How low for how long? a monetary policy perspective.

E. C. Mamatzakis[1] C. Staikouras[2] & C. Triantopoulos[3]

June 2022

Abstract

This paper examines the impact of euro-area quantitative easing on the banking industry. We provide a dynamic threshold panel model that endogenously identifies the low threshold of the monetary policy rate. And we also provide insights into the long vs the short-run impact of quantitative easing on bank-level resilience and competition. Results show that there is a negative relationship between low rates and bank risk.. For the low levels of main refinancing operation, which is below 0.1097%, quantitative easing would reduce bank resilience, whereas for higher thresholds it will increase bank resilience. We also report the long-run impact of UMP on bank risk, as well as the short-run dynamics using a panel VAR model. This paper provides empirical estimates of low thresholds for the ECB's rate and responses to shocks in monetary policy. The main findings of our analysis show that asymmetry is present because in a low regime we observe that an increase in MRO would decrease Z-score, increasing bank risk and reducing bank stability. Policy implications are of interest in the current conjecture that there are voices for hikes in the interest rates despite the anemic euro-area recovery and the geopolitical tensions.

Keywords: Quantitative easing, Dynamic Threshold Analysis, low rates.

JEL classification: G21; G01; E43; E52

[1] Department of Management, Birkbeck College, University of London, Malet Street WC1E 7HX, UK; Corresponding author, email: e.mamatzakis@bbk.ac.uk. [2] Department of Accounting and Finance, Athens University of Economics and Business, Athina, Greece, Greece. email: cstaik@aueb.gr. [3] Centre of Planning and Economic Research, 11, Amerikis str., 106 72 Athens, Greece. email: ctrianto@kepe.gr.

1. Introduction

We are interested in investigating whether a threshold of low interest rate could be identified endogenously by employing euro-area bank level data. We hypothesise, based on recent literature (Altunbas et al., 2014; Claessens, et al. 2018; Gambacorta et al. 2014; Lyonnet and Werner 2012) that quantitative easing could have short run effects that are heterogenous to the long run effects.

So, our contribution in a nutshell is as follows: rather than imposing what is low, we provide unbiased estimations of low interest rates (possibly thresholds of UMP measures as they can be selected as threshold variables), treating also for endogeneity. We also test for the long-term impact of low interest rate (UMP) on bank profitability, capitalisation lending. Robustness analysis could provide other channels, such as consumption and savings, mis allocation of resources.

It is also of interest to investigate the risk-taking of banking industry as the result of QE. To this end, the degree of competition in the banking industry could also influence the quantitative easing-risk linkage (Altunbas et al., 2014; Claessens, et al. 2018; Gambacorta et al. 2014; Lyonnet and Werner 2012). Therefore, we control for the effect of quantitative easing when measuring the competition-risk relationship, and vice versa. We also explore in depth the underlying causality among quantitative easing, competition and risk.

The relationship between competition and bank risk-taking has not been settled (Beck et al., 2013; Boyd and De Nicolo, 2005; Jiménez et al., 2013; Tabak et al., 2015). Owing to the variations in the details of the regulatory environment and interpretations of risk in different jurisdictions, a single risk factor may vary in scope across countries (Menezes et al., 2014). The complexity of global financial regulations and codes is likely to have a particular influence on the nature of the financial "business risks" that investors face (Foden and Nguyen, 2013). Indeed, several studies have focused on the global bank business models (such as crisis-driven consolidation) and the mechanisms that drive them (World Bank, 2012), resulting in large differences in the global distribution of bank business risks across countries (Scharf and Barac, 2016). This is also reflected in cross-country measures of "systemic financial risk" such as systemic leverage, which are much higher in European and Scandinavian countries than in North America, Australia, and New. Other research demonstrates an inverse relationship between bank competition and bank risk taking. Although bank competition encourages risk taking in a positive feedback loop, bank competition can potentially reverse the detrimental effects of bank risk taking on the system (Bertrand and Meyer, 2004; Gertler et al., 2007; Li et al., 2011). Furthermore, several studies have shown that countries with greater bank competition have better policy governance and lower levels of risk (Stringer and Barac, 2016). For example, a higher level of bank competition is associated with more efficient bank regulation (Xing et al., 2010). In addition, the UK, Sweden, Norway, Switzerland, and Denmark are seen to be the banks with the strongest bank competition (Voracek and Gzankowski, 2006). Bank competition is also positively associated with the availability of capital (Bernanke and Bernanke, 1999), the incentives that lenders impose on their borrowers (Scharf and Barac, 2016), and the competitive pressure on banks (Smith and Stowe, 2010). Moreover, increased bank competition is associated with lower capital requirements, less stringent supervisory enforcement, and more lenient capital ratios (Menezes et al., 2014).

Schaeck and Cihák, (2008) and Stiroh and Strahan, (2003) show that smaller banks may have a low-risk profile and that, indeed, the relationship between scale and credit risk may be negative in certain circumstances. Schaeck and Cihák, (2008) highlighted the importance of competition for encouraging innovation and financial innovation in financial services.

