The Effect of Bank Competition on Financial Stability: Much Ado About Nothing?

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Abstract

The dichotomy in theoretical as well as empirical literature on the relationship between bank competition and financial stability results in an ambiguous overall impact of bank competition on stability. We show that there is no robust relationship between competition and stability in general. For computation, we collect 598 coefficient estimates reported in 31 studies and compile a set of 35 aspects of study design and estimation specifications that could potentially bias the reported competition coefficient estimates in the literature. By means of Bayesian model averaging we resolve model uncertainty and find that estimation methods and variables used as proxies for competition and stability are, among others, a source of variation in the reported estimates. We also identify a publication bias in the literature as outlets with more citations and a higher impact factor favor larger and statistically significant estimates.

Keywords: Bayesian model averaging, bank competition, financial stability, publication selection bias, meta-analysis

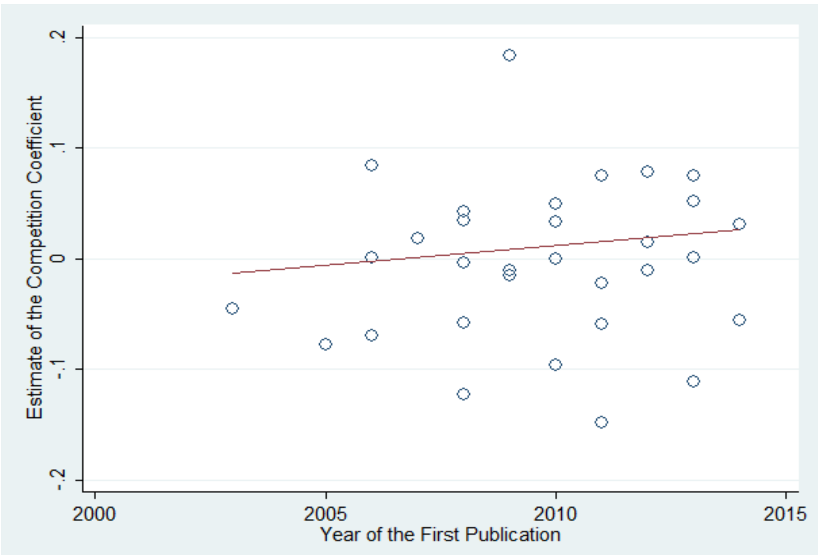
JEL Codes: C83, C11, G21, L16

1 Introduction

The effect of banking sector competition on financial stability has not been conclusive in the empirical literature. Theory equally supports two opposing views on the competition-stability relationship: the competition-fragility hypothesis, advocating that more competition leads to more fragility, and the competition-stability view, arguing that competition fosters stability. Narrative surveys of the literature in the field (e.g. Beck, 2008; Carletti and Hartmann, 2002) do not succeed in resolving the ambiguity and only tentatively conclude that competition is not necessarily detrimental for banking system stability.

In this paper we endeavour to resolve this ambiguity using a quantitative method of research synthesis, the meta-analysis (Stanley, 2001). Meta-analysis originates in medical science where it was used to summarize results of clinical trials (Pearson, 1904). Gradually, meta-analysis spread to other research fields, including economics. For example, Babecký and Havránek (2013) evaluate the impact of structural reforms on economic growth, Doucouliagos et al. (2012) investigate the link between firm directors' pay and corporate performance, and Chetty et al. (2011) explore the intertemporal elasticity of substitution in labour supply. For our meta-analysis we collect 598 estimates of competition coefficient from 31 studies along with 35 aspects of these studies, such as number of citations, publication outlet specifications, estimation methods, control variables and proxies for competition and stability. Figure 1 depicts increasing dispersion in collected competition coefficient estimates overtime.

Figure 1: The reported estimates of the competition coefficient diverge in time



Notes: The figure depicts median PCC of competition coefficient estimates (PCC of the β estimate from equation (1)) reported in individual studies. The horizontal axis measures the year when the first drafts of studies appeared in Google Scholar. The red line shows the linear fit.

In this paper, we aim to identify sources of variation in the reported competition coefficient estimates and calculate the benchmark value of competition coefficient conditional upon our definition of best practice in estimation. In this calculation we attempt to correct for errors in the coefficient estimation and place more weight on such study design aspects as number of citations and impact factor. We identify the sources of heterogeneity in reported effect estimates by means of Bayesian model averaging (Raftery et al., 1997), a method that resolves model uncertainty in meta-analysis.

We find that several aspects of study design and estimation specification impact the reported coefficient estimates; size of the sample, treatment of nonlinearities, measures of competition and stability in regressions, estimation method, regulatory and supervisory controls, group of countries examined and publication characteristics. However, we do not find any robust relationship between bank competition and financial stability in general. The literature, we show, exhibits the presence of publication bias which is a common occurrence in economics. The survey by Doucouliagos and Stanley (2013) shows that preferential selection of intuitive and significant estimates for publication encompasses most fields of empirical economics.

The paper is organized as follows: Section 2 introduces the dichotomy in the relevant literature, and presents various measures of competition and stability while section 3 describes transformations of collected estimates and offers their summary statistics. Section 4 checks for the presence of publication bias in the literature. Section 5 describes variables and methodology used, investigates sources of heterogeneity in reported estimates and calculates benchmark competition coefficient values. In section 6 we perform robustness checks of our results, and section 7 concludes. Appendix A presents diagnostics of the BMA exercise and appendix B lists the studies included in the meta-analysis.

2 The Effect of Bank Competition on Financial Stability

The impact of bank competition on financial stability remains a controversial issue in academia as the question whether bank competition fosters or harms stability in the banking system has not been resolutely resolved. The two opposing theories, competition-stability and competition-fragility, justify the conflicting results in the empirical literature.

On the one hand, the competition-fragility view asserts that more competition among banks leads to more fragility. Marcus (1984) and Keeley (1990) model theoretically the "charter value" proposition, where banks choose the risk of their asset portfolios. In this world of limited liability, bank owners, who are often given incentives to shift risks to depositors, tend to engage only in the up-side part of risk-taking. In more competitive systems, that place substantial emphasis on profits, banks have higher incentives to take excessive risks, which leads to higher instability. In addition, in competitive systems the incentives of banks to properly screen borrowers are reduced, which again contributes to system fragility (Allen and Gale, 2000; Allen and Gale, 2004; Boot and Thakor, 1993). Conversely, when entry barriers are in place and competition in sector is limited, banks have better profit opportunities, larger capital cushions and as such are not prone to taking aggressive risks. This impacts financial stability in a positive way (Boot and Greenbaum 1993, Hellman, Murdoch, and Stiglitz 2000, Matutes and Vives 2000).

The competition-stability hypothesis, on the other hand, proposes that more competitive banking systems imply greater stability. Specifically, Boyd and De Nicolo (2005) show that lower lending rates facilitate lending as they reduce entrepreneurs' cost of borrowing. Lower cost of borrowing thus raises the chance of investment success which in turn lowers banks' credit portfolio risk and leads to increased stability within the sector. Some theoretical studies reveal that banks in uncompetitive systems are more likely to originate risky loans that lay ground to systemic vulnerabilities (Caminal and Matutes 2002). Similarly, Mishkin (1999) stresses that in concentrated systems regulators are prone to implement "too big to fail" policies that encourage banks' risk-taking behaviour.

The more recent empirical studies provide conflicting evidence in the strand of the competition and stability literature (e.g. Levy Yeyati and Micco, 2007; Fungacova and Weill, 2009; Schaeck and Cihak, 2008; Anginer et al., 2012; Uhde and Heimeshoff, 2009; Liu et al., 2012; Boyd et al., 2006; Berger et al., 2009).

Overall, it appears that empirical studies for specific countries have not reached conclusive evidence for either a stability-enhancing or a stability-deteriorating view of competition (Fungacova and Weill, 2009; Fernández and Garza-García, 2012; Liu and Wilson, 2011). The cross-country literature has shown that more concentrated as well as more competitive banking systems are less likely to experience a systemic banking crisis (Beck et al., 2006a; Schaeck et al., 2009). In contrast, other studies (Levy Yeyati and Micco, 2007; Uhde and Heimeshoff, 2009; Boyd et al., 2006) have revealed that bank failures are more frequent in more competitive and concentrated systems. Further research also provides evidence that in more concentrated systems banks have higher capital ratios, and as such balance out a possibly more risk-taking behaviour on their part (Berger et al., 2009; Schaeck and Cihak, 2012).

In this meta-analysis we focus on the following model, used in the literature, to examine the effect of bank competition on stability:

$$Stability_{it} = \alpha + \beta \cdot Competition\ Measure_{it} + \sum_{k=1}^{N} \gamma_{kit} X_{kit} + e_{it} \qquad (1)$$

where *i* is a bank index, *t* a time index, *X* is a set of control variables, both bank-specific as well as country-specific. Measures of stability and competition tend to vary across individual studies.

Bank stability is usually measured in a negative way, i.e. by considering individual or systemic banking distress. In this spirit, the non-performing loan ratio (NPL) is used as a fragility indicator. However, NPL comprises only credit risk and cannot be directly linked to the likelihood of bank failure (Beck, 2008). Another measure of individual bank distress extensively used in the literature is the Z-score (e.g. Boyd and Runkle, 1993; Lepetit et al., 2008; Laeven and Levine, 2009; Cihak and Hesse, 2010). The measure indicates how many standard deviations in return on assets a bank is away from insolvency and by extension from the likelihood of failure. The Z-score is calculated as follows:

$$Z_{it} = \frac{ROA_{it} + {}^{E_{it}}/_{TA_{it}}}{\sigma_{ROA_{it}}} \qquad (2)$$

where ROA is return on assets, E/TA is the ratio of equity to total assets and σ_{ROA} is the standard deviation of return on assets. Bank profitability, measured by ROA and ROE, profit volatility, approximated by ROA and ROE volatility, or bank capitalization, expressed by capital adequacy ratio (CAR) or ratio of equity over total bank assets, are additional measures of individual bank distress frequently used in the literature. Additionally, some studies (e.g. Beck, Demirguc-Kunt and Levine, 2006 a,b) model fragility in the banking sector by means of systemic banking crisis dummies. Other studies (e.g. Fungacova, Weill, 2009) apply individual bank failure dummies or measures of a bank's distance-to-default to proxy for financial stability.

As for competition proxies, Lerner index is one of the indicators adopted to measure competition. The index quantifies the price power capacity of a bank by expressing the difference between price and marginal cost as a percentage of price:

$$Lerner_{it} = \left(P_{TA_{it}} - MC_{TA_{it}}\right)/P_{TA_{it}} \tag{3}$$

where $P_{TA_{it}}$ is the price of total assets, expressed in practice by total revenues to total bank assets, and $MC_{TA_{it}}$ is the marginal cost of total assets for bank *i*. The index thus adopts values between 0 and 1, with values of 0 and 1 reached only in case of perfect competition and under pure monopoly, respectively. Alternatively, the degree of competition in the banking sector can be measured by H-statistic, introduced in the study by Panzar and Rosse (1987). H-statistic measures competition by summing elasticities of a bank's revenue with respect to the bank's input prices. Another competition measure, the Boone (2008) indicator, applied by Schaeck and Cihak (2012), expresses the effect of competition on the performance of efficient banks and offers organization-based explanation for how competition can improve stability.

