BANK OF ENGLAND

Staff Working Paper No. 885

The link between bank competition and risk in the United Kingdom: two views for policymaking

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September 2020

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Abstract

We use quantile regression to examine the links between competition and firm-level solvency risk for all banks and building societies in the United Kingdom between 1994 and 2013. Quantile regression provides a finer picture of the relationship (as compared with standard regression techniques) across institutions ranked according to how close each is to insolvency. We find that for domestic banks and building societies already close to insolvency the association is favourable, suggesting that risk decreases (increases) with more (less) competition. For foreign-owned banks and for relatively healthy building societies farther from insolvency we find the opposite, indicating that risk increases (decreases) with more (less) competition. We find that regulation is effective in moderating adverse links between risk and competition. Our results highlight real differences in the links between competition and risk at the individual level that are useful for assessing the link at the system-wide level.

Key words: Bank competition, bank risk, Boone indicator, quantile regression.

JEL classification: G21, G28, L22.

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The views expressed in this paper are those of the authors and do not represent those of the Bank of England or Prudential Regulation Authority. We are grateful to Meyer Aaron, Peter Andrews, Thorsten Beck, Laura D'Amato, Stephen Dickinson, Paul Grout, Klaus Schaeck, Paolo Siciliani, Rhiannon Sowerbutts and participants at the Bank of England's Research Tea Party, One Bank Research Seminar and Prudential Policy Forum. We would also like to thank economics seminar participants at Brunel University, the London School of Economics (FMG) and the UK Financial Conduct Authority as well as conference participants at the Norwegian School of Economics (NHH) 2018 Conference on Competition and Stability in the Banking Market in Bergen, Norway, at the 2018 Inter-American Development Banks (IDB) International Workshop on the Cost of Credit at the Central Bank of Brazil in Brasilia and at the 4th annual International Workshop on Financial System Architecture and Stability in Victoria British Columbia for helpful discussion and comments. All remaining errors are ours.

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ISSN 1749-9135 (on-line)

1. Introduction

Because of the critical role that banks play in supporting the economy, understanding the factors that influence banks' capacity in that role has been of long-standing interest to regulators, policymakers and academics. Competition in banking markets – and, in particular, whether it is positively or negatively related to bank risk – has received a lot of attention. While this focus has led to a vast body of research, there is no definitive consensus on the relationship, challenging policymakers to make informed decisions about policy designs that might mitigate economic costs or support economic benefits that derive from competition.

Theories suggest that the relationship may be positive, the 'competition-stability' hypothesis, or negative, the 'competition-fragility' hypothesis (see, among others, Carletti and Hartmann, 2003; Beck, 2008; Vives, 2016 for good overviews). Empirical studies reveal varying degrees of support for both views. Providing a sense of just how widely varied these findings have been, Zigraiova and Havranek (2016) use meta-data analysis to examine almost 600 empirical estimates from 31 studies of the competition-stability link and find no definitive systematic evidence on the connection. A common theme throughout that study and much of the extant empirical research is a reliance on regression setups that force conclusions to be drawn on the competition-risk relationship based on a summary measure of the average effect for a bank with average risk. However, this average effect may not adequately reflect the relationship at different parts of the conditional risk distribution, especially when there is significant heterogeneity. This is pertinent for the UK deposit-taking sector where the risk distribution exhibits non-normal characteristics. Estimates of the average (conditional mean) can therefore miss important effects, because the average relationship inherently combines the magnitudes of a variety of relationships across different parts of the conditional distribution.

We contribute to the literature by characterising empirically the relationship between competition and risk at different points of the conditional risk distribution, where institutions are ranked according to how close they are to insolvency. We use quarterly data on all banks and building societies in the United Kingdom spanning 1994 to 2013, which provides the sufficient variation in individual risk profiles (both over time and across firms) needed for our study. Our study is motivated by several recent papers that document evidence showing that the strength and direction of the relationship may also depend on a firm's underlying risk profile. Using a cross-country panel of banks, Beck, De Jonghe and Schepens (2013) finds that competition has a stronger positive relationship with bank fragility for distressed banks. Schaeck and Čihák (2014) finds evidence consistent with the competition-stability hypothesis, but that this relationship is less (more) pronounced for European banks closer to (farther from) insolvency. Using data on nonperforming loans for euro area banks, Karadima and Louri (2019) finds that profit margins (market power) exert a positive impact on the change in nonperforming loans for firms in the medium and upper quantiles of its distribution, supporting the competition-stability view. Cummins, Rubio-Misas and Vencappa (2017) documents a negative association between risk and competition for European insurance firms, but that the relationship is stronger for weak insurers compared with financially-healthy ones. Liu and Wilson (2013) finds evidence that Japanese banks farther from insolvency take on more risk in response to more intense competition, consistent with the competition-fragility hypothesis, while those closer to insolvency reduce risk, consistent with the competition-stability hypothesis. Using data from the UK and multiple measures of bank competition and risk, de-Ramon, Francis and Straughan (2018) document relationships similar to those reported in Liu and Wilson (2013), further supporting the idea that the link between bank competition and risk may vary depending on the underlying solvency risk of the firm.