Nonetheless, competition may be subject to external factors that are not within the control of the market participants (for example, structural and regulatory constraints). It may be argued that competition is not always beneficial and that there are likely to be winners and losers when financial institutions compete. One question for this literature is how competition amongst financial institutions affects the borrowers' incentive to take risk.

Fu et al., (2014) and Liu and Wilson, (2013) show that competition could lead to very high bank risk. These studies consider the credit cycle, default rates, asset quality, and loan performance in their discussion. The argument is that when the credit-to-GDP ratio reaches an unsustainable level, there will be a problem in the banking sector. According to this theory, the banking sector is the main victim of credit crisis. In the long term, however, this theory underplays the role of credit cycle. Hence, whether higher competition destabilises the banking system by accumulating bank risk remains yet to reach unanimity.

In the paper, we examine the impact of euro-area quantitative easing on the banking industry. A concern that has emerged refers to the historically low rates. We provide a dynamic threshold panel model that endogenously identifies the low threshold of monetary policy rate. And we also provide insights of the long vs the short run impact on quantitative easing on bank level resilience and competition.

When interest rates are very low banks would grant more risky loans with low internal ratings, and weak ex-post performance (Ioannidou et al., 2015; Jiménez et al., 2014). As borrowers perceive less risk of default, such practices increase the variation in loan portfolios and shift the risks away from one pool of borrowers towards banks, creating a new risk of instability. However, surveys in the US and the UK showed that there is no excessive bank risk-taking due to QE (Claeys and Darvas, 2015).

Given the above literature, this paper contributes as follows: we identify a dynamic threshold panel model that endogenously identifies the low threshold of monetary policy rate. In addition, we provide insights of the long vs the short run impact on quantitative easing on bank level resilience and competition. Bank risk-taking is measured by non-performing loans and Z-score.

The rest of the paper includes section 2 presents the methodology. Section 3 reports the result and final section offers some conclusions.

2. Methodology: Dynamic Panel Threshold Model.

The starting point of our analysis is Claessens, et al. (2018) where the basic model is:

$$y_{ijt} = \beta_0 + \beta_1\, y_{ijt-1} + \theta_1\, 3MonthRate_{jt} + \theta_2 RateSpread_{jt} + \theta_2\, Low_{jt} + \theta_4\, 3MonthRateXLow_{jt} + \theta_5\, RateSpreadXLow_{jt} + \gamma_1 GDPgrowth_{jt} + \gamma_2\, X_{it} + \delta_i + \zeta_t + \varepsilon\_{ijt} \quad (1)$$

where: y_{ijt} is the NIM (or ROA) of bank i in country j in year t. $3MonthRate_{jt}$ is the yearly average 3-month government bond yield. $RateSpread_{jt}$ is the spread between the 10-year government bond yield and 3-month government bond yield.

The above model is then applied in a panel of countries that are classified as Low or High based on whether their yearly average 3-month yield is above or below 1.25 percent, respectively.

The main criticism arises because to measure low (high) as above is subject to measurement issues, and one could argue that to define what is low would be rather be an exercise that treats low as not a pre-defined variable (see 3-month yield is below 1.25 percent). Also, in Stijn's paper as the main model is an AR(1) one would argue that it refers to the short run by specification. Long term effects should be modelled accordingly.

Then we raise the following questions:

- would it be possible to observe *how low is low* whilst treating for endogeneity?
- would it be possible to test for *how long remains low*?

It is possible. We would observe *low* and whether the *low* stays *low for long*. We shall opt for a dynamic panel threshold model (see Hansen, 1999).

This model (Hansen, 1999) enables us to identify regime changes of important determinants of, for example, y_{ijt} that could be defined as ROA (or capitalisation as Stijns suggests) of bank *i* in country *j* in year *t*. The important determinant, we would argue is the central interest rate, that would be the threshold variable.

Note that we shall specify the variable that would trigger changes in the underlying regimes, i.e. low vs high regimes (structural breaks so to speak). In this respect, we could select measures of UMP and not only the central rate. Also, it is worth noting that we could explore regime changes focusing on banking (selecting NIM, risk, profitability or bank lending), but we could also explore regime changes in consumption and savings or in resource misallocation (see Borio and Hofmann, 2017; and Hesse, et al. 2017 that have no copy and it would be useful to have a look as it provides IRFs of monetary shocks). It could be also useful to read Hofmann and Kohlscheen (2017).

In some detail, the threshold model takes the following form:

$$y_{ijt} = \mu_i + \beta_1 z_{ijt} I(r_{ijt} \leq \gamma) + \beta_2 z_{ijt} I(r_{ijt} > \gamma) + \varepsilon_{ijt}, \quad (2)$$

where subscripts $i = 1,\ldots, N$ represent the bank, $j = 1,\ldots, M$ country, and $t = 1,\ldots, T$ index the time. y_{ijt} is the ROA of bank i in country j in year t. μ_i is the country-specific fixed effect, and the error term is $\varepsilon_{ijt} \overset{iid}{\sim} (0,\sigma^2)$. $I()$ is the indicator function indicating the regime defined by the threshold variable r (rate in our case), and the threshold level γ.
z_{it} is a m-dimensional vector of explanatory regressors which may include lagged values of y and other endogenous variables.