In addition, concentration ratios were first used as bank competition proxies, e.g. Herfindahl-Hirschman index or C3 concentration ratio, which indicates the share of the three largest banks' assets to the total assets of the banking system within the country. However, some studies have shown (e.g. Claessens and Laeven, 2004) that bank concentration is not an adequate indicator of the competitive nature of the system as concentration and competition highlight different banking sector characteristics. Nevertheless, we include the estimates between bank competition, as measured by concentration ratios, and stability in this meta-analysis given that several of the collected studies utilize measures of concentration to proxy for banking sector competition.

3 Dataset of the Effect of Bank Competition on Financial Stability

Given the broad scope of measures used in the literature to proxy for both competition and financial stability, it is imperative that we place the individual estimates from studies on the common ground. While some stability proxies measure financial fragility and competition proxies investigate how uncompetitive the market is (e.g. larger values of Lerner index imply less competitive nature of the system), in order to remove this disparity we adjust signs of the collected estimates in such a way that they directly reflect the relationship between competition and stability. After this adjustment the collected estimates imply either that higher competition increases bank stability or that higher competition decreases bank stability.

Due to the inconsistency in competition and stability measures used in the studies while measurement units of variables in regressions equally vary, we apply transformation of estimates into partial correlation coefficients (PCC). PCC are unitless measures of the strength and direction of the association between two variables, competition and stability in our case, while holding other variables constant (Stanley, Doucouliagos, 2012). They enable direct comparison between estimates in different studies. This technique is widely used in meta-analysis research, such as in Havranek et al. (2013).

Partial correlation coefficient, PCC, is calculated by the following formula:

$$PCC = \frac{t}{\sqrt{t^2+df}} \tag{4}$$

Where *t* is the t-statistic of the Competition coefficient and *df* are degrees of freedom of the t-statistic. The corresponding standard errors of PCC are calculated as follows:

$$SEPCC = \sqrt{\frac{(1-PCC^2)}{df}} \tag{5}$$

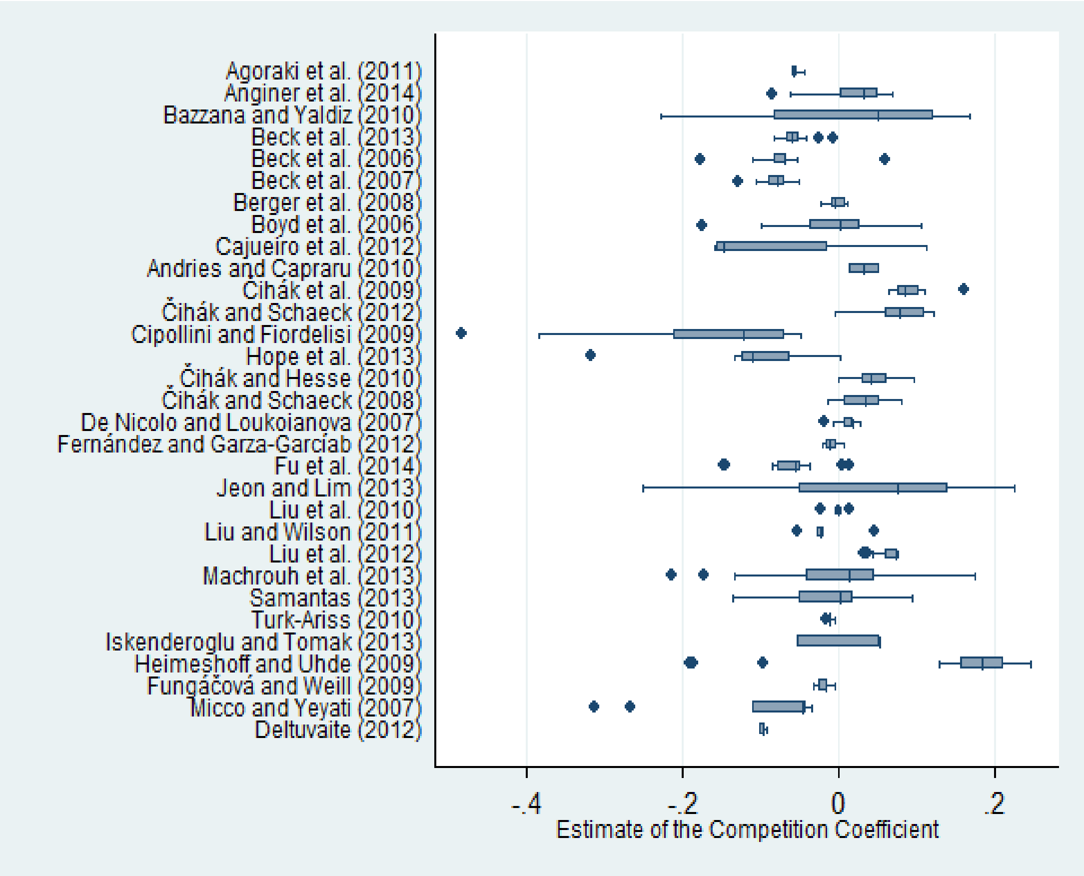
Moreover, if an original study investigates for nonlinear relationship between competition and stability and thus it reports two coefficients associated with the measure of competition, the overall impact on stability needs to linearized via the following formula for both, coefficient estimates and their corresponding standard errors:

$$\beta = \widehat{\beta_1} + \widehat{\beta_2}\bar{x} \qquad SE(\beta) = \sqrt{SE\left(\widehat{\beta_1}\right)^2 + 4SE\left(\widehat{\beta_2}\right)^2\bar{x}^2} \tag{6}$$

where $\widehat{\beta_1}$ is the estimate of the competition coefficient at the linear term, $\widehat{\beta_2}$ is the estimate of the competition coefficient at the quadratic term, $\bar{x}$ is sample mean of the competition measure in individual studies, $SE\left(\widehat{\beta_1}\right)$ is standard error of the reported coefficient at the linear term and $SE\left(\widehat{\beta_2}\right)$ is standard error of the reported coefficient at the quadratic term. The resulting coefficient of bank competition after linearization is subsequently transformed into PCC as detailed in equations (4) and (5).

Figure 2 below depicts partial correlation coefficients of the collected competition estimates over 31 studies that we have accumulated for this meta-analysis.

Figure 2: Variability in the estimated competition coefficient across individual studies



Notes: The figure shows a box plot of the PCC of the competition coefficient estimates (PCC of the β estimate from equation (1)) reported in individual studies. Full references for the studies included in the meta-analysis are available in Appendix B.

Table 1: Estimates of the competition coefficient across countries

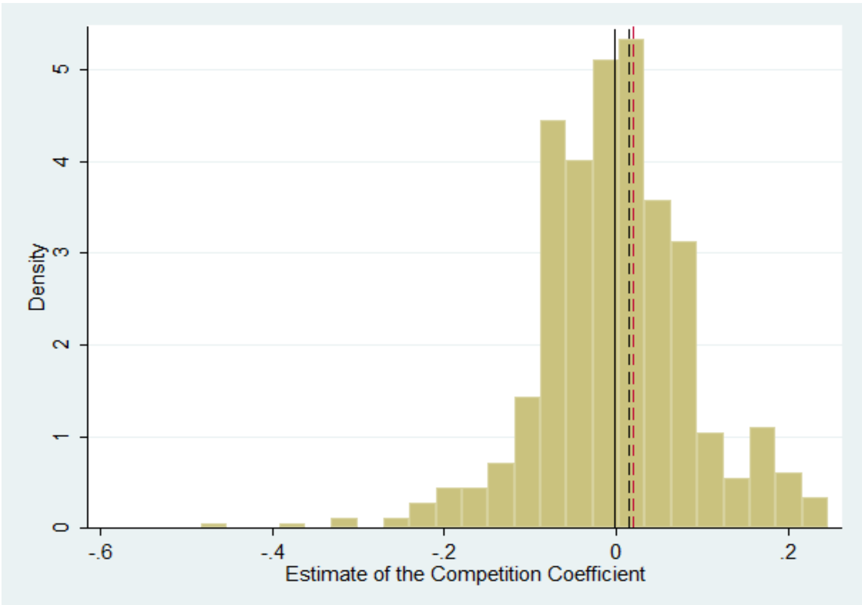
	Unweighted			*Weighted*			No. of estimates
	Mean	95% Conf. Int.		Mean	95% Conf. Int.		
All	-0,001	-0,025	0,023	-0,012	-0,035	0,011	598
Developed	0,020	-0,032	0,073	0,011	-0,030	0,052	201
Developing and transition	0,001	-0,022	0,023	-0,019	-0,051	0,012	194

Notes: The table presents mean PCC of the competition coefficient estimates (PCC of the β estimate from equation (1)) over all countries and for selected country groups. The confidence intervals around the mean are constructed using standard errors clustered at the study. In the right-hand part of the table the estimates are weighted by the inverse of the number of estimates reported per study.

All means reported in Table 1 are close to zero while PCC means of competition coefficient estimates for developed countries are slightly higher than those for developing and transition countries. No strong inference could be made however, as none of the reported means is significant on 5% level of significance.

Figure 3 depicts the distribution of partial correlation coefficients of all competition coefficient estimates via histogram. Overall, it appears that PCC are symmetrically distributed around zero with the mean value of PCC equal to -0.0009 while mean of the median of PCC from individual studies is also close to zero and equals 0.0099. Moreover, we report also mean of PCC of such estimates of the competition coefficient that originate from studies published in peer-reviewed journals as opposed to those reported in working paper series. The mean for published studies equals 0.0116. Altogether 21 of 31 studies in total were published in peer-reviewed journals, yielding 376 estimates of the competition coefficient. Given that the mean for estimates from published studies is moderately larger, it appears that journals report slightly larger estimates of the competition coefficient.

Figure 3: Studies published in journals report low positive estimates of the competition coefficient



Notes: The figure shows the histogram of the PCC of the competition coefficient estimates (PCC of the β estimate from equation (1)) reported in individual studies. The solid vertical line denotes the mean of all the PCC. The black dashed line denotes the mean of the median PCC of estimates from studies. The red dashed line denotes the mean of the PCC of those estimates that are reported in studies published in peer-reviewed journals.

