computation of confidence intervals based on bootstrapped causality measures. Firstly, the bias-corrected coefficients are imposed in equation (16) and \(B\) new bootstrap replications of \(\hat{W}_t\) are generated. Afterwards, the obtained

\textsuperscript{14} Kilian (1998) provides all the details of the bootstrap-after-bootstrap methodology. An empirical application is also included in the paper, which proves that among four considered methodologies – bootstrap-after-bootstrap, delta method, standard bootstrap and Monte Carlo – the bootstrap-after-bootstrap is the best technique to estimate confidence intervals.

\textsuperscript{15} The vector of \(p\) initial observations is kept the same for each of the \(B\) simulations. This is meant to avoid any bias arising when data is non stationary. More precisely, changing initial values would lead to different density functions of the coefficients \(\Phi^*\).
model is estimated through OLS. The same bias from the first round of bootstrap is used to correct the estimated coefficients. The residuals from this model are used to determine the covariance matrix based on which long-run causality measures are computed. Using the same bootstrap sample, the two constrained models are also estimated through OLS regressions, where coefficients also need to be bias-corrected (i.e., the two rounds of bootstrap are applied to the constrained models). Causality measures as defined by equations (12), (13), (14) and (15) are next computed. Finally, $\alpha$ and $1 - \alpha$ percentile intervals are calculated for each of the four types of long run causality.

5 Data description

The variable chosen to account for the monetary policy stance in our analysis (corresponding to $x$ in the methodology) is the short-term interest rate gap discussed in Section 3 ($igap$). The variable representing the risk indicator ($y$ in the methodology presentation) is the $SRisk$ of Engle et al. (2015) equally discussed above. Besides these monetary policy and risk measures, we also need data on the auxiliary variable, $z$.

We consider several options for this variable $z$. In the risk-taking channel literature, it is argued that accommodative monetary policy increases risk because low interest rates have first an influence on the risk perception and the risk tolerance of economic agents. Accordingly, the first group of variables used in our analysis is one strictly related to this channel. We consider in this group the volatility index for the Eurozone ($VSTOXX$) which captures risk aversion and uncertainty (Bekaert et al., 2013) and a Global Risk Aversion Indicator ($GRAI$). We also include the BBB Euro Non Financial Index ($BBB$). This variable is meant to provide the evolution of risk in the non financial sector, thus it is a good indicator of perceived risk.

As previously asserted, the risk-taking channel is difficult to dissociate from the financial accelerator mechanism and the bank capital channel. As a matter of fact, the effects of these three transmission mechanisms are overlapping and difficult to disentangle. For this reason, we also include in our analysis variables related to these two channels. Regarding the financial accelerator mechanism, we argue that an increase in collateral value (captured by a stock market index — $stock$ — or a housing price index — $hprice$) leads to lower risk premiums ($rprem$) and
financing costs \((cost\_eq\_firms)\) and lower expected default frequency for non financial institutions \((edf\_nfc)\), more credit and potentially more risk. Monetary policy can also influence risk through the bank capital channel in the following way: expansionary monetary policy improves the liquidity \((liq)\) and capital position \((cap)\) of banks which leads to better financing conditions – lower cost of equity \((cost\_eq\_bk)\) and lower expected default frequency \((edf\_bk)\). These developments translate eventually in higher risk-taking and a hidden deterioration of banks’ credit portfolios. The two expected default frequencies (of firms and banks) can also be seen as proxies for risk perception.\(^{16}\)

To analyze long-run causality between monetary policy and risk, we apply the methodology described in Section 4 to Eurozone monthly data over the period 2000M1 – 2008M4 (100 observations). Data is retrieved from Datastream and from the ECB Statistical Data Warehouse. The time span is chosen so that a complete economic cycle is covered in the analysis, from peak to peak.

As Buch et al. (2014), we exclude the period after the outbreak of the subprime crisis as unconventional monetary policy measures have been taken by the ECB and our \(x\) variable would not capture this. Moreover, the Taylor rule would be negative whereas the central bank’s main refinancing rate cannot comply with negative values. Equally important in our decision is the fact that when the crisis started, all macroeconomic variables have experienced a sudden and violent break in their trends, which would bias our results. We do however include in our sample the period of the Dot-Com crisis (2000 – 2002). During these years, monetary policy was accommodating and the actions taken by the central bank to reduce the consequences of the crisis represented for financial firms an important source of moral hazard. As we have seen, moral hazard is one mechanism through which the RTC may work as it incites financial institutions to continue their risk-taking.