The vector of explanatory variables is partitioned into a subset z_{1ijt} of exogenous variables uncorrelated with ε_{ijt}, and a subset of endogenous variables z_{2it}, correlated with ε_{ijt}. In addition to the structural equation, the model requires a suitable set of instrumental variables x_{ijt} including z_{1ijt}.

Note that the above can further be transformed so as the central rate could be the threshold variable and the regime dependent regressor. That transformation would allow to examine the long-term impact of the rate on, for example, NIM.

$$y_{ijt} = \mu_i + \beta_1 r_{ijt} I(r_{ijt} \leq \gamma) + \delta_1 I(r_{ijt} \leq \gamma) + \beta_2 r_{ijt} I(r_{ijt} > \gamma) + + \varphi z_{ijt} + \varepsilon_{ijt}, \quad (3)$$

z_{ijt} is the vector of other endogenous control variables. Note that slope coefficients are regime independent.

The flexibility of the above also rests on Bick (2010) that permits to test for differences in the regime intercepts by providing estimation of δ_1. This coefficient is not bank specific but the same for all cross-sections. According to Bick (2010), ignoring the regime intercepts would result to biased estimates for both the threshold value and the coefficient magnitude of the regimes.

In addition, as Hansen (1999) model is based on balanced panel data set, we shall opt for Kremer et al. (2013) that relaxes this. This model also uses GMM estimators that treat for endogeneity. This model by Kremer et al. (2013) treats z_{ijt} as a vector of explanatory variables, which includes one regressor that is correlated with the error term and other regressors, which are not.

Kremer et al. (2013) employ the GMM estimation method (Arellano and Bover, 1995) to control for serial correlation in the error terms. To this end, Kremer et al. (2013) as in Caner and Hansen (2004) opt a reduced type of model with instrumental variables to estimate the predicted values. As a first step, the endogenous variable is instrumented by the predicted values, while in the second step OLS estimation is used for a fixed threshold value. The threshold variable in the second step is replaced by its predicted values obtained in the first step. Subsequently, the optimal threshold value comes from the minimisation of the sum of squared errors (see Chan, 1993; Hansen, 1997). And, $\Gamma = \{\gamma : LR(\gamma) \leq C(a)\}$ provides the 95% confidence interval of the threshold value. The $C(a)$ is the asymptotic distribution of the Likelihood Ratio (LR) test at the 95% level as in Hansen, (1999) and Caner and Hansen, (2004). The LR test is adjusted and controls for the time observations across countries (Hansen, 1999). As a last step, the coefficients β_1 and β_2 are estimated using GMM (Caner and Hansen, 2004).

3. Data and Results

The data sample consists of banks in 19 countries of the Euro-area for the 2007-2015 period. All bank-specific variables are obtained from Bankscope, at annual frequency, and in thousand USD. There are 23,917 observations of 3,229 banks specialised as commercial, investment, savings, and real estate banks. Table 1 describes the summary statistics of the data.

Regarding UMP, there are three proxies from the ECB Statistical Data Warehouse. The first proxy (APP&LTRO) is the amount of asset purchases for the whole Eurosystem and LTROs. The value is computed by adding all the amounts of different asset purchase programmes (APPs, since 2009, reported as a total figure under the '*Securities Held for Monetary Policy Purposes*' in the ECB's annual balance sheets) and the Longer-Term Refinancing Operations (LTROs, also available from the ECB's annual balance sheets). This variable is constructed in a similar way to how Bluwstein, Canova (2016) calculate their UMP variable. LTROs are carried out as fixed rate tender procedures with full allotment and a maturity of three years (announcements on 20/12/2011 and 28/02/2012).[2] Historically, the six-month LTROs were announced on 28/03/2008 and 04/09/2008 with variable rate tender procedures and pre-set amounts.[3] The one-year LTROs were subsequently announced on 23/06/2009, 29/09/2009, and 15/12/2009.[4] APPs comprise the Securities Market Program (SMP, effective from 05/2010 to 09/2012), the Covered Bond Purchase Programs 1 and 2 (CBPP 1, CBPP 2, terminated), and the current Asset Purchase Program. CBPP 1 was in effect from 06/2009 to 06/2010, while the second one was carried out between 11/2011 and 10/2012. The ongoing Asset Purchase Program (expanded APP) has been in place since 2014 and extended to the end of 2017. This