4 Checking for Publication Bias

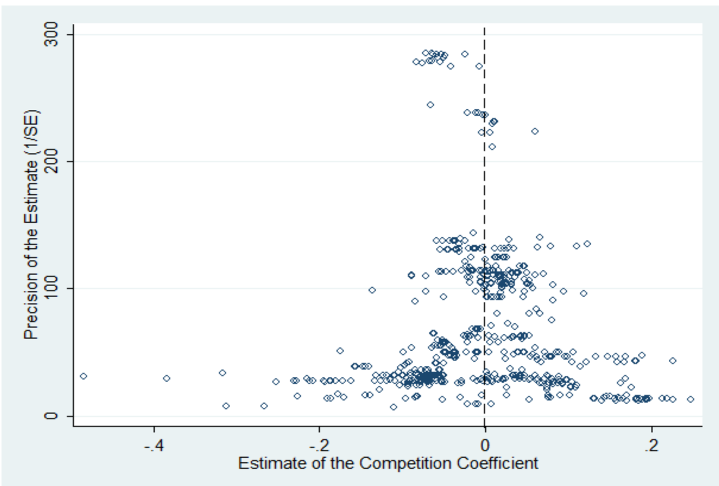
Publication selection bias arises when the probability of the estimates to be reported differs based on their sign or statistical significance. Rosenthal (1979) named this phenomenon the "file drawer problem", signifying the possibility that researches may "hide in their file drawers" such estimates that are either insignificant or have counterintuitive sign and seek other estimates that might be easier to publish. A number of studies, e.g. by DeLong and Lang (1992), Card and Krueger (1995), and Ashenfelter et al. (1999), have identified publication bias in empirical economics. In addition, Doucouliagos and Stanley (2013) have revealed by means of examinations of publication bias survey that most fields of empirical economics suffer from publication selection bias. The consequences of such a preferential reporting of significant estimates with an expected sign lead to inflating the observed effect by the overall literature. For example, Doucouliagos and Stanley (2009) reveal that adverse employment effect of minimum wage is many times exaggerated in the literature. In this section, we test for the publication bias before we continue with the heterogeneity analysis in the next section.

First of all, we execute visual tests for the presence of publication bias. One such test is a so-called funnel plot (Egger et al., 1997) that plots the estimates into the mapping with the magnitude of the estimated effects on the horizontal axis and precision (the inverse of the estimated standard errors) on the vertical axis. If the literature does not suffer from publication bias, the most precise estimates (located at the top of funnel) are close to the true underlying effect in the literature. With decreasing precision, the estimates are more dispersed and overall they should form a symmetrical inverted funnel plot. In case there is publication bias in the literature, the inverted funnel is either visually asymmetrical due to exclusion of estimates of certain sign or size, or hollow due to omission of insignificant estimates, or for both those reasons.

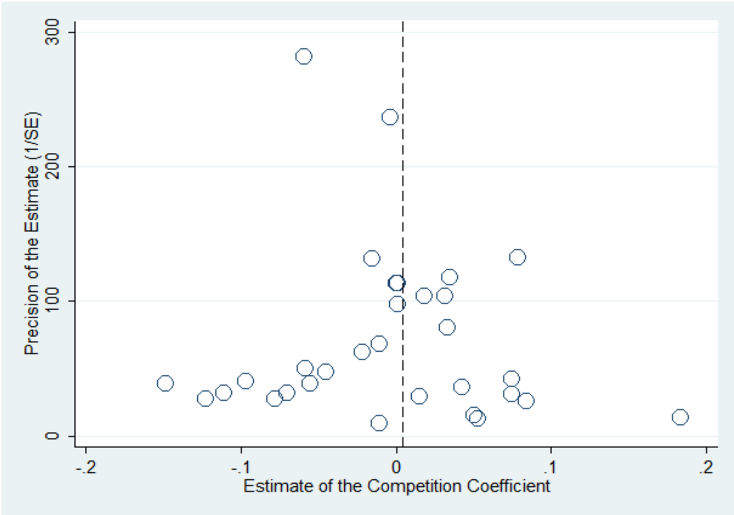
Figure 4A shows the funnel plot for PCC of all competition coefficient estimates from collected studies while Figure 4B depicts the funnel plot for median values of PCC of the estimates in individual studies.

Figure 4: Funnel plots do not suggest significant publication bias

A) All estimates



B) Median estimates from studies



Notes: In the absence of publication bias the funnel should be symmetrical around the most precise PCC of the estimates of the competition coefficient (PCC of the β estimate from equation (1)). The black dashed vertical lines denote the mean of PCC of all estimates in Figure 4A and the mean of median PCC of the estimates reported in studies in Figure 4B.

We can observe that both funnels are to a large extent symmetrical while the most precise estimates are close to the average reported PCC of the estimates. Moreover, the funnels are not hollow, and even estimates with very little precision (and small p-values) at the bottom of both plots are reported. Therefore, we can infer that these funnel plots do not exhibit clear signs of the publication bias in the competition-stability literature as opposed to findings in other meta-analyses in economics (e.g. Havranek and Kokes, 2013)

A more rigorous approach to testing for publication bias constitutes of funnel asymmetry tests. These tests explore the relationship between collected coefficient estimates and their standard errors, following the methodology by Card and Krueger (1995). In the presence of publication selection, the reported coefficient estimates are correlated with their standard errors, all else held unchanged. For example, in case that negative estimates are omitted, a positive relationship resurfaces between the reported coefficient estimates and their standard errors because of heteroskedasticity (Stanley, 2008). Conversely, if there is no publication bias in the literature, coefficient estimates and their standard errors are then independent. Thus we estimate the following equation:

$$PCC_i = \beta_0 + \beta_1 SE(PCC_i) + \varepsilon_i \qquad (7)$$

where PCC_i is partial correlation coefficient of the competition coefficient estimate, $SE(PCC_i)$ is the standard error of the partial correlation coefficient, β_0 is the mean PCC of the coefficient estimate corrected for the potential publication bias, β_1 measures the extent of publication bias and ε_i is a normal disturbance term.

Equation (7) is called a funnel asymmetry test as it rotates the axes of the funnel plot and inverts the values on the new horizontal axis that shows standard errors instead of precision.

The results of the funnel asymmetry tests arising from equation (7) are presented in table 2 below. The coefficient estimates in the upper part of the table result from fixed effects panel estimation with errors clustered at the level of individual studies and from instrumental variable estimation with fixed effects. Fixed effects control for method or other quality characteristics specific to individual studies. We also report results for estimates from only published studies for both estimation techniques. The bottom half of the table presents results from regressions weighted by the inverse number of estimates per study in order to balance out the effect of studies reporting a large number of competition coefficient estimates. We estimate the weighted regressions with fixed effects only. In all specifications in table 2, both coefficient estimates are significant at least on 5% significance level. A moderate negative publication bias is present while the estimated size of the competition-stability effect beyond publication bias appears to be close to zero.

Table 2: Funnel asymmetry tests reveal the presence of publication bias

Unweighted regressions	Fixed Effects	Fixed Effects_Published	Instrument	Instrument_Published
SE (publication bias)	-1.671**	-1.898**	-1.614***	-2.291***
Constant (effect beyond bias)	0.044**	0.073**	0.043***	0.086***
No. of estimates	598	376	598	376
No. of studies	31	21	31	21
Weighted regressions	Fixed Effects		Fixed Effects_Published	
SE (publication bias)	-1.568***		-1.636***	
Constant (effect beyond bias)	0.034***		0.044***	
No. of estimates	598		376	
No. of studies	31		21	

Notes: The table presents the results of regression specified in equation (6). The standard errors of the regression parameters are clustered at the study level. Published = we only include published studies. Fixed Effects = we use study dummies. Instrument = we use the logarithm of number of observations in equation (1) as an instrument for the standard error and employ study fixed effects. The regressions at the bottom half of the table are estimated by weighted least squares, where the inverse of the number of estimates reported per study is taken as the weight. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level.

Furthermore, we can observe from columns presenting results for estimates from published studies only that editors or referees seem to prefer larger and statistically significant coefficient estimates, which inflate the mean reported competition coefficient estimates, resulting in a slightly larger negative publication bias.

Equation (6) is heteroskedastic as the explanatory variable directly captures the variance of the response variable. To achieve efficiency, many meta-analysis applications divide equation (7) by the corresponding standard error, i.e. multiply the equation by the precision of the estimates. This specification further places more importance on precise results. Table 3 below presents results from heteroskedasticity-corrected equation (7) in the same vein as table 2.

Table 3: Heteroskedasticity-corrected funnel asymmetry tests confirm the presence of publication bias

Unweighted regressions	Fixed Effects	Fixed Effects_Published	Instrument	Instrument_Published
1/SE (effect beyond bias)	0.005	0.065	0.019**	0.053***
Constant (publication bias)	-0.757	-4.000*	-1.706**	-3.344***
No. of estimates	598	376	598	376
No. of studies	31	21	31	21

Weighted regressions	Fixed Effects	Fixed Effects_Published
1/SE (effect beyond bias)	0.013	0.056**
Constant (publication bias)	-1.539**	-4.339**
No. of estimates	598	376
No. of studies	31	21

Notes: The table presents the results of regression specified in equation (7). The standard errors of the regression parameters are clustered at the study level. Published = we only include published studies. Fixed Effects = we use study dummies. Instrument = we use the logarithm of number of observations in equation (1) as an instrument for the standard error and employ study fixed effects. The regressions at the bottom half of the table are estimated by weighted least squares, where the inverse of the number of estimates reported per study is taken as the weight. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level.

Dividing equation (7) by the corresponding SE of PCC, the transformation yields the following equation:

$$t_i = \beta_1 + \beta_0(1/SE(PCC_i)) + \mu_i \tag{8}$$

where β_0 is the mean PCC of the coefficient estimate corrected for the potential publication bias, β_1 measures the extent of publication bias and t_i is the corresponding t-statistic.

We can observe from table 3 that publication bias is not equally persistent across all specifications as was the case in table 2. Moreover, the true underlying effect beyond bias is significant only when equation (8) is estimated by means of instrumental variables or by fixed effects for estimates from published studies. However, we can confirm that competition-stability effect beyond bias is indeed close to zero. Similarly to our previous observations about selection of larger and significant estimates for journal publication, estimates from equation (8) support this result while publication bias is more profound for estimates published in journals.

To judge the extent of publication bias, Doucouliagos and Stanley (2013) provide a framework for the value of the constant in the funnel asymmetry test specified by equation (8) in order to distinguish the degree of publication bias. They identify that the literature suffers from substantial selectivity if $\hat{\beta}_1$ from equation (8) is statistically significant and $1 \leq |\hat{\beta}_1| \leq 2$. Both conditions hold for the value of the constant estimated in weighted regressions by fixed effects as well as for the constant in unweighted regressions estimated by instrumental method. However, the magnitude of the constant term as well as its statistical significance varies over different specifications in table 3. Ultimately, based on our funnel asymmetry testing we can conclude that publication bias is present in the literature.

5 Why Competition Coefficients Vary

5.1 Variable Description and Methodology

In this section we add characteristics of competition coefficient estimates and studies into equation (7) to explore what characteristics collected from individual studies explain the estimate of the competition coefficient in a significant way. We do not weight the extended equation by precision as is the case in equation (8) though for just one regressor, SE of PCC. Weighting by the precision of estimates causes artificial variation in variables at the study level (e.g. endogeneity or macro). We, however, weight regressions by the inverse number of estimates per study to place the same weight on each collected study. In the next section, we perform also a robust check for regressions unweighted by the inverse number of estimates per study.

Table 4 presents overview of all variables that we collected from primary studies as well as shows their mean, standard deviation and mean weighted by inverse number of estimates per study in the last three columns, left to right. The collected variables are divided into eight groups.