To explore whether and how the relationship between bank competition and risk differs across the conditional risk distribution, we employ quantile regression (Koenker and Basset, 1978).[1] This technique allows us to take the heterogeneity of bank risk explicitly into account when examining the competition-stability relationship and produces multiple coefficients at various points across the conditional risk distribution.[2] We show how this more detailed picture of the relationships at the individual bank level can have important implications for assessing the relationship at the broader banking sector level.

De-Ramon, Francis and Straughan (2018) used quantile regression to highlight differences across the bank risk distribution and exposed some drivers of these differences. In particular, the competition-stability hypothesis held for higher-risk banks while the competition-fragility hypothesis held for lower-risk banks. Moreover, when overall bank risk was decomposed into asset- and capital-risk components, the relationship between competition and capital broadly followed that of the overall bank risk, while less competition reduces risk-adjusted asset returns across the distribution.

In this paper, we evaluate whether firm type, characterized by asset size and ownership, and regulatory pressure, proxied by the proximity of a firm's capital ratio to its regulatory capital minimum, affect the relationship between competition and risk. Previous research provides evidence of heterogeneous relationships across firm type (Tabak, Fazio and Cajueiro, 2012; Liu and Wilson, 2013; Kick and Prieto, 2015). However, to our knowledge, none has explicitly examined whether the relationships vary across the conditional risk distribution. We are also unaware of any studies that

[1] Literature on the estimation of quantile treatment effects, including, for example, Basset and Chen (2001); Bilter, Gelbach and Hoynes (2006); and Abrevaya and Dahl (2008), demonstrates the limitations of conditional mean estimation.

[2] With the exception of Schaeck and Čihák (2014), de-Ramon, Francis and Straughan (2018) and Karadima and Louri (2019), the use of quantile regression to explore the competition-risk nexus issue is noticeably absent from the previous banking research.

have considered the role that regulatory pressure has played in shaping the competition-risk nexus. Both extensions are new contributions to the existing empirical literature.

We carry out our analysis of the relationship between risk and competition by regressing bank Z-scores on the Boone indicator, controlling for bank-level and macro-economic factors. The Z-score is an accounting-based measure of distance to insolvency that commonly features in this line of research (Berger, Klapper and Turk-Ariss, 2009; Houston et al., 2010; Tabak, Fazio and Cajueiro, 2012; Beck, De Jonghe and Schepens, 2013; Schaeck and Čihák, 2014). The Boone indicator (Boone, 2008) is an estimated measure of competition based on the output reallocation effect: more intense competition leads to a reallocation of output (profits) toward relatively more efficient banks. Several papers have used the Boone indicator to investigate the role that the efficiency channel plays in linking competition with bank stability (Tabak, Fazio and Cajueiro, 2012; Schaeck and Čihák, 2014; Kick and Prieto, 2015). Our paper adds to that literature by examining whether the transmission via the efficiency channel depends on the underlying risk of the firm.

Our focus on the UK is motivated by several factors. First, the UK was subject to a number of legislative and regulatory changes aimed at broadening competition within both UK and European financial markets in the two decades prior to our estimation period: the 1979 UK Banking Act; the 'big bang' reforms of 1986; changes to the Building Societies Act of 1986; the 1991 Basel Accord; and the European Second Banking Coordination Directive in 1993 (Matthews, Murinde and Zhao, 2007; de-Ramon and Straughan, 2019). These measures removed restrictions on competition between banks and building societies within the UK and reduced barriers to entry across European (including UK) markets, as well as giving banks greater flexibility over their risk strategies. The start of our estimation period (1994-2013) coincides with the considerable upheaval in the competitive climate for the UK banking system that followed these changes.

Second, the data are based on regulatory returns and include a much broader range of risk-profiles, deposit-taking business models and organizational forms (shareholder-owned banks and mutually-owned building societies) that is not otherwise publicly available. Our study therefore offers a unique country-level perspective and supplements the growing list of single-country studies investigating the relationship in settings outside the US.

Third, the data allow us to examine the competition-risk relationship in a single country setting which provides greater freedom in estimation by avoiding the need for cross-country controls. Finally, our database includes proprietary information on UK banks' capital requirements recorded under this country's long-standing practice (since the 1980's) of setting firm-specific requirements to deal with risks not adequately addressed in the international (Basel) capital standards. These requirements, which vary across firms and over time, permit us to evaluate the role that regulatory pressure, as measured by proximity to such individual capital requirements, plays in affecting the competition-risk relationship across the risk distribution.