---

[2] Source : https://www.ecb.europa.eu/press/pr/date/2011/html/pr111208_1.en.html
[3] Source : https://www.ecb.europa.eu/press/pr/date/2008/html/pr080328.en.html; https://www.ecb.europa.eu/press/pr/date/2008/html/pr080904_3.en.html
[4] Source : https://www.ecb.europa.eu/press/pr/date/2009/html/pr090507_2.en.html

consists of all purchases of the public and private sector securities to address the issue of prolonged low inflation and provide credit to the real economy. The breakdown of the expanded APPs includes the CBPP 3 (since 20/10/2014), Asset-backed Securities Purchase Program (ABSPP, started 21/11/2014), Public Sector Purchase Program (PSPP, started 09/03/2015), and Corporate Sector Purchase Program (CSPP, since 08/06/2016). The time span of the annual data is 2007-2015, thus the CSPP is not included as part of the UMP variable. The securities covered by the PSPP are: i) nominal and inflation-linked central government bonds, ii) bonds issued by recognised agencies, regional and local governments, international organisations and multilateral development banks located in the euro area.[5]

In a cross-country study of UMP, Gambacorta et al. (2014) use the central bank assets to represent the UMP instrument. As Lyonnet and Werner (2012) argue, central banks can use both sides of the balance sheet to exert the impact of asset purchases. While the asset side provides an alternative source for private financial intermediation through outright purchase of credit products, the liability side captures a cushion for funding liquidity risk. Following the literature, I include two additional proxies for UMP, namely the ECB's assets and excess reserves, available from the ECB Statistical Data Warehouse. Excess reserves are the total excess reserves of credit institutions subject to minimum reserve requirement in the euro area. As bank-specific variables are in thousand USD, I opt for the EUR/USD exchange rate from Bankscope to convert the UMP data from million EUR to thousand USD. Cour-Thimann, Winkler (2012) emphasise that ECB's non-standard measures complement key interest rate decisions rather than acting as a substitute. To account for conventional monetary policies (CMPs), I use the marginal lending facility (MLF) rate, the deposit facility rate (DF), and the main refinancing rate (MR). These variables are available from the ECB's website.

[5] Sources: https://www.ecb.europa.eu/mopo/implement/omt/html/index.en.html

Z-score is the dependent variable representing bank stability, computed as $Z_{it} = \left(ROA_{it} + Capital\,ratio_{it}\right) / \sigma ROA_{it}$, which shows the number of standard deviations below the average return on assets that will lead to insolvency due to liquidity shocks (Beck, De Jonghe, Schepens, 2013). I use the time-varying Boone indicator as a measure of bank competition. The method to obtain this measure is provided in the next section. Bank specific variables include size, asset diversification, liquidity, and revenue diversification.[6] Size is the natural logarithm of total assets (Beck et al., 2013; Delis, Kouretas, 2011; Liu, Wilson, 2013).

In the identification we control for revenue diversification measured as the ratio of non-interest income to total operating income (Anginer, Demirguc-Kunt, Zhu, 2014; Beck et al., 2013), assets diversification represented by the ratio of securities to assets (Zhang et al., 2013), and liquidity which is defined as liquid assets[7] to total assets (Altunbas et al., 2007; Jeon, Olivero, Wu, 2011). GDP growth is included to reflect the influence of macroeconomic environment (Jiménez, Lopez, Saurina, 2013). Data for GDP growth are available from World Bank database and IMF Statistics.

[6] It is understood that the capital to asset ratio is usually among the control variables as bank capitalisation affects bank risk. Nevertheless, we do not include it as by definition, Z-score takes into account the capital to asset ratio. Hence, there may exist a mechanical relationship between them.

[7] Liquid assets are also obtained from Bankscope.

Table 1. Main variables of our identification.

Variable	Obs	Mean	S.D.	Min	Max
Z-score	23,917	4.9706	7.0858	-11.7670	142.1103
HHI	23,917	0.1088	0.0481	0.0627	0.6916
UMP	23,917	754,285	311,321	268,477	1,312,924
Size	23,917	13.9240	1.8887	6.0798	21.9074
Asset diversification	23,917	0.2314	0.1572	0.0000	0.9990
Liquidity ratio	23,917	0.1785	0.1726	0.0000	1.0000
Revenue diversification	23,917	0.2014	0.2834	-21.0620	0.9999
GDP growth	23,917	0.6180	2.8244	-14.8142	11.0870

Notes: Z-score $Z_{it} = (ROA_{it} + Capital ratio_{it}) / \sigma ROA_{it}$; HHI is Herfindahl-Hirschman index; UMP is unconventional monetary policy (mil EUR) calculated as the sum of the amount of asset purchases under the Securities Markets Program, Covered Bond Purchase Program (1 and 2), and Longer-Term Refinancing Operations; size=*ln*(total assets); asset diversification is securities/assets; liquidity is liquid assets/total assets, revenue diversification is non-interest incomes/total operating income; GDP growth (%); The sample includes 19 countries in the Eurozone.

3.1 Results Dynamic Panel Threshold Analysis

This section presents the dynamic panel threshold results and identify the presence of thresholds in the QE of the ECCB. We employ this econometric method setting as threshold variable the MRO (the main refinancing operation rate) or the UMP (for this paper we define UMP as the unconventional monetary policy calculated as the sum of the amount of asset purchases under the Securities Markets Program, Covered Bond Purchase Program 1 & 2, and Longer-Term Refinancing Operations).