Table 4: Overview and summary statistics of regression variables

Variable	Description	Mean	SD	WM
Data Characteristics				
Competition coefficient	The coefficient from competition-stability regression capturing the effect of competition on financial stability	-0,001	0,090	-0,012
SEPCC	The estimated standard error of Competition coefficient	0,027	0,022	0,029
Samplesize	The logarithm of no. observations in competition-stability regression	7,835	1,615	7,760
T	The logarithm of number of time periods (years)	2,224	0,743	2,264
sampleyear	Mean year of sample period on which competition-stability regression is estimated (base: 1992,5)	8,889	4,328	9,340
Countries examined				
developed	equals 1 if a country is an OECD member country	0,336	0,473	0,366
developing and transition	equals 1 if a country is a non-OECD country	0,324	0,469	0,376
Design of the analysis				
quadratic	equals 1 if square of competition coefficient is included in competition-stability regression	0,119	0,324	0,217
endogeneity	equals 1 if estimation method of competition-stability regression accounts for endogeneity	0,635	0,482	0,713
macro	equals 1 if competition-stability regression is estimated on a country scope (macro level)	0,256	0,437	0,133
someAveraged	equals 1 if competition-stability regression uses many variables in the form of averages	0,120	0,326	0,085
Treatment of stability				
dummies	equals 1 if stability is measured by inverse of crisis dummy or inverse of bank failure dummy	0,142	0,349	0,129
NPL	equals 1 if stability is measured by inverse of non-performing loans as a share of total loans	0,050	0,218	0,095
Zscore	equals 1 if stability is measured by Z-score statistic	0,452	0,498	0,537
profit_volat	equals 1 if stability is measured by negative of ROA volatility and negative of ROE volatility	0,075	0,264	0,039

Variable	Description	Mean	SD	WM
profitability	equals 1 if stability is measured by ROA and ROE	0,043	0,204	0,045
capitalization	equals 1 if stability is measured by capital adequacy ratio (CAR) and equity/total assets	0,069	0,253	0,040
DtoD	equals 1 if stability is measured by inverse of Logistic R2 Merton's distance-to-default and negative of probability of bankruptcy (i.e. distance to default)	0,065	0,247	0,047
Treatment of competition				
Hstatistic	equals 1 if competition is measured by H-statistic	0,090	0,287	0,098
Boone	equals 1 if competition is measured by negative of Boone indicator	0,075	0,264	0,108
Concentration	equals 1 if competition is measured by negative of concentration measures (i.e. C3 and C5)	0,157	0,364	0,147
Lerner	equals 1 if competition is measured by inverse of Lerner index	0,360	0,480	0,414
HHI	equals 1 if competition is measured by negative of Herfindahl-Hirschman index of concentration	0,266	0,442	0,197
Estimation methods				
Logit	equals 1 if logit or probit model is used in estimation of competition-stability regression	0,172	0,378	0,161
OLS	equals 1 if OLS is used in estimation of competition-stability regression	0,137	0,344	0,115
FE	equals 1 if panel fixed effects is used in estimation of competition-stability regression	0,229	0,421	0,136
RE	equals 1 if panel random effects is used in estimation of competition-stability regression	0,067	0,250	0,043
GMM	equals 1 if GMM model is used in estimation of competition-stability regression	0,182	0,386	0,309
TSLS	equals 1 if two stage least squares method is used in estimation of competition-stability regression	0,149	0,356	0,110
Control variables				
regulation	equals 1 if regulatory/supervisory variables are included in competition-stability regression	0,239	0,427	0,282
ownership	equals 1 if bank ownership is controlled for in competition-stability regression	0,166	0,372	0,271
global	equals 1 if macroeconomic variables are included in competition-stability regression	0,794	0,405	0,764
Publication characteristics				
citations	Logarithm of normalized no. of Google Scholar citations by the difference between year 2015 and the year the study first appeared in Google Scholar (collected in June 2014)	2,045	1,222	1,790
firstpub	Year when the study first appeared in Google Scholar (base: 2003)	6,453	2,979	6,677
IFrecursive	Recursive impact factor of the outlet from RePEc (collected in June 2014)	0,243	0,210	0,205
reviewed_journal	equals 1 if a study is published in a peer reviewed journal	0,629	0,484	0,677

Notes: SD = standard deviation. WM = mean weighted by the inverse of the number of estimates reported per study. All variables except for citations and the impact factor are collected from studies estimating the competition coeffcient from equation (1) (the search for studies was terminated on July 1, 2014, and the list of studies is available in Appendix B). Citations are collected from Google Scholar and the impact factor from RePEc.

Group 1 - Data Characteristics: We control for the age of the data collected by means of the variable sampleyear that represents the midpoint of the sample. Moreover, we consider the number of data points, used to estimate the competition coefficient in equation (1), and the number of observations for each estimate. The underlying reasoning is that larger samples over more years could have an impact on the estimate of the competition coefficient.

Group 2 – Countries examined: As the estimates of the competition coefficient may have different size and sign for various countries or blocks of countries, we control for this potential source of heterogeneity by including dummies for developed (OECD member) countries and developing and transition (non-OECD) countries. In our sample, 34% of all collected estimates use a sample of developed countries while 32% of estimates were extracted from studies focusing on developing and transition countries.

Group 3 – Design of the analysis: Here we control for specific aspects of studies in our sample, such as endogeneity, macro, quadratic and averaged. The dummy endogeneity captures if individual studies capture potential endogeneity in their analysis, either via estimation methods or lags of dependent variables in equation (1). The dummy macro assigns 1 to an estimate if it was calculated for the entire banking sector as opposed to bank-level, and as such designates the impact of banking sector competition on the stability of the whole sector or on the outbreak of a systemic banking crisis. Next, the dummy someAveraged assigns 1 to an estimate if several of the regressors in equation (1) in the original study were in the form of averages, i.e. either a moving average or an average of an independent variable was used in the estimation of the competition coefficient. Last but not least, dummy quadratic controls for incorporation of the square of the competition measure in regressions. 12% of estimates in our sample required linearization as researchers tested for nonlinear relationship between bank competition and stability.

Group 4 – Treatment of stability: We control for differences in the way how stability is measured in individual studies. Due to a large diversity of approaches to measuring financial stability in the literature, it is possible that a portion of variation in the competition coefficient estimates is due to measurement. We distinguish 7 most common approaches to quantifying stability. First, dummy dependent in the literature can represent either an outbreak of systemic banking crisis or a bank failure (e.g. Beck et al., 2006 a,b; Fungacova and Weill, 2009). Popular methods to measure individual bank stability is a ratio of non-performing loans as a percent of total bank loans, return on assets (ROA) and return on equity (ROE) as measures of bank profitability, fluctuations in ROA and ROE as indicators of bank profit volatility, Z-score, an aggregate measure of bank stability, measures of capitalization, CAR and equity as a share of total bank assets and measures of distance to default.

Group 5 – Treatment of competition: Similarly to indicators of stability, there is a large diversity in approaches to quantifying competition within the banking sector. We control for five most commonly used measures. In 36% of estimates in our sample, competition was measured via Lerner index. Other indicators include Panzar and Rosse's (1987) H-statistic and Boone's (2008) Boone index. Quite frequently measures of market structure are applied to assess intensity of competition in the sector, such as concentration ratios and Herfindahl-Hirschman indices (HHI) that were used in generating 42% of estimates in the sample. We decided to include competition coefficient estimates arising from these market structure measures in our analysis despite the more recent assertions that concentration is not a suitable proxy for a lack of competition (e.g. Claessens and Laeven, 2004; Bikker, 2004). Several studies in our sample, though, rely on these measures as indicators of competition (e.g. Beck et al., 2006 a,b; Berger et al., 2008; Boyd et al., 2006; Cipollini and Fiordelisi, 2009). As a robustness check in section 5, we estimate the impact of competition on stability after having excluded such coefficient estimates from our sample that originate from regressions where competition is proxied by market structure measures (i.e. concentration ratios and HHI).

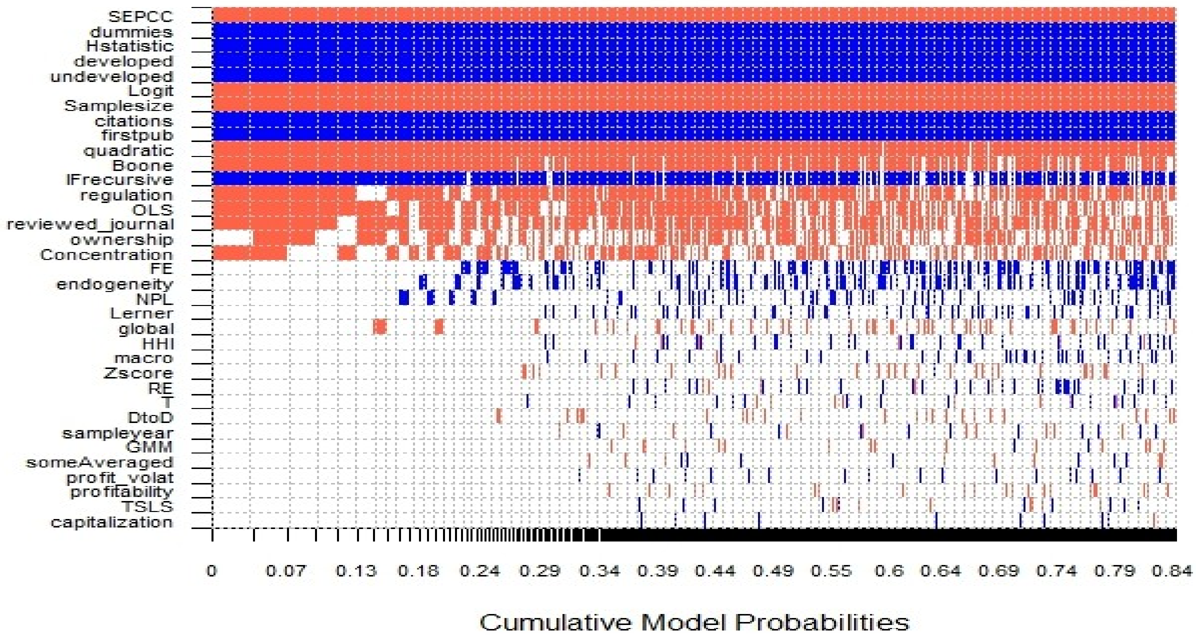
Group 6 – Estimation methods: We control for 6 different estimation methods in our analysis, i.e. OLS, FE, RE, GMM, TSLS and logit. We assume that different estimation approaches of equation (1) might affect the resulting estimates of competition coefficient. The most frequently used estimation methods in our sample are panel fixed effects (23% of estimates), followed by GMM (18%) and logit (17%).