\(^{16}\) Table 1 and Figure 9 in the Appendix A give more details about the auxiliary variables and their evolution during the analyzed time span.
6 Results

Our main objective in this econometric analysis is to measure the causality from monetary policy to risk (Policy \rightarrow Risk). Nevertheless, our methodology also allows us to compute causality from \( y \) to \( x \) (Risk \rightarrow Policy). While the former can be viewed as a confirmation or a rejection of the risk-taking channel theory, the latter helps us to see whether or not monetary policy reacted to increasing risk before the financial crisis.

The analysis is performed with three variables in the VAR system \((k_z = 1)\). The order of the VAR is selected by AIC. We include a time trend in all models and compute the measures for a horizon \( h \) of 24 periods.

Figure 4 presents causality measures (solid lines) from \( x \) to \( y \) (Policy \rightarrow Risk, upper left panel), from \( y \) to \( x \) (Risk \rightarrow Policy, upper right panel), instantaneous causality between \( x \) and \( y \) (Policy $\leftrightarrow$ Risk, lower left panel) as well as total linear dependence (Policy $\rightarrow$ Risk, lower right panel). Dashed lines represent the 95% confidence interval. On the x-axis we have the time horizon in months, from 1 to 24. The auxiliary variable is the volatility index, VSTOXX. As volatility was low in financial markets during the period of accommodating monetary policy, this index could have contributed to the misperception of risk and encouraged investors to take more risk. One interesting feature that can be seen in the first panel, is that at horizon one causality does not appear to be significant, underlying the importance of conducting this study in a long-run perspective. Indeed, using only short-run causality measures, would have led, in this case, to the wrong conclusion of no causality. Starting with horizon two, the measure becomes significant. Moreover, it increases until horizon 12, and remains significant up to horizon 16. This result implies that the actions of the central bank have indeed an impact on the risk-taking behavior of economic agents in the long run. Turning to the causality from Risk to Policy, we remark that the level of risk in the economy does not seem to cause at any horizon the monetary policy stance. This is consistent with the fact that financial stability did not represent an objective for the ECB before the global financial crisis, in line with the “cleaning up” belief that prevailed at that time.

In accordance to the theory of the risk-taking channel, this result suggests that the policy stance does not have an immediate influence on risk. Additionally, instantaneous causality
appears only starting with horizon 15 and has an increasing pace. The lower right panel shows the linear dependence between risk and monetary policy, computed as the sum of the three types of causality measures.

Figure 4: Causality measures for \( z = VSTOXX \)

Note: This figure presents causality measures for the variables \( x \) (Policy) and \( y \) (Risk). More precisely, \( x = \text{igap} \) and \( y = \text{SRisk} \). The auxiliary variable is \( VSTOXX \). The order of the VAR, selected by AIC, is 3. Confidence intervals at 95% are represented by the dashed lines.

When changing the auxiliary variable to \( GRAI \), the risk aversion indicator, results do not change much. In Figure 5, the monetary policy stance influences risk only starting with horizon 3, confirming that interest rates have to be kept low for a longer period of time in order to have an impact on risk.

Figure 6 presents causality measures when the auxiliary variable is the BBB Euro Non Financial Index. This index was at its low during the period of expansionary policy, implying that firms with a BBB investment grade were perceived as less risky at that time. In this scenario, the policy stance is an evident predictor of risk. Starting with period 6, the causality measure Policy \( \rightarrow \) Risk becomes significant and increases, proving, as in the other cases that monetary policy needs to be accommodating for a longer time period in order for the risk-taking channel to become active.