We examine outcomes using both standard and quantile regression techniques first for all firms, then for different firm types, and finally for regulatory pressure. When using standard regression for all firms, we find that bank risk (solvency) is adversely associated with competition on average, consistent with the competition-fragility hypothesis. Our findings suggest the dominant channel driving this outcome is banks electing to hold significantly lower risk-adjusted capital ratios, supportive of the franchise value theory (Marcus, 1984; Keeley, 1990). However, results from quantile regression indicate that this destabilising relationship is evident only in the low-risk tail of the conditional risk distribution. For the most fragile firms in the high-risk tail of the risk distribution, we find that competition is favourably related to risk, supportive of the competition-stability hypothesis. These contrasting results for different quantiles are consistent with both the competition-fragility and competition-stability hypotheses holding simultaneously for different institutions in the United Kingdom. This finding is in line with the conclusions reached by Berger, Klapper and Turk-Ariss (2009), which also found evidence supportive of both theories holding simultaneously in a cross-country setting. These results suggest that there are trade-offs to evaluate when considering the effects of competition, especially on overall banking system stability.

Our analyses of whether firm type influences the relationship between competition and risk show that, under standard regression, the adverse, competition-fragility relationship is driven mainly by small UK-owned banks and mutually-owned building societies on average. For large, UK-owned banks we find evidence consistent with the competition-stability relationship. Results from quantile regression also confirm that the favourable relationship between competition and stability is evident for small UK-owned banks and building societies in the high-risk end of the risk distribution. At the same time, these results show a destabilising relationship at relatively less-risky building societies and foreign-owned banks.

Our analysis of the influence of regulatory pressure reveals that the destabilising relationship is less pronounced at institutions facing heightened regulatory pressure. Results suggest that at these institutions, regulatory pressure is effective at moderating risk-taking incentives that arise as competition mounts. This result also holds under quantile regression, where we find that the destabilising links at the healthiest firms are significantly lower if they are also under regulatory pressure.

Our results support the idea that the relationship between competition and risk at the individual bank level can be different within the banking system. This means that the relationship with banking system stability overall will depend on how these individual relationships combine. To illustrate this point, we use the results from the standard and quantile regression techniques and simulate the effects of an increase in competition on percentile-based measures of banking system Z-scores used in previous research (Houston et al., 2010) and by policymakers (Beck, De Jonghe and Schepens, 2013) to assess system soundness. This exercise demonstrates that standard and quantile regression techniques together can give a more detailed view of the relationship between competition and risk, which can help inform policymaking.

The remainder of this paper is structured as follows. Section 2 describes our empirical approach and the measures of risk and competition used in this paper. Section 3 discusses our data and sample. Section 4 reports results, while Section 5 discusses robustness tests. Section 6 concludes.

2. Empirical approach

We investigate the relationship between bank risk and competition by estimating models of the form:

$$Risk_{i,t} = \alpha + \beta Competition_{t-2} + \Phi X_{i,t-2} + \Theta Y_{t-2} + \varepsilon_{i,t}\ , \tag{1}$$

where $Risk_{i,t}$ is a measure of bank-level solvency for bank i at time t, $Competition_{t-2}$ is the level of industry-wide competition at time $t-2$, $X_{i,t-2}$ and Y_{t-2} are vectors reflecting bank-level and macroeconomic controls, respectively, and $\varepsilon_{i,t}$ are error terms. Our main coefficient of interest in this setup is that associated with competition, β. We recognize that competition may be endogenous if weaker, less-efficient institutions increase leverage and balance sheet size (potentially raising accounting return on assets) in an attempt to avoid insolvency in periods of market-wide instability. These actions can be misinterpreted as a sign of increased competition. We address this problem in two ways. First, we do not use bank-level competition measures, some of which (e.g., Lerner indices) can be prone to this issue because they may be mechanically linked with bank-level risk-measures due to the fact that each uses similar measures in their calculation. Second, as is common practice in the banking literature (Beck, Demirgüç-Kunt and Levine, 2010; Beck, De Jonghe and Schepens, 2013; De Nicolo and Turk-Ariss, 2010; Liu and Wilson, 2013), we lag competition and bank level controls by two periods (i.e., six-months). Our choice of lag length is supported by results of exogeneity tests (discussed in Section 5.4) that formally evaluate the null hypothesis that the specified endogenous regressor, i.e., competition in this case, can be treated as exogenous.

Equation (1) is often estimated using standard regression techniques, producing conditional mean estimates of β and allowing inferences to be made of the average effect of changes in competition on expected bank risk. If there is unobserved heterogeneity, however, then the estimated coefficient is not representative of the entire conditional risk distribution. To deal with this issue, we consider the way competition influences other parts of the risk distribution by employing quantile regression (Koenker and Basset, 1978) to generate multiple estimates of β, which are considered robust relative to least squares estimates. Compared with the least squares estimator, the quantile regression estimates place less weight on outliers and are robust to departures from normality. Using our setup in (1), we can illustrate quantile regression as follows:

$$Q_\theta\left(Risk_{i,t}\middle|Competition_{t-2}, X_{i,t-2}, Y_{i,t-2}\right) = \alpha_\theta + \beta_\theta Competition_{t-2} + \Phi_\theta X_{i,t-2} + \Theta_\theta Y_{t-2} + \upsilon_{i,t}, \tag{2}$$

where the term $Q_\theta\left(Risk_{i,t}\middle|Competition_{t-2}, X_{i,t-2}, Y_{i,t-2}\right)$ denotes the θ^{th} conditional quantile of bank risk given competition, bank-level and macroeconomic controls; β