Group 7 – Control variables: The most commonly used controls in the estimation of competition-stability relationship in equation (1) are macroeconomic variables on a country level, regulatory and supervisory variables, such as capital stringency, supervisory power, investor protection index, economic and banking freedom, share of market entry restrictions or governance (e.g. Cihak et al., 2009; Beck et al., 2006 a,b; Beck et al., 2013; Anginer et al., 2014; Agoraki et al., 2011), and ownership controls, i.e. foreign and state bank ownership (e.g. Bazzana and Yaldiz, 2010; Berger et al., 2009; De Nicolò and Loukoianova, 2007). Macroeconomic variables are used as controls in 79% of regressions, from which we collected estimates of competition coefficient while regulatory and supervisory controls are used in 24% of regressions and ownership variables in 17%.

Group 8 – Publication characteristics: In order to observe if studies published in a peer-reviewed journal report different competition coefficient estimates to those published in other outlets after we control for all other main aspects, we include a journal dummy among the regressors. Moreover, we control for study quality by means of a number of citations and the recursive RePEc impact factor. Finally, for each study we add the year when a given study first appeared in Google Scholar to control for the time dimension of estimates within a study.

In this section, we would like to run a regression with PCC of the estimates of competition coefficient as a dependent and all the variables from table 4 as explanatory variables. However, including all the above mentioned variables would introduce many redundant regressors into the regression. With such a large number of explanatory variables, we initially do not know which ones should be excluded from the model. An ideal approach would be to run regressions with different subsets of independent variables to ensure robustness of results. A manual approach to solving model uncertainty would be very time consuming, thus we employ Bayesian model averaging (BMA) to resolve this issue. BMA runs many regressions with different subsets of 2^{35} possible combinations of explanatory variables (we include 35 regressors into the model). To make sampling efficient, we use Monte Carlo Markov Chain algorithm to scope the potential models (we use the bms R package by Feldkircher & Zeugner, 2009). BMA provides a weight, equivalent to R-squared, for each model to capture the model's fit to the data. Finally, BMA reports weighted averages of many sampled models as the regression coefficients while it returns posterior standard deviations, that represent distributions of regression parameters from individual models, instead of standard errors. Moreover, a posterior inclusion probability is reported for each variable to show the probability with which a variable is included in the true model. Raftery et al. (1997) and Eicher et al. (2011) provide further details on BMA. Detailed BMA diagnostics can be found in Appendix A.

Figure 5: Bayesian model averaging – Model inclusion



Notes: Response variable: PCC of the estimate of the competition coefficient (PCC of the β estimate from equation (1)). All regressions are weighted by the inverse of the number of estimates reported per study. Columns denote individual models; variables are sorted by posterior inclusion probability in descending order. Blue color (darker in grayscale) = the variable is included and the estimated sign is positive. Red color (lighter in grayscale) = the variable is included and the estimated sign is negative. No color = the variable is not included in the model. The horizontal axis measures cumulative posterior model probabilities. Numerical results of the BMA estimation are reported in Table 5. A detailed description of all variables is available in Table 4.

5.2 Results

Figure 5 shows the results of the BMA exercise. The columns in the figure denote individual regression models while their width indicates models' posterior probabilities. The lines of figure 5 show posterior inclusion probabilities (PIP) of individual explanatory variables. The variables are sorted by their PIP in a descending order. If the sign of a variable's regression coefficient is positive, it is denoted by blue color. Conversely, if the sign of a variable's coefficient is negative, it is colored in red. In case, a variable is excluded from a model, a corresponding cell is left blank. We consider only variables that have PIP greater than 0.5 useful for explaining variation in PCC of the estimate of competition coefficient. Given the nature of the BMA exercise, the signs of estimated regression parameters of these variables are also robust to inclusion of additional explanatory variables.

The further results of the BMA exercise are reported in table 5 below. On the right-hand side of the table, there are results of OLS estimation with standard errors clustered at the level of individual studies including only variables with PIP larger than 0.5. OLS regression thus includes 15 variables identified by BMA that best explain the variation in PCC of competition coefficient estimate. Overall, OLS with clustered standard errors yields similar results to BMA for variables with high inclusion probabilities. Signs of variables' regression parameters are the same and the size of their parameter estimates is similar as well. Eicher et al. (2011) provide a framework for identification of the strength of variables' posterior inclusion probabilities. PIP is considered weak if it is between 0.5 and 0.75, substantial if in between 0.75 and 0.95, strong if between 0.95 and 0.99 and decisive if exceeding 0.99.

Table 5: Explaining heterogeneity in estimates of the competition coefficient

Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Estimate of Competition	Post. Mean	Post. SD	PIP	Coef.	Robust Std. Err.	P-value
Data Characteristics						
SEPCC	-1.7883	0.2046	1.0000	-1.1940	0.6511	0.067
Samplesize	-0.0367	0.0035	1.0000	-0.0240	0.0089	0.007
T	0.0005	0.0039	0.0517			
sampleyear	0.0000	0.0005	0.0456			
Countries examined						
developed	0.2015	0.0219	1.0000	0.1761	0.0295	0.000
developing and transition	0.1072	0.0169	1.0000	0.0985	0.0262	0.000
Design of the analysis						
quadratic	-0.0533	0.0124	0.9971	-0.0441	0.0128	0.001
endogeneity	0.0100	0.0212	0.2371			
macro	0.0025	0.0124	0.0699			
someAveraged	-0.0004	0.0047	0.0397			
Treatment of stability						
dummies	0.2115	0.0282	1.0000	0.1841	0.0194	0.000
NPL	0.0020	0.0060	0.1323			
Zscore	-0.0005	0.0027	0.0630			
profit_volat	0.0006	0.0051	0.0371			
profitability	-0.0003	0.0030	0.0354			
capitalization	0.0001	0.0029	0.0271			
DtoD	-0.0013	0.0078	0.0504			
Treatment of competition						
Hstatistic	0.1083	0.0217	1.0000	0.1140	0.0181	0.000
Boone	-0.0709	0.0313	0.8974	-0.0583	0.0225	0.010
Concentration	-0.0185	0.0226	0.4742			
Lerner	0.0036	0.0130	0.1217			
HHI	0.0023	0.0108	0.0847			
Estimation methods						
Logit	-0.1874	0.0230	1.0000	-0.1599	0.0190	0.000
OLS	-0.0352	0.0244	0.7558	-0.0382	0.0184	0.038
FE	0.0113	0.0211	0.2774			
RE	0.0018	0.0115	0.0581			
GMM	-0.0003	0.0029	0.0402			
TSLS	-0.0001	0.0030	0.0323			
Control variables						
regulation	-0.0321	0.0197	0.7982	-0.0356	0.0138	0.010
ownership	-0.0147	0.0175	0.4811			
global	-0.0017	0.0058	0.1156			
Publication characteristics						
citations	0.0497	0.0092	1.0000	0.0461	0.0095	0.000
firstpub	0.0219	0.0044	1.0000	0.0233	0.0033	0.000
IFrecursive	0.1060	0.0528	0.8749	0.0964	0.0477	0.043
reviewed_journal	-0.0249	0.0186	0.7254	-0.0151	0.0142	0.289
Constant	-0.0004	NA	1.0000	-0.1184	0.0860	0.169

Studies	31	31
Observations	598	598

Notes: Estimate of Competition = PCC of the β estimate from equation (1). PIP = posterior inclusion probability. Post. SD = posterior standard deviation. In the frequentist check we only include explanatory variables with PIP > 0.5. The standard errors in the frequentist check are clustered at study level. More details on the BMA estimation are available in Table A1 and Figure A1. A detailed description of all variables can be found in Table 4.

We showed in section 4 that the true effect beyond publication bias is virtually zero. Now we aim to shed some light on why a sign and a magnitude of reported coefficient estimates between competition and stability differ in the literature.

The results of our BMA exercise support the notion of the presence of publication bias; it seems that positive and insignificant estimates might be underreported in the literature. Next, the larger the size of the data sample that is used to estimate competition coefficient from equation (1), the smaller the reported coefficient. Larger sample size lowers the coefficient estimate by 0.04. As for country coverage, it seems that estimates for developed countries tend to be slightly larger than those for non-OECD countries. Investigating for nonlinear relationship between competition and financial stability yields on average estimates 0.05 smaller, with a decisive post inclusion probability.

Moreover, when financial stability is measured in a binomial framework, i.e. 1 for a crisis or a bank failure, 0 for a nonevent, the resulting competition coefficient estimates are inflated by 0.21. Furthermore, distinguishing between the coefficient estimates of competition and bank-level stability, and competition and sectoral stability does not impact the sign and size of reported estimates (as indicated by results for the variable macro in table 5). This finding is at odds with an observation from the literature survey by Beck (2008), who summarizes that ”while bank-level studies do not provide unambiguous findings on the relationship between competition and stability, cross-country studies point mostly to a positive relationship”. Similarly, our results contrast the finding by Schaeck and Cihak (2012) who showed that banks have higher capital ratios in more competitive environments, thus capitalization is one of the channels through which competition enhances stability. On the contrary, our BMA exercise shows that capitalization as a proxy for stability does not impact the coefficient estimate between competition and stability in any way while the variable’s inclusion probability is also very low.

As for measures of competition, reported coefficient estimates tend to be larger by 0.11 when Panzar and Rosse’s (1987) H-statistic is used to measure bank competition. This systematic measurement problem could be due to the fact that H-statistic imposes restrictive assumptions on a bank’s cost function that are only valid when the market in question is in equilibrium (Beck, 2008). Competition measured by Boone index yields lower reported estimates by 0.05 with substantial inclusion probability. Estimating equation (1) by a logit or a probit regression tends to bias competition coefficient estimates downward by 0.19, while estimation by ordinary least squares causes a moderate downward bias of 0.04. Controlling in equation (1) for regulatory and supervisory measures decreases the estimated coefficient by 0.03 which is in line with the observation by Barth, Caprio and Levine (2004) and Beck et al. (2006 a,b) that “banking systems with more restrictions on banks’ activities and barriers to bank entry are more likely to suffer systemic banking distress”.

All publication characteristics we control for have high post inclusion probabilities. It is interesting to observe that a larger recursive impact factor and more numerous study citations have both an increasing effect on the estimated competition coefficient, 0.11 and 0.05, respectively. In practice, we can infer that larger estimates are reported in outlets with higher impact factors and more citations. Conversely, peer reviewed journals seem to favor estimates 0.02 smaller, though inclusion probability for this variable is weak. Moreover, our results reveal with decisive PIP that reported estimates of competition coefficient increase overtime. As for the suitability of market structure measures of competition, i.e. concentration ratios and HHI, neither of these measures has been selected in our BMA exercise as useful in explaining the variation in the estimates of competition coefficient. To further check for relevance of this result, we repeat the analysis in section 6 after excluding coefficient estimates obtained from regressions where competition was proxied by measures of concentration and HHI.

Next, we attempt to calculate the mean estimate of the coefficient between competition and stability in a way that corrects for potential estimation mistakes and places greater weight on estimates in quality outlets and those published in journals. This part of the analysis is the most subjective as it requires a researcher's definition of "best practice" in estimating competition coefficient. For each variable identified useful by the BMA exercise, i.e. with PIP larger than 0.5, we plug in a preferred value, a sample minimum or a sample maximum, or in case of no preference, a sample mean. Then we compute a linear combination of regression parameters for variables deemed significant by BMA. This approach enables us to quantify the "best practice" competition coefficient estimate by plugging sample maxima for the size of the sample from which competition coefficient was estimated in equation (1), SE of PCC of competition coefficient estimate as publication bias was identified in the literature, recursive impact factor, number of citations and reviewed journal to account for importance of quality outlets and year of the first publication to account for time trend in estimates. We plugged in sample means for all remaining variables, i.e. dummies, H-statistic, logit, regulation, quadratic, Boone index, developed and developing and transition countries.