Our dynamic threshold analysis reveals a threshold value of MRO to be 0.1097% (see Table 1 below). Interestingly our findings suggest that the MRO exerts an asymmetric effect on bank stability as in the high regime its effect is positive whilst on the low regime its effect turns negative on Z-score.

Table 1. Dynamic Panel Threshold Analysis for the Risk-MRO Nexus.

Dependent variable	lnZ-score	
Threshold estimates	0.1097	
95% confidence interval	[0.1097 0.1097]	
Impact of threshold variables	Est.	S.e.
Low regime	-0.1717***	0.0310
High regime	0.5125***	0.0377
Intercept	-1.7509***	0.0865
Impact of covariates		
UMP	0.0587*	0.0031
Size	0.0344**	0.0015
Asset diversification	-0.1596***	0.0456
Liquidity	-0.2993***	0.0473
Revenue diversification	0.0782***	0.0170
GDP growth	0.0161***	0.0021
D_2008	-0.1071***	0.0204
D _2009	-0.0408*	0.0222
D _2010	-0.0501***	0.0146
D _2011	-0.0976***	0.0341
D _2012	-0.0532	0.0402
D _2013	-0.0881***	0.0293
D _2014	-0.0575***	0.0208
d D _2015	-0.3121***	0.0385

Obs in low regime	19058
Obs in high regime	4859

Notes: This Table reports results from the dynamic panel threshold analysis using the first lag of the endogenous variable as its instrument. The threshold variable is MRO. Z-score $Z_{it} = (ROA_{it} + Capitalratio_{it}) / \sigma ROA_{it}$, UMP (in log): unconventional monetary policy calculated as the sum of the amount of asset purchases under the Securities Markets Program, Covered Bond Purchase Program (1 and 2), and Longer-Term Refinancing Operations; size=*ln*(total assets); asset diversification=securities/assets; liquidity=liquid assets/total assets, revenue diversification=non-interest incomes/total operating income; d_: year dummy; S.E.: standard error; Obs: number of observations. ***,**,*: significance at 1%, 5%, 10% levels respectively.

In some detail, there exists a negative association between risk of banks in the high (low) regime and the UMP, as λ_2= 0.5125 (-0.1717). This suggests that for the low levels of MRO below 0.1097%, the relationship between QE and bank resilience is negative. However, for the high levels of MRO above 0.1097%, the relationship between QE and bank resilience turns positive and the monetary policy impact also has a higher in magnitude impact if compared to the low regime.

Thus, in a nutshell, asymmetry is present because in low regime we observe negative relationship between MRO and Z-score which implies that an increase in MRO would decrease Z-score, that is increases bank risk. Therefore, the MRO would reduce bank stability.

In high regime we observe positive relationship between MRO and Z-score. This result insinuates that an increase in MRO would increase Z-score. Thus, the MRO in high regime would positively affect bank stability.

Table 2 presents the sample observations per regime as our dynamic threshold analysis reveals a threshold value of MRO to be 0.1097%.

Table 2: Number of Observations in Each Regime for the Risk-MRO Nexus.

Time	Low regime	High regime
2007	1945	746
2008	1964	776
2009	1984	803
2010	2557	330
2011	2633	392
2012	2640	410
2013	2646	404
2014	2552	404
2015	137	594
Total	19058	4859

Notes: Authors estimations.

Nex, we examine the Risk-Unconventional Monetary Policy nexus. Our dynamic threshold analysis reveals a threshold value of UMP to be 616,662 mil EUR (see Table 3). Our findings suggest that the UMP exerts a strong negative impact on Z-score for both regimes. Moreover, both in low and high regimes we observe negative relationship between UMP and lnZ-score because an increase in UMP would decrease Z-score. Thus, we provide evidence that UMP reduces bank stability.

Table 3. Dynamic Panel Threshold Analysis for the Risk-Unconventional Monetary Policy Nexus

Dependent variable		Z-score
Threshold estimates		616,662 mil EUR
95% confidence interval		[616,662 616,662]
Impact of threshold variables	Est.	S.E.
Low regime	-0.0653**	0.0288
High regime	-0.0578*	0.0318
Intercept	0.0579	0.8438
Impact of covariates		
HHI	0.4559***	0.0510
Size	0.0197	0.0016
Asset diversification	-0.1014**	0.0470
Liquidity	-0.2397***	0.0471
Revenue diversification	0.0728***	0.0155
GDP growth	0.0104***	0.0022
Year Dummies	yes	
Obs in low regime	8318	
Obs in high regime	15599	

Notes: S.E.: standard error; Obs: number of observations. ***,**,*: significance at 1%, 5%, 10% levels respectively.

In some detail, there exists a negative association between risk of banks in the high (low) regime and the UMP, as λ_2= -0.0578 (-0.0653). This suggests that for the low levels of UMP below 616,662 mil EUR, the relationship is negative, and the coefficient estimate is somewhat higher than the coefficient of the high regime. This result illustrates that lower values of the UMP dampens bank risk somewhat more than the high regime.