For all the three cases considered thus far, we find no causality from our risk variable to the conduct of monetary policy. We continue the study of the risk-taking channel with variables that can also be connected to other monetary policy transmission mechanisms, \( i.e. \) the financial
accelerator or the bank capital channel. In Figure 7, we present causality measures for the case where the auxiliary variable is the expected default frequency of non financial corporations. A decrease in this probability implies a reduction in perceived risk and a decrease in the external finance premium. According to the risk-taking channel, financial institutions should lower their lending standards and agree to finance riskier projects from entrepreneurs. Results in Figure 7 seem to confirm this fact, as the causality measure from Policy to Risk is significant and increasing starting with period 7.
Considering as an auxiliary variable banks’ capital-to-asset ratio further confirms our results. This ratio was rather stable during the period 2003 to 2007, implying no particular problems for the banking sector. The impact of the policy stance on risk is present in this configuration, starting with period 2 and until period 22. These last two figures validate our intuition about the connections between the three monetary policy transmission channels: the risk-taking channel, the financial accelerator mechanism and the bank capital channel. The graphs for all the other auxiliary variables are provided in Appendix B (Figures 10 to 16). No causality (neither from Risk to Policy, nor from Policy to Risk) is found when the auxiliary variable is the risk premium, the stock market index or the liquidity-to-asset ratio. The result is rather surprising for the risk premium, a key element in the financial accelerator mechanism. The evolution of this premium over the sample period shows a decrease from 2004 to the end of our sample period, which implies a decline in perceived risk. This should have normally contributed to the accumulation of real risk.

Otherwise, evidence of causal relationships from monetary policy to risk is found with most of the auxiliary variables, namely: the volatility index (denoted by $VSTOXX$), the risk aversion index ($GRAI$), the bond index of BBB rated firms ($BBB1$), the house price index ($hprice$), the expected default frequency of non financial corporations and of banks ($edf_{nfc}$ and $edf_{bk}$), the cost of equity for firms and for banks ($cost \_eq \_firms$ and $cost \_eq \_bk$) and the capital-to-asset ratio ($cap$). The fact that these variables are not only related to the risk perception and risk tolerance of economic agents, but can also be connected to the credit channels, proves the
strong relation between these three monetary policy transmission mechanisms. Furthermore, our results seem to confirm the fact that central banks were not concerned with financial risk in the period preceding the crisis. More importantly, we reject the presence of short-run causality from monetary policy to risk. This justifies the adequacy of the methodology, although it has never been employed before in this literature. All in all, the results conclude to the existence, at a macroeconomic level, of the RTC in the Eurozone. To confirm these results, the above analysis was conducted using several auxiliary variables, \( z \). In the next section, more robustness tests concerning the measures of monetary policy stance and real risk are presented.

7 Sensitivity analysis

To verify the robustness of our results, we explore several alternative specifications of the VAR model. First, we replace the monetary policy indicator with the gap between the short term interest rate and the Taylor rate (\( \text{gapTaylor} \)). The results are shown in the Appendix C (Figures 17 to 21 and Table 2). For the auxiliary variables strictly connected to the risk-taking channel — \( \text{VSTOXX}, \text{GRAI} \) and \( \text{BBB} \) — the causality from the policy stance to the level of risk appears significant only after several periods. Moreover, the measure of causality is increasing, suggesting that when the central bank keeps its rates too low for a protracted period of time, financial agents will be more and more incited to take risk. Just as in the main analysis, there seems to be no causality from Risk to Policy. For variables related to the financial accelerator mechanism, the risk-taking channel theory seems verified only for two out of the five considered
auxiliary variables. When the auxiliary variable relates to the bank capital channel, results are similar to the ones obtained in the baseline analysis. The difference comes from the shape of causality measures. Whereas before the measure was at first increasing and then declining, in our robustness analysis, the measures is zero for several periods, and increases afterwards.

The second sensitivity analysis concerns the $y$ variable. We consider two alternative risk measures: the SRisk computed only for the banking sector ($SRisk_{bk}$) and the credit-to-GDP ratio. For $SRisk_{bk}$, the risk-taking channel seems to be confirmed in most of the cases, the only two variables for which there is no causality from Policy to Risk being $stock$ and $edf_{bk}$.$^{17}$ After the subprime crisis, the Basel III committee underlined the importance of adopting a macroprudential framework. The indicator they proposed for risk monitoring is the credit-to-GDP ratio. We therefore include in our model this variable, instead of $SRisk$. Results are reported in the Appendix C (Figures 22 to 26 and Table 3). Once more, the results for most of the $z$ variables considered indicate the existence of long-run causality from Policy to Risk, but not from Risk to Policy. As in the main analysis, $liq$ and $stock$ do not represent variables through which the policy stance may impact risk in the medium and long run.