Table 6: Best practice estimates of the competition coefficient

Best practice	*Weighted*				*Unweighted*			
	Estimate	95% Conf. Int.		Diff.	Estimate	95% Conf. Int.		Diff.
All	0,022	-0,170	0,215	0,034	0,049	-0,186	0,284	0,050
Developed	0,097	-0,094	0,288	0,086	0,112	-0,122	0,347	0,092
Developing and transition	0,019	-0,178	0,217	0,038	0,076	-0,161	0,313	0,075

Notes: The table presents estimates of the competition coefficient for selected country groups implied by Bayesian model averaging and our definition of best practice. We take the regression coefficients estimated by BMA with PIP>0.5 and construct fitted values of competition coefficient conditional on control for publication characteristics and other aspects of methodology (see the text for details). Diff. = the difference between these estimates and the means reported in table 1. The confidence intervals are constructed using the study-level clustered standard errors estimated by OLS. The right-hand part of the table presents results based on the robustness check using unweighted regressions (Table 8).

Table 6 summarizes the results of "best practice" estimation. Apart from baseline results in the left-hand part of the table, we report also results for unweighted regressions in the right-hand part of the table. The column denoted Diff. shows the difference between "best practice" coefficient estimates and means presented in table 1 for all countries, developed countries and developing and transition countries. Overall, all best practice coefficient estimates are larger than reported means from table 1 potentially owing to the fact that we placed greater weight on quality estimates in our best practice. Moreover, none of the estimates, either from weighted or unweighted regressions, is significant on 10% significance level. It would appear that the competition coefficient estimate for developed countries is larger than that for developing and transition countries. However, no such inference can be made as our results suggest there is no relationship between bank competition and financial stability on the whole.

6 Robustness Checks

6.1 Alternative BMA Specifications

In this subsection we present the results of heterogeneity analysis by means of the BMA exercise with alternative specifications. First, we report the results of BMA with alternative priors. Second, the results for unweighted regressions with the same BMA specifications as in the baseline estimation in section 5 are presented.

The baseline estimation employs unit information prior for Zellner's g-prior. In this specification, the prior contains the same amount of information as one observation in the dataset. Moreover, the uniform model prior in this specification places the same prior probability on each model as well as it achieves the best predictive performance (Eicher et al. 2011). However, the uniform model prior favors models with mean number of regressors, i.e. 35/2 = 17.5 which also makes these models the most numerous among all the possible model combinations. Therefore, our first alternative specification uses the beta-binomial prior that places the same probability on each model size (Ley and Steel, 2009). We accompany the uniform model prior with BRIC g-prior as in Fernandez et al. (2001).

Table 7 presents the numerical results of our BMA exercise with alternative priors. The results are qualitatively as well as quantitatively very similar to those of baseline specification. Virtually no large divergence was reported in posterior means of individual variables, nor in their PIP. The subset of regressors identified as useful fully coincides with that of the baseline specification.

Table 7: Results with alternative BMA priors

Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Estimate of Competition	Post. Mean	Post. SD	PIP	Coef.	Robust Std. Err.	P-value
Data Characteristics						
SEPCC	-1.7527	0.2120	1.0000	-1.1940	0.6511	0.067
Samplesize	-0.0362	0.0036	1.0000	-0.0240	0.0089	0.007
T	0.0003	0.0034	0.0373			
sampleyear	0.0000	0.0005	0.0335			

Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Estimate of Competition	Post. Mean	Post. SD	PIP	Coef.	Robust Std. Err.	P-value
Countries examined						
developed	0.1976	0.0248	1.0000	0.1761	0.0295	0.000
developing and transition	0.1030	0.0188	1.0000	0.0985	0.0262	0.000
Design of the analysis						
quadratic	-0.0517	0.0141	0.9884	-0.0441	0.0128	0.001
endogeneity	0.0159	0.0269	0.3037			
macro	0.0028	0.0132	0.0672			
someAveraged	-0.0004	0.0043	0.0310			
Treatment of stability						
dummies	0.2179	0.0315	1.0000	0.1841	0.0194	0.000
NPL	0.0012	0.0047	0.0818			
Zscore	-0.0004	0.0023	0.0427			
profit_volat	0.0004	0.0043	0.0255			
profitability	-0.0002	0.0024	0.0236			
capitalization	0.0001	0.0024	0.0186			
DtoD	-0.0007	0.0060	0.0313			
Treatment of competition						
Hstatistic	0.1074	0.0228	1.0000	0.1140	0.0181	0.000
Boone	-0.0637	0.0375	0.8020	-0.0583	0.0225	0.010
Concentration	-0.0182	0.0244	0.4183			
Lerner	0.0032	0.0128	0.0946			
HHI	0.0021	0.0107	0.0659			
Estimation methods						
Logit	-0.1883	0.0237	1.0000	-0.1599	0.0190	0.000
OLS	-0.0296	0.0265	0.6208	-0.0382	0.0184	0.038
FE	0.0160	0.0258	0.3261			
RE	0.0020	0.0119	0.0521			
GMM	-0.0002	0.0023	0.0272			
TSLS	-0.0002	0.0031	0.0258			
Control variables						
regulation	-0.0313	0.0205	0.7625	-0.0356	0.0138	0.010
ownership	-0.0129	0.0176	0.4014			
global	-0.0013	0.0051	0.0837			
Publication characteristics						
citations	0.0476	0.0101	1.0000	0.0461	0.0095	0.000
firstpub	0.0207	0.0050	1.0000	0.0233	0.0033	0.000
IFrecursive	0.0958	0.0622	0.7699	0.0964	0.0477	0.043
reviewed_journal	-0.0211	0.0198	0.6028	-0.0151	0.0142	0.289
Constant	-0.0004	NA	1.0000	-0.1184	0.0860	0.169
Studies		31			31	
Observations		598			598	

Notes: Estimate of Competition= PCC of competition coefficient estimated in equation (1). PIP = posterior inclusion probability. SD = standard deviation. In the frequentist check we only include explanatory variables with PIP > 0.5. The standard errors in the frequentist check are clustered at study level. In this specification we use the beta-binomial prior advocated by Ley & Steel (2009) (the prior model probabilities are the same for all model sizes) and BRIC g-prior following Fernandez et al. (2001). More details on the BMA estimation are available in Table A2 in Appendix A. A detailed description of all variables is available in Table 4.

Second, we run the BMA exercise with the same priors as in our baseline specification but for unweighted regressions. In this case the studies with fewer reported competition coefficient estimates are less influential in the meta-analysis. The results differ from baseline in the number of regressors with PIP greater than 0.5 as well as in identifying in some cases other variables as useful in explaining heterogeneity.

In this case BMA selects only 14 variables with inclusion probability higher than 0.5 as opposed to 15 variables in the baseline specification. In addition, measuring stability by means of bank profitability, i.e. ROA and ROE, lowers the coefficient estimate by 0.03 while estimating equation (1) by fixed effects panel regression and by instrumental variable regression increases the estimated competition coefficient by 0.05 with decisive probability in both cases. Furthermore, including controls for bank ownership in equation (1) was found to decrease the coefficient estimate 0.06 with decisive probability. This finding supports the results by e.g. Barth, Caprio and Levine (2004) that bank ownership matters for bank stability. In particular, they find that foreign bank entry tends to be positively related to banking system stability while government ownership impacts competitiveness as well as stability in mostly a negative way. On the other hand, BMA did not identify controlling for nonlinear relationship between competition and stability, measuring competition via Boone index, estimating equation (1) by means of OLS, controlling for regulation and supervision in the banking sector, nor accounting for estimates published in journals as sources of variation in estimates of competition coefficient, unlike the baseline specification. As for the sizes and magnitudes of estimated coefficients for individual regressors, they broadly coincide with estimates in baseline regressions. However, coefficient estimate for standard error of PCC is a much larger negative number, indicating a smaller bias in the literature. Similarly, the gap between coefficient estimates of developed and developing and transition countries is much smaller, shrinking the difference between the reported estimates for different country groups. Finally, estimates reported in outlets with higher impact factors appear to be inflated by only 0.05 as opposed to 0.1 in the baseline specification.

Table 8: Results for unweighted regressions

Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Estimate of Competition	Post. Mean	Post. SD	PIP	Coef.	Robust Std. Err.	P-value
Data Characteristics						
SEPCC	-0.7259	0.5667	0.7003	-0.5768	0.7862	0.4630
Samplesize	-0.0258	0.0082	1.0000	-0.0248	0.0092	0.0070
T	0.0008	0.0034	0.0735			
sampleyear	0.0006	0.0015	0.1946			
Countries examined						
developed	0.1529	0.0172	1.0000	0.1519	0.0175	0.0000
developing and transition	0.1127	0.0172	1.0000	0.1156	0.0170	0.0000
Design of the analysis						
quadratic	0.0012	0.0050	0.0755			
endogeneity	0.0056	0.0110	0.2461			
macro	-0.0103	0.0161	0.3408			
someAveraged	0.0000	0.0024	0.0219			
Treatment of stability						
dummies	0.1861	0.0281	1.0000	0.1660	0.0176	0.0000
NPL	0.0138	0.0249	0.2739			
Zscore	0.0091	0.0166	0.2660			
profit_volat	0.0176	0.0238	0.4350			
profitability	-0.0281	0.0233	0.6587	-0.0451	0.0246	0.0660
capitalization	0.0101	0.0196	0.2437			
DtoD	-0.0015	0.0080	0.0674			
Treatment of competition						
Hstatistic	0.1294	0.0223	1.0000	0.1123	0.0173	0.0000
Boone	-0.0021	0.0088	0.0873			

Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Estimate of Competition	Post. Mean	Post. SD	PIP	Coef.	Robust Std. Err.	P-value
Concentration	0.0159	0.0244	0.3626			
Lerner	0.0136	0.0211	0.3566			
HHI	0.0103	0.0199	0.2488			
Estimation methods						
Logit	-0.1304	0.0303	0.9999	-0.1275	0.0121	0.0000
OLS	0.0000	0.0019	0.0214			
FE	0.0621	0.0134	1.0000	0.0503	0.0113	0.0000
RE	0.0128	0.0204	0.3355			
GMM	0.0000	0.0018	0.0221			
TSLS	0.0532	0.0132	0.9999	0.0515	0.0147	0.0000
Control variables						
regulation	0.0002	0.0020	0.0281			
ownership	-0.0595	0.0096	1.0000	-0.0588	0.0289	0.0420
global	0.0016	0.0054	0.1033			
Publication characteristics						
citations	0.0377	0.0063	0.9996	0.0407	0.0087	0.0000
firstpub	0.0179	0.0033	0.9997	0.0205	0.0029	0.0000
IFrecursive	0.0470	0.0419	0.6405	0.0490	0.0379	0.1960
reviewed_journal	0.0019	0.0080	0.0807			
Constant	-0.1269	NA	1.0000	-0.1263	0.0870	0.1460
Studies		31			31	
Observations		598			598	

Notes: Estimate of Competition = PCC of competition coefficient estimated in equation (1). PIP = posterior inclusion probability. SD = standard deviation. In the frequentist check we only include explanatory variables with PIP > 0.5. The standard errors in the frequentist check are clustered at the study level. In this specification we do not weight the regressions by the inverse of the number of estimates reported per study. More details on the BMA estimation are available in table A3 in Appendix A. A detailed description of all variables is available in table 4.