So, the threshold value of 616,662 mil EUR is recorded in 2008 and splits the sample into two regimes. The high regime includes all the bank-observations whereby the level of the monetary easing, i.e., UMP is above the 616,662 mil EUR. By contrast, in the low regime belong all these bank-observations for which the value of Taylor gap is below 616,662 mil EUR.

As part of sensitivity analysis, we proceed in examining the bank competition and UMP nexus. Our dynamic threshold analysis reveals a threshold value of UMP to be 977,748 mil EUR (see Table 4). Our findings suggest that the UMP exerts a strong negative impact on competition in high regime, but a positive effect in the low regime. It is worth noting that there is a positive relationship between HHI and Z-score. Thus, a decrease in HHI would decrease Z-score that is in line with the competition-fragility hypothesis.

Table 4. Dynamic Panel Threshold Analysis for the Competition-Unconventional Monetary Policy Nexus

Dependent variable	HHI	
Threshold estimates	977,748 mil EUR	
95% confidence interval	[977,748 977,748]	
Impact of threshold variables	Est.	S.E.
Low regime	0.0095	0.0154
High regime	-0.0721	0.2010
Intercept	-1.7405	4.1628
Impact of covariates		
lnZscore	0.7068	0.5614
Size	-0.0106	0.0151
Asset diversification	0.1274	0.1285
Liquidity	0.1942	0.1750

Revenue diversification	-0.0505	0.0417
GDP growth	-0.8476	0.8485
Year Dummies	yes	
Obs in low regime	20136	
Obs in high regime	3781	

Notes: S.E.: standard error; Obs: number of observations. ***,**,*: significance at 1%, 5%, 10% levels respectively.

3.2 GMM estimation of panel VAR.

Next, we implement a second stage regression of the form:

$$V_{it}=a_{it}+ AV_{i,t-1}+ (I\otimes w_{it})\, \pi +e_{it} \tag{4}$$

where V_{it} is a vector of dependent variables resulting as functions of interest from the basic model, π is a parameter vector, A is a matrix of parameters, w_{it} is a vector of predetermined variables and e_{it} is an error term whose conditional mean is zero and the conditional covariance matrix is Ω. Moreover, a_{it} is a full set of country and time dummies. The dependent variables V_{it} are derived on the structural parameters of the model in the first stage.

The first stage is implemented using the local likelihood approach. The w_{it} may be a subset of the first stage instruments z_{it}. The above equation (3) is a panel vector autoregression (PVAR) which is estimated by an Arellano, (1991) style GMM using, additionally, the same instruments as in the first stage. To avoid biases due to second stage regression set up, we use the bootstrap.

The bootstrap procedure is described below in more detail:

- We bootstrap the available data by resampling over blocks consisting of 100 observations each.
- We perform local likelihood estimation as described previously and we compute the dependent variables V_{it} for each bootstrap replication. Smoothing constants for local likelihood estimation are re-estimated for each replication using the leave-one-out cross-validation technique.
- We estimate (3) using an Arellano, (1991) style GMM and we employ, additionally, the same instruments as in the first stage, for the appropriate time period. For each replication we compute a Hansen J-statistic.
- We repeat the bootstrap procedure 10,000 times.

From (3) we can derive long-run or steady-state values as:

$$V = (I-A)^{-1}[a+ (I\otimes w)\,\pi], \tag{5}$$

where a star indicates a steady-state value. We are more interested in the effect of a one-standard-deviation shock in e_{it} on V_{it}.

To compute such effects, we rely on an extension of the generalized impulse response function (GIRF). The GIRF is invariant to the ordering of variables in V_{it} or e_{it}. We fix the covariates at their sample median values for each country, and we compute:

$$GIRF_{i,h} = E[V_{ih|ai,}w_{ih}= w_i+d_i,e_{ih}]- E[V_{ih}|a_i,w_{ih}= w_i,e_{ih}],\ h=1,2,\ldots,H, \tag{6}$$

where h denotes the time horizon, a_i, w_i are set to their sample median values and di denotes the change in a certain covariate for the i^{th} country. The d_{is} are set to 10% of the lowest value of the covariate in each country. We set the e_{ih} to a random draw from the distribution of e_{it}.

We take 100 draws and we average the resulting $GIRF_{i,h}$. We set H=20 although the effects are trivial after about H=10. We compute the long-run effect for the i^{th} country as:

$$LR_i=\sum_{h=1}^{H} GIRF_{i,h} \tag{7}$$

3.3. The long run impact of unconventional monetary policy

Here we provide evidence of second stage analysis based on GMM estimation of a panel VAR. This analysis considers of the impact of the combined conventional and unconventional monetary policy on bank risk. Table 5 reports the long run impact of unconventional monetary policy on the generalized measure of bank risk which is reported to carry a negative sign in most of the cases.