The results obtained in the baseline analysis and in all the robustness checks are clearly in favor of the existence of the RTC in the Eurozone. Since these results are conclusive when using only one auxiliary variable in the model, we argue that accounting for more auxiliary variables at a time would be redundant. This is even more the case as these variables are closely connected and therefore their impact would be difficult to disentangle in VAR model with four or more variables, therefore adding nothing new to our analysis.

8 Concluding Remarks

The risk-taking channel has gained a lot of attention since the outbreak of the financial crisis, as it represents a way of explaining why the crisis was so sever and why risk accumulation went unnoticed. The different studies conducted thus far mainly perform micro-econometric analyses that seem in favor of the influence of the monetary policy stance on risk. Yet, macroeconomic studies on this subject are scarce and the long-term perspective is not considered. Moreover,

$^{17}$ Results are not presented in this work due to space constraints, but they are available upon request.
none of the existing papers employs causality measures which, as we have shown, are suitable for treating the existence of the RTC. To extend the literature treating this subject, we propose a different and original methodology based on long-run causalities between monetary policy and risk.

Several aspects of the risk-taking channel are addressed in this paper. First, given that the duration of expansionary monetary policy represents a key element in the functioning of this channel, we adopt a long-run perspective, and compute causality measures over several horizons. We find that in most cases, causality from the monetary policy stance to risk becomes significant only after several quarters. Therefore, usual short-run causality measures à la Geweke would not have been adequate for the research question at hand.

Second, causality from risk to the monetary policy stance is also estimated. Once more, the long-term perspective is important, as the central bank may choose not to react at first, when, even if risk is increasing, it remains at a low acceptable level, but decides to react latter on, when risk becomes a danger to the economy. Interestingly, our results show no such causal relation in this direction. This finding is not so surprising if we recall that the ECB’s mandate concerns only inflation and that before 2008 no worries were raised in this respect. However, as part of the two pillar strategy adopted by the ECB, financial indicators were supposed to be monitored as they may contain information about future inflation. If evidence provided here proves that this was not the case, the explanation may come not from a lack of vigilance of the central bank, but most probably from an absence of good risk measures. We address this second issue by employing in our analysis a recently proposed systemic risk measure, namely the so-called SRisk indicator, that reproduces the slow and long risk accumulation that preceded the crisis.

Finally, the third aspect deals with the possible connections between the credit channel and the risk-taking channel. To account for these interconnections, we consider in our VAR model, not only variables strictly related to risk aversion and risk perception, but also information that is usually associated to the financial accelerator mechanism and to the bank capital channel. The results show that it is difficult to disentangle the three channels.

The existence of the risk-taking channel partly relies on behavioral bias like myopia, herding
or excessive euphoria. Our results confirm that the element which triggers this behavior is expansionary monetary policy. This implies that excessive risk-taking becomes a negative externality of the central bank’s behavior and should be treated as such. More attention needs to be paid to periods when interest rates are very low, especially if they are accompanied by signs of increased risk-taking. Therefore, this study opens the way to new research questions and policy guidance. On the one hand, one could wonder what could the central bank do during periods like the Great Moderation, when the inflation rate is low, justifying low interest rates. Should central banks’ mandates be modified to account for this new channel in order to avoid the negative spillovers of accommodating monetary policy? This question is especially important nowadays, eight years since monetary policy around the world has been accommodating and interest rates have been near the zero lower bound. On the other hand, one of the measures taken after the crisis was the introduction of macroprudential tools and policies to insure the financial stability objective. However, in this new configuration another question might arise. What should be done in case of trade-offs appearing between objectives? Indeed, our results seem to indicate that this is the case when interest rates are low because they encourage risk-taking which is of course damaging to financial stability. The interplay between monetary policy and macroprudential rules should therefore be thoroughly studied.
References


## Appendix

### A. Data description

Table 1: Auxiliary variables, \( z \)