6.2 Exclusion of Concentration-Stability Estimates

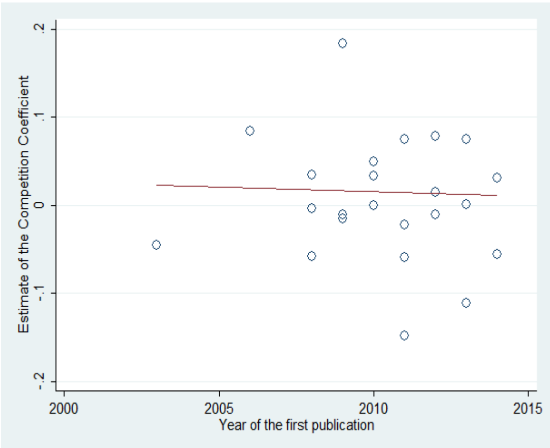
In this subsection we verify robustness of our results after having excluded estimates arising from equation (1) in which market structure measures, such as concentration ratios and HHI, were used as proxies for competitiveness in the banking sector. Concern about the suitability of use of market structure measures to proxy for market competition is justified. For example, Claessens and Laeven (2004) conclude that concentration is an unsuitable proxy for competition and that the two measures, concentration and competition, highlight different banking sector characteristics. Furthermore, Beck (2008) based on in his survey of the literature advocates that “market structure measures such as concentration ratios are inadequate measures of bank competition. Higher concentration might result in more stability through channels other than lack of competitiveness, such as improved risk diversification.” Therefore, a higher degree of market concentration does not necessarily imply less competition.

Such assertions are a motivation to exclude concentration-stability estimates from our sample. The new sample thus consists of 345 reported coefficient estimates from regressions where competition is measured by either Lerner index, H-statistic or Boone index. The robustness check takes the form of the main analysis; tests for publication bias and attempts to quantify “best practice” estimate analogously as for the whole sample.

Figure 6 plots PCC medians of pure competition-stability coefficient estimates against the first year of publication of the study from which they were collected. We observe again increasing spread among the reported coefficient estimates overtime.

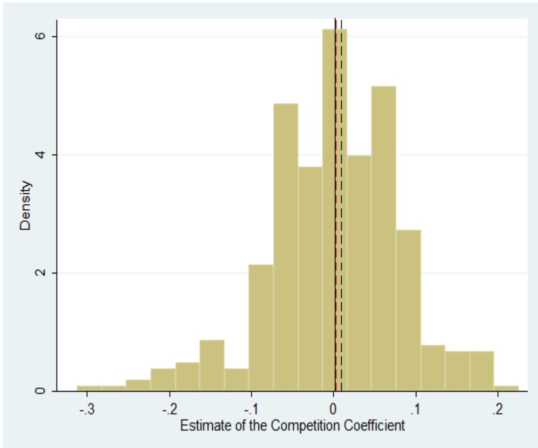
Figure 7 displays histogram of PCC of coefficient estimates. The black solid line depicts the mean PCC value over all studies equal to 0.0011 while black dashed line signifies mean of median PCC of competition coefficient estimates equal to 0.0104. In addition, the red dashed line highlights mean PCC value of estimates published in journals which takes the value of 0.0016. All in all, these statistics coincide with results for the whole sample, apart for the fact that journals do not seem to favour larger estimates of competition-stability coefficient.

Figure 6: Competition coefficient estimates in time



Notes: The figure depicts median PCC of pure competition coefficient estimates (PCC of the β estimate from equation (1)) reported in individual studies. The horizontal axis measures the year when the first drafts of studies appeared in Google Scholar. The red line shows the linear fit.

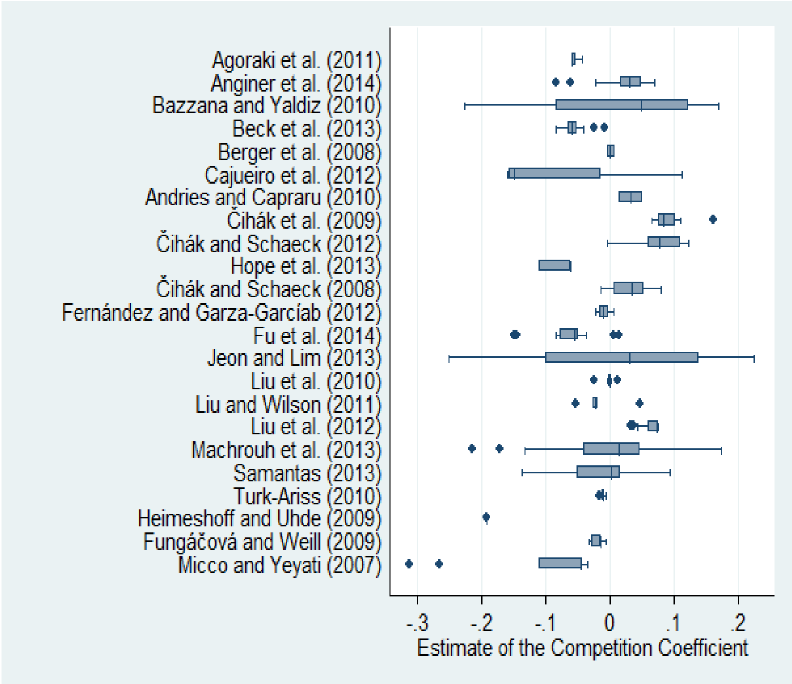
Figure 7: Histogram of competition coefficient estimates



Notes: The figure shows the histogram of the PCC of the pure competition coefficient estimates (PCC of the β estimate from equation (1)) reported in individual studies. The solid vertical line denotes the mean of all the PCC. The black dashed line denotes the mean of the median PCC of estimates from studies. The red dashed line denotes the mean of the PCC of those estimates that are reported in studies published in peer-reviewed journals.

Figure 8 depicts partial correlation coefficients of pure competition coefficient estimates from equation (1) as reported in individual studies. After omitting concentration-stability coefficient estimates from the sample, the number of individual studies decreased from 31 in the original sample to 23.

Figure 8: Estimates of competition coefficient over individual studies



Notes: The figure shows a box plot of the PCC of the competition coefficient estimates (PCC of the β estimate from equation (1)) reported in individual studies. Full references for the studies included in the meta-analysis are available in Appendix B.

Following the main analysis, table 9 presents simple means of PCC of pure competition coefficient estimates for all countries as well as for only developed and only developing and transition countries. Means weighted by inverse number of estimates reported per study are negative for all country groups, though they are again close to 0 and not significant on 10% significance level. Unweighted means are, on the other hand, positive, though also close to 0 and not significant. Both, weighted and unweighted means, again appear to be slightly higher for developed countries.

Table 9: Simple means of the PCC of pure competition coefficient estimates

	Unweighted			Weighted			No. of
	Mean	95% Conf. Interval		Mean	95% Conf. Interval		estimates
All	0,001	-0,019	0,021	-0,016	-0,041	0,009	345
Developed	0,011	-0,009	0,030	-0,008	-0,049	0,033	109
Developing and transition	0,004	-0,036	0,044	-0,024	-0,061	0,012	83

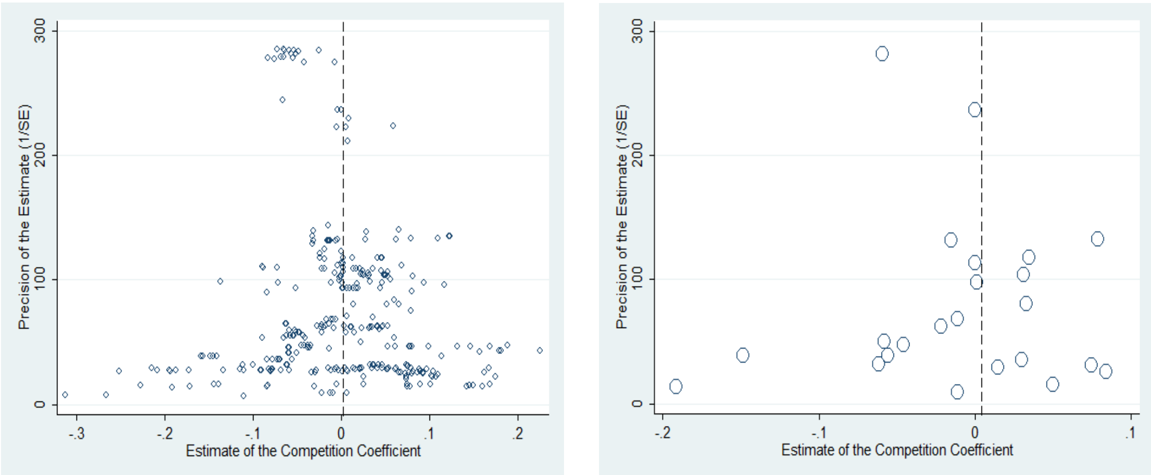
Notes: The table presents mean PCC of the competition coefficient estimates (PCC of the β estimate from equation (1)) over all countries and for selected country groups. The confidence intervals around the mean are constructed using standard errors clustered at the study. In the right-hand part of the table the estimates are weighted by the inverse of the number of pure competition estimates reported per study.

Following the main analysis in section 4, we again investigate for the presence of publication bias in the literature. Figure 9 presents funnel plots for all estimates and for median estimates per study. In case of no publication bias, funnel plots should be symmetrical around mean PCC of pure competition coefficient estimates. Moreover, it should not be hollow (missing estimates) and it should report also low-precision estimates (the ones at the bottom). It appears that funnel plots are quite symmetrical and report low-precision estimates though perhaps a small hollowness appears at the level of precision between 150 and 200. Overall, visual perusal does not point to a major publication bias.

Figure 9: Funnel plots do not suggest substantial publication bias

A: All estimates

B: Median estimates per study



Notes: In the absence of publication bias the funnel should be symmetrical around the most precise PCC of the estimates of the competition coefficient (PCC of the β estimate from equation (1)). The black dashed vertical lines denote the mean of PCC of all estimates in Figure 9A and the mean of median PCC of the estimates reported in studies in Figure 9B.