Table 5. Panel VAR-Granger causality Wald test

Equation variable	Excluded variable	Chi^2	d.f.	$Prob>chi^2$
UMP	MRO	7.930	1	0.005
	lnZ-score	43.594	1	0.000
	All	43.652	2	0.000
HHI	UMP	523.891	1	0.000
	lnZ-score	108.172	1	0.000
	All	524.914	2	0.000
Z-score	UMP	7.612	1	0.006
	HHI	4.158	1	0.041

All	10.105	2	0.006

Notes: Ho: Excluded variable does not Granger-cause Equation variable; Ha: Excluded variable Granger-causes Equation variable; UMP (in log): unconventional monetary policy calculated as the sum of the amount of asset purchases under the Securities Markets Program, Covered Bond Purchase Program (1 and 2), and Longer-Term Refinancing Operations; Z-score $Z_{it} = \left(ROA_{it} + Capital\,ratio_{it}\right)/\,\sigma ROA_{it}$; MRO.

Table 6 reports the variance decompositions over 5 and 10 periods which show the importance of UMP for bank risk as measured by Z-score. 80% of the variation in Z-score is explained by variation in UMP, while 9.34% of the variation in UMP is explained by variation in Z-score. On the other hand, only 1.08% of the variation in Z-score is explained by variation in HHI, while 31.90% of the variation in HHI is explained by variation in Z-score.

Table 6. Variance Decompositions

	Periods	MRO	UMP	Z-score
MRO	5	90.3832%	0.3044%	9.3124%
UMP	5	22.7687%	46.5888%	30.6425%
lnZ-score	5	0.7466%	1.0367%	98.2167%
MRO	10	90.3414%	0.3181%	9.3406%
UMP	10	22.9945%	45.1084%	31.8972%
lnZ-score	10	0.8033%	1.0767%	98.1200%

Notes: This Table reports the variance decompositions of the panel vector autoregression model for 5 and 10 periods ahead. UMP (in log): unconventional monetary policy calculated as the sum of the amount of asset purchases under the Securities Markets Program, Covered Bond Purchase Program (1 and 2), and Longer-Term Refinancing Operations; Z-score $Z_{it} = \left(ROA_{it} + Capital\,ratio_{it}\right)/\,\sigma ROA_{it}$; HHI: Herfindahl-Hirschman Index.

4.2.3 The short run impact of conventional and unconventional monetary policy: Generalised Impulse Response Functions (GIRFs)

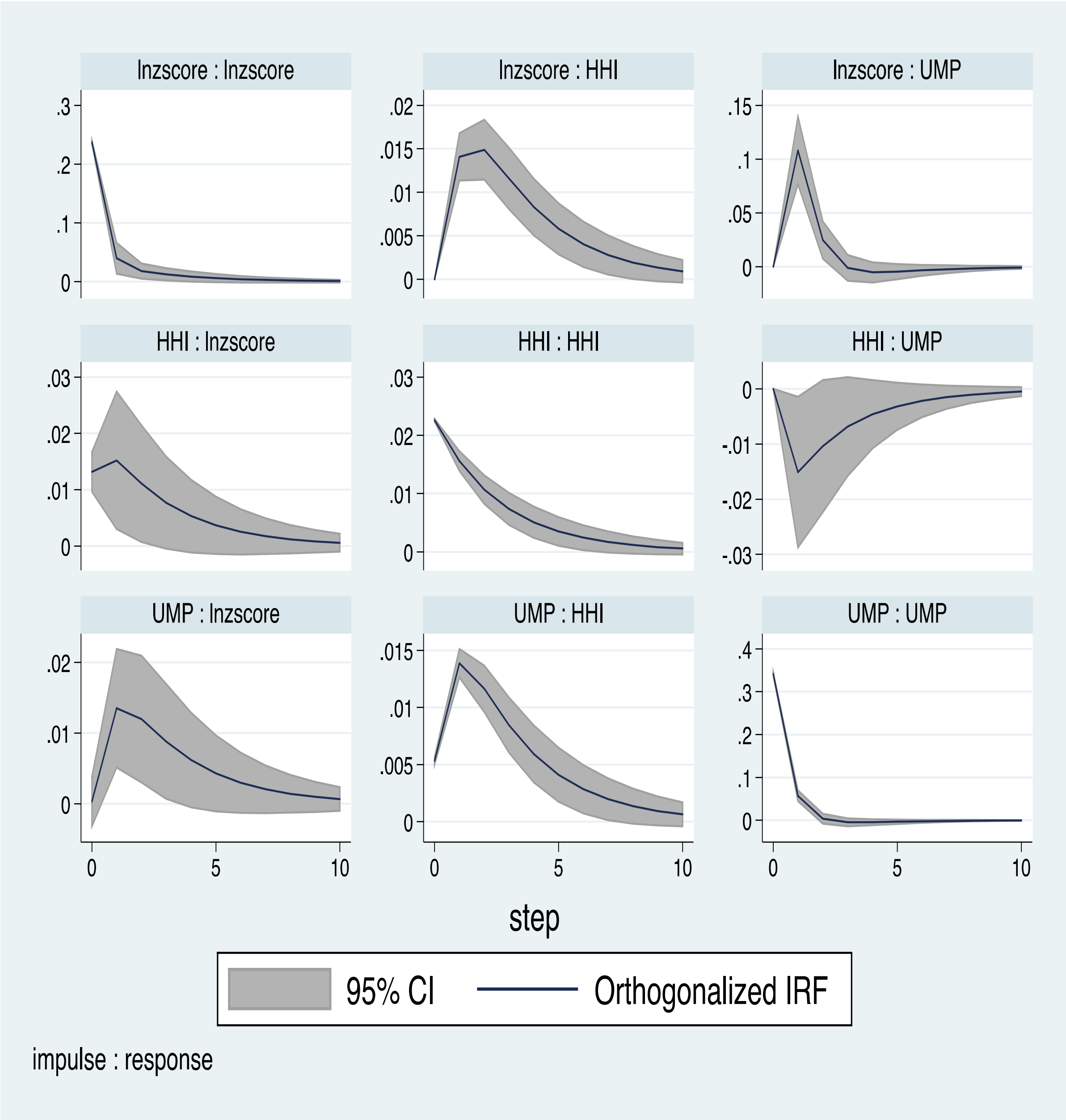
Following from the long run effect of monetary policy on bank risk, we report next the underlying short run dynamics by applying a panel VAR. This panel VAR model lessens *a priori* assumptions about the underlying relationships between bank risk and monetary policy. All variables enter panel VAR as endogenous within a system of equations.