<table>
<thead>
<tr>
<th>Group</th>
<th>Variable</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>RTC</td>
<td>VSTOXX</td>
<td>The VSTOXX Index is based on EURO STOXX 50 real time options prices and is designed to reflect market expectations of volatility.</td>
<td>Datastream</td>
</tr>
<tr>
<td></td>
<td>GRAI</td>
<td>Global Risk Aversion Indicator</td>
<td>ECB Data Warehouse</td>
</tr>
<tr>
<td></td>
<td>BBB1</td>
<td>The BofA Merrill Lynch BBB Euro Non-Financial Index. The index is computed based on the cost of bonds issued by firms with an investment grade BBB.</td>
<td>Datastream</td>
</tr>
<tr>
<td>Financial Accelerator</td>
<td>rprem</td>
<td>The risk premium computed as the difference between the bank lending rate and the short term interest rate.</td>
<td>Datastream and author’s calculations</td>
</tr>
<tr>
<td></td>
<td>hprice</td>
<td>Housing price index for the Eurozone. Quarterly data transformed by linear extrapolation into monthly data.</td>
<td>ECB Data Warehouse</td>
</tr>
<tr>
<td></td>
<td>stock</td>
<td>Stock market index for the Eurozone</td>
<td>Datastream</td>
</tr>
<tr>
<td></td>
<td>edf_nfc</td>
<td>Expected default frequency of non financial corporations</td>
<td>Moody’s</td>
</tr>
<tr>
<td></td>
<td>cost_eq_firms</td>
<td>The cost of equity for firms</td>
<td>ECB Data Warehouse</td>
</tr>
<tr>
<td>Bank Capital Channel</td>
<td>edf bk</td>
<td>Expected default frequency for banks</td>
<td>Moody’s</td>
</tr>
<tr>
<td></td>
<td>cost_eq_bk</td>
<td>Cost of equity for banks</td>
<td>ECB Data Warehouse</td>
</tr>
<tr>
<td></td>
<td>cap</td>
<td>Capital to assets ratio</td>
<td>ECB Data Warehouse</td>
</tr>
<tr>
<td></td>
<td>liq</td>
<td>Liquidity to assets ratio</td>
<td>ECB Data Warehouse</td>
</tr>
</tbody>
</table>

Note: All variables have a monthly frequency.
Figure 9: All z variables

Note: This figure presents the evolution of all auxiliary variables employed in the main analysis, over the period 2000 – 2013. The shaded area corresponds to the subprime crisis and it is not included in the analysis, but is presented here in order to give a global view for the dynamics of these variables. Source: see Table 1.
B. Results - Figures

Figure 10: Causality measures for $z=r_{prem}$

Note: This figures presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = igap$ and $y = S_{Risk}$. The auxiliary variable is $r_{prem}$. The order of the VAR, selected by AIC, is 4. Confidence intervals at 95% are represented by the dashed lines.

Figure 11: Causality measures for $z=h_{price}$

Note: This figures presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = igap$ and $y = S_{Risk}$. The auxiliary variable is $h_{price}$. The order of the VAR, selected by AIC, is 7. Confidence intervals at 95% are represented by the dashed lines.

Figure 12: Causality measures for $z=stock$

Note: This figures presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = igap$ and $y = S_{Risk}$. The auxiliary variable is $stock$. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.
Figure 13: Causality measures for $z = \text{cost}_{eq.firms}$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{igap}$ and $y = \text{SRisk}$. The auxiliary variable is $\text{cost}_{eq.firms}$. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.

Figure 14: Causality measures for $z = \text{edf}_{bk}$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{igap}$ and $y = \text{SRisk}$. The auxiliary variable is $\text{edf}_{bk}$. The order of the VAR, selected by AIC, is 4. Confidence intervals at 95% are represented by the dashed lines.

Figure 15: Causality measures for $z = \text{cost}_{eq.bk}$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{igap}$ and $y = \text{SRisk}$. The auxiliary variable is $\text{cost}_{eq.bk}$. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.

Figure 16: Causality measures for $z = \text{liq}$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{igap}$ and $y = \text{SRisk}$. The auxiliary variable is $\text{liq}$. The order of the VAR, selected by AIC, is 2. Confidence intervals at 95% are represented by the dashed lines.
C. Robustness - Figures

Robustness to $x$

Figure 17: Causality measures with $x = gapTaylor$ and $z = VSTOXX$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = gapTaylor$ and $y = SRisk$. The auxiliary variable is $VSTOXX$. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.

Figure 18: Causality measures with $x = gapTaylor$ and $z = GRAI$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = gapTaylor$ and $y = SRisk$. The auxiliary variable is $GRAI$. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.