Next we turn to a more formal check for the presence of publication bias, i.e. by means of funnel asymmetry tests. We follow the steps in section 4 and investigate if there is a correlation between pure competition coefficient estimates and their standard errors. Table 10 reports the results for the subsample of competition coefficient estimates. The reported coefficient estimates in all the regressions are very similar to those for the whole sample in table 2. The estimates of the underlying effect beyond bias are all significant at least on 5% significance level and again close to zero. Similarly, regressions yield comparable estimates of publication bias as to the magnitude and size as for the whole sample. In contrast to the main analysis, the publication bias for effect estimates from published studies does not appear to be higher than for the whole subsample. Moreover, estimates of the true effect for published studies do not seem to as biased upward as they were for the entire sample.

Table 10: Funnel asymmetry tests again confirm the presence of publication bias

Unweighted regressions	FE	FE_Published	Instr	Instr_Published
SE (publication bias)	-1.855**	-1.881**	-2.059***	-2.237***
Constant (effect beyond bias)	0.048**	0.054**	0.053***	0.064***
No. of estimates	345	272	345	272
No. of studies	23	17	23	17
Weighted regressions	FE		FE_Published	
SE (publication bias)	-1.683***		-1.697***	
Constant (effect beyond bias)	0.032***		0.026***	
No. of estimates	345		272	
No. of studies	23		17	

Notes: The table presents the results of regression specified in equation (6). The standard errors of the regression parameters are clustered at the study level. Published = we only include published studies. Fixed Effects = we use study dummies. Instrument = we use the logarithm of number of observations in equation (1) as an instrument for the standard error and employ study fixed effects. The regressions at the bottom half of the table are estimated by weighted least squares, where the inverse of the number of estimates reported per study is taken as the weight. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level.

Table 11 presents the results of heteroskedasticity-corrected funnel asymmetry tests. By weighting the equations by precision, the estimation now places more weight on more precise pure competition coefficient estimates. In contrast to the main analysis in table 3, the bias now appears to be persistent through different estimation techniques and specifications. The publication bias estimates are also larger in absolute terms and significant at least on 10% significance level. In line with the main analysis, estimates of the true effect are still similar in sign and magnitude and also close to zero. Applying the framework by Doucouliagos and Stanley (2013) as in section 4 reveals the presence of a severe publication bias after we exclude all concentration-stability coefficient estimates from our dataset.

Table 11: Heteroskedasticity-corrected funnel asymmetry tests

Unweighted regressions	FE	FE_Published	Instr	Instr_Published
1/SE (effect beyond bias)	0.024	0.064*	0.039**	0.050**
Constant (publication bias)	-2.210*	-4.651*	-3.285***	-3.744***
No. of estimates	345	272	345	272
No. of studies	23	17	23	17
Weighted regressions	FE		FE_Published	
1/SE (effect beyond bias)	0.021		0.062**	
Constant (publication bias)	-2.207*		-5.369**	
No. of estimates	345		272	
No. of studies	23		17	

Notes: The table presents the results of regression specified in equation (7). The standard errors of the regression parameters are clustered at the study level. Published = we only include published studies. Fixed Effects = we use study dummies. Instrument = we use the logarithm of number of observations in equation (1) as an instrument for the standard error and employ study fixed effects. The regressions at the bottom half of the table are estimated by weighted least squares, where the inverse of the number of estimates reported per study is taken as the weight. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level.

Finally, we apply "best practice" estimation from section 5 to the subsample containing only pure competition coefficient estimates. We use the same "best practice" definition and plug in sample means and sample maxima for the same variables as discussed in section 5. The resulting coefficient estimates are presented in table 12. Same as in section 5, estimates arising from weighted equations are closer to zero than those resulting from equations not weighted by the inverse number of estimates per study. For weighted equations, estimated competition coefficient for developed countries is again higher than that for developing and transition countries. However, none of the estimates in table 12 is significant on 5% significance level as was the case in the main analysis. Overall, we can conclude that there is no relationship between bank competition and financial stability.

Table 12: Best practice estimates of the pure competition coefficient

Best practice	Weighted				Unweighted			
	Estimate	95% Conf. Interval		Diff.	Estimate	95% Conf. Interval		Diff.
All	-0,011	-0,313	0,095	-0,093	-0,217	-0,461	0,027	-0,218
Developed	0,090	-0,296	0,116	-0,082	0,167	-0,412	0,078	-0,178
Developing and transition	-0,122	-0,345	0,101	-0,098	0,183	-0,419	0,053	-0,187

Notes: The table presents estimates of the competition coefficient for selected country groups implied by Bayesian model averaging and our definition of best practice. We take the regression coefficients estimated by BMA with PIP>0.5 and construct fitted values of competition coefficient conditional on control for publication characteristics and other aspects of methodology (see the main text for details). Diff. = the difference between these estimates and the means reported in table 9. The confidence intervals are constructed using the study-level clustered standard errors estimated by OLS. The right-hand part of the table presents results based on the robustness check using unweighted regressions (Table 8).

The robustness check in subsection 6.2 validates our main results in section 5. Excluding coefficient estimates arising from regressions where market structure measures are used as proxies for competition does not change our main results that there exists a publication bias in the competition-stability literature, with journals favoring larger and significant competition coefficient estimates. More importantly, based on our meta-analysis of the relevant literature we can conclude after multiple robustness checks that there is, in fact, no relationship between bank competition and financial stability.

7 Conclusion

In this paper we run a meta-analysis on the effect of banking sector competition on financial stability using 598 estimates of the effect originating from 31 studies. The main robust result of our analysis is that ultimately bank competition does not affect financial stability in any way. In other words, no relationship has been found between bank competition and financial stability based on our quantitative survey of the literature. Furthermore, we have identified the presence of publication bias in the literature as outlets with higher impact factor and a larger number of citations tend to prefer larger and statistically significant estimates of competition coefficient.

There are several aspects of estimation and study design that influence the magnitude and sign of competition coefficient estimates. First, controlling for supervisory and regulatory conditions in regressions decreases the estimated effect estimates, supporting the notion that banking systems with more activity restrictions and greater barriers to entry are more likely to suffer from systemic banking distress (e.g. Beck et al., 2006 a,b). Second, some proxies for competitiveness within the banking sector, i.e. H-statistic and Boone index, tend to systematically bias effect estimates. Similarly, measuring stability by means of dummy variables biases the estimated coefficient upwards. Third, estimating the competition-stability equation by logistic and OLS regressions biases the resulting effect estimates downwards. Next, investigating for potential nonlinearities between competition and stability, as well as having a greater number of observations available for the estimation of competition coefficient, both lower the reported effect. Last, reported coefficient estimates are somewhat larger for developed countries than for non-OECD countries and in general, estimates of the effect have been increasing overtime.

As the literature finds that market structure measures, i.e. concentration, are not suitable proxies for bank competition, we repeat the analysis after excluding concentration-stability coefficient estimates from the dataset. Ultimately we find that exclusion of these estimates does not change our main results; there is publication bias in the literature and competition does not impact stability in any way. This robustness check is further supported by results of our BMA exercise for the full dataset; market structure measures as proxies for competition have low inclusion probabilities and do not bias effect estimates.

To conclude, our meta-analysis resolves the ambiguity originating from the two opposing theoretical views in the literature, the competition-fragility and the competition-stability hypotheses. Narrative surveys of the literature by e.g. Beck (2008) and Carletti and Hartmann (2002) observe that predictions of the effect of competition on banking stability are ambiguous and tentatively conclude that competition is not necessarily detrimental to banking system stability, without being able to draw any general conclusions. In contrast, our meta-regression analysis of the literature can effectively conclude that there is no robust relationship between bank competition and stability.

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Appendix A: BMA Diagnostics

Table A1: Summary of BMA estimation, baseline

Mean no. regressors	*Draws*	*Burnins*	*Time*	*No. models visited*
16.7873	2,00E+06	1,00E+06	8.946665 mins	428100
Modelspace 2^K	*% visited*	*% Topmodels*	*Corr PMP*	*No. Obs.*
3.4e+10	0.0012	85	0.9991	598
Model Prior		*g-Prior*	*Shrinkage-Stats*	
uniform / 17.5		UIP	Av=0.9983	

Notes: In this specification we employ the priors suggested by Eicher et al. (2011) based on predictive performance: the uniform model prior (each model has the same prior probability) and the unit information prior (the prior provides the same amount of information as one observation of data).

Figure A1: Model size and convergence, baseline

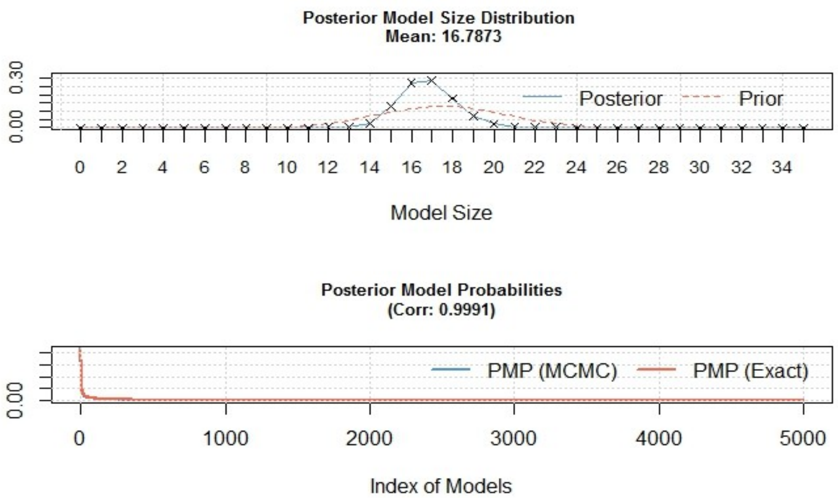

Table A2: Summary of BMA estimation, alternative priors

Mean no. regressors	*Draws*	*Burnins*	*Time*	*No. models visited*
15.9376	2,00E+06	1,00E+06	9.016166 mins	340570
Modelspace 2^K	*% visited*	*% Topmodels*	*Corr PMP*	*No. Obs.*
3.4e+10	0.00099	92	0.9988	598
Model Prior		*g-Prior*	*Shrinkage-Stats*	
random / 17.5		BRIC	Av=0.9992	

Notes: The “random“ model prior refers to the beta-binomial prior used by Ley & Steel (2009): the prior model probabilities are the same for all possible model sizes. In this specification we set Zellner's g prior in line with Fernandez et al. (2001).

Table A3: Summary of BMA estimation, unweighted regressions

Mean no. regressors	*Draws*	*Burnins*	*Time*	*No. models visited*
17.3801	2,00E+06	1,00E+06	9.342384 mins	544485
Modelspace 2^K	*% visited*	*% Topmodels*	*Corr PMP*	*No. Obs.*
3.4e+10	0.0016	69	0.9966	598
Model Prior		*g-Prior*	*Shrinkage-Stats*	
uniform / 17.5		UIP	Av=0.9983	

Notes: In this specification we employ the priors suggested by Eicher et al. (2011) based on predictive performance: the uniform model prior (each model has the same prior probability) and the unit information prior (the prior provides the same amount of information as one observation of data).

Appendix B: Studies Included in the Meta-Analysis

Agoraki, Maria-Eleni K., Delis, Manthos D. & Fotios Pasiouras, 2011. "Regulations, competition and bank risk-taking in transition countries". Journal of Financial Stability 7(1): pp. 38-48.

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