Figure 1 draws the Generalized Impulse Response Functions (GIRFs) over ten periods ahead, reporting the response of the bank risk to a one standard deviation shock in the conventional and unconventional monetary policy.[8]

The GIRFs show that the response of bank risk, to a shock on UMP, and HHI (competition). UMP assists to mitigate uncertainty in the banking industry in the short run. Moreover, there is a positive response of Z-score to a one standard deviation shock in UMP and HHI. Similarly, to the results of the dynamic threshold models when UMP and HHI are control variables: we find a positive relationship between UMP and Z-score, and between HHI and Z-score).

[8] The panel VAR is of order one as indicated by the Schwarz criterion. Unobserved cross country heterogeneity is taken into account by specifying country specific fixed terms. To facilitate the presentation we do not report GIRFs for the response of bank risk to its own shocks. Standard errors are found to be low, suggesting that GIRFs are significant at 5%. Results are available upon request.

Figure 1. Impulse Response Function



Notes: This figure illustrates the impulse-response functions (IRFs) of each endogenous variable with respect to shocks in other variables. UMP: unconventional monetary policy (in log) calculated as the sum of the mount of asset purchases under the Securities Markets Program, Covered Bond Purchase Program (1 and 2), and Longer-Term Refinancing Operations; Z-score $Z_{it} = \left(ROA_{it} + Capital\,ratio_{it}\right) / \sigma ROA_{it}$; HHI: Herfindahl-Hirschman index. Errors are 5% on each side generated by Monte-Carlo simulation.

4 Conclusion

In this paper we examine the impact of QE on bank risk in the euro-area. The main findings of our analysis show that asymmetry is present because in low regime we observe that an increase in MRO would decrease Z-score, increasing bank risk and reducing bank stability. However, in high regime we observe positive relationship between MRO and Z-score, insinuation that in high regime UMP enhances bank stability. The nexus between UMP and bank competition also provides results that show variability between low and high regime. Given this evidence, we demonstrate that there are thresholds in UMP and thereby cautious approach of the interpretation of UMP is warranted. We continue with an investigation of the long run and short run dynamics between UMP and bank stability, competition. Results demonstrate some uniformity here as both in short and long run UMP enhances bank stability.

In addition, the current conjecture is of interest because there are voices for hikes in the interest rates despite the anaemic euro-area recovery and the geopolitical tensions.

References:

Arellano, M., and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68, pages 29-51.

Bick A (2010). Threshold effects of inflation on economic growth in developing countries. Econ Lett 108(2):126–129.

Borio Claudio and Boris Hofmann, (2017). Is monetary policy less effective when interest rates are persistently low? BIS Working Papers, No 628, BIS WP.

Caner, M., and Hansen, B. (2004). Instrumental variable estimation of a threshold model. Econometric Theory, 20, pages 813–843.

Claessens, Stijn, Nicholas Coleman, Michael Donnelly, (2018). "Low-For-Long" interest rates and banks' interest margins and profitability: Cross-country evidence, Journal of Financial Intermediation, Volume 35, Part A, Pages 1-16.

Hansen, B. (1997). Inference in TAR models. Studies in Nonlinear Dynamics and Econometrics, 2, pages 1-14.

Hansen, B. (1999). Threshold effects in non-dynamic panels: estimation, testing and inference. Journal of Econometrics, 93, pages 345–368.

Hesse, H., B. Hofmann and J Weber (2017): "The macroeconomic effects of asset purchases revisited", mimeo, Bank for International Settlements.

Hofmann, B and E Kohlscheen (2017). Consumption and interest rates: a cross country analysis, mimeo, Bank for International Settlements.

Kremer, S., Bick, A., and Nautz, D. (2013). Inflation and growth: new evidence from a dynamic panel threshold analysis. Empirical Economics, 44, pages 861-878.