Figure 19: Causality measures with $x = gapTaylor$ and $z = BBB$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = gapTaylor$ and $y = SRisk$. The auxiliary variable is $BBB$. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.
Figure 20: Causality measures with $x=\text{gapTaylor}$ and $z=\text{edf}_{\text{nfc}}$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{gapTaylor}$ and $y = \text{SRisk}$. The auxiliary variable is $\text{edf}_{\text{nfc}}$. The order of the VAR, selected by AIC, is 2. Confidence intervals at 95% are represented by the dashed lines.

Figure 21: Causality measures with $x=\text{gapTaylor}$ and $z=\text{cap}$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{gapTaylor}$ and $y = \text{SRisk}$. The auxiliary variable is $\text{cap}$. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.

The rest of the results are summarized in the following table:

Table 2: Causality measures with $x=\text{gapTaylor}$ and $y = \text{SRisk}$

<table>
<thead>
<tr>
<th>$z$</th>
<th>$x \to y$</th>
<th>$y \to x$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$rprem$</td>
<td>Yes (20 - )</td>
<td>No</td>
</tr>
<tr>
<td>$hprice$</td>
<td>Yes (10 - )</td>
<td>Yes (1-3)</td>
</tr>
<tr>
<td>$stock$</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>$cost_{eq_firms}$</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>$edf_bk$</td>
<td>Yes (15 - )</td>
<td>No</td>
</tr>
<tr>
<td>$cost_{eq_bk}$</td>
<td>Yes (15 - )</td>
<td>No</td>
</tr>
<tr>
<td>$liq$</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

Note: “Yes” means that causality measures are significant. In parenthesis, the interval represents the periods during which the measure is significant. If there is only one number, it means that the measure stays significant until the end of our horizon, $h=24$. “No” indicates that causality measures are not significant.
Robustness to $y$

Figure 22: Causality measures with $y=\text{credit}_t/\text{gdp}$ and $z=\text{VSTOXX}$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{gapTaylor}$ and $y = \text{credit}_t/\text{gdp}$. The auxiliary variable is VSTOXX. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.

Figure 23: Causality measures with $y=\text{credit}_t/\text{gdp}$ and $z=\text{GRAI}$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{gapTaylor}$ and $y = \text{credit}_t/\text{gdp}$. The auxiliary variable is GRAI. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.

Figure 24: Causality measures with $y=\text{credit}_t/\text{gdp}$ and $z=\text{BBB}$

Note: This figure presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{gapTaylor}$ and $y = \text{credit}_t/\text{gdp}$. The auxiliary variable is BBB. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.
Figure 25: Causality measures with $y=\text{credit to gdp}$ and $z=\text{edf } nfc$

Note: This figures presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{gapTaylor}$ and $y = \text{credit to gdp}$. The auxiliary variable is $\text{edf } nfc$. The order of the VAR, selected by AIC, is 2. Confidence intervals at 95% are represented by the dashed lines.

Figure 26: Causality measures with $y=\text{credit to gdp}$ and $z=\text{cap}$

Note: This figures presents causality measures for the variables $x$ (Policy) and $y$ (Risk). More precisely, $x = \text{gapTaylor}$ and $y = \text{credit to gdp}$. The auxiliary variable is $\text{cap}$. The order of the VAR, selected by AIC, is 1. Confidence intervals at 95% are represented by the dashed lines.

The rest of the results are summarized in the following table:

| Table 3: Causality measures with $x=\text{gapTaylor}$ and $y=\text{credit to gdp}$ |
|---|---|---|
| $z$          | $x \rightarrow y$ | $y \rightarrow x$ |
| $rprem$      | Yes (3 - )         | No |
| $hprice$     | No                  | No |
| $stock$      | Yes (5 - )         | No |
| $cost_eq_firms$ | Yes (12 - )    | No |
| $edf bk$     | Yes (4 - )         | No |
| $cost_eq bk$ | Yes (9 - )         | No |
| $liq$        | Yes (4 - 7)        | Yes (21 - ) |

Note: “Yes” means that causality measures are significant. In parenthesis, the interval represents the periods during which the measure is significant. If there is only one number, it means that the measure stays significant until the end of our horizon, $h=24$. “No” indicates that causality measures are not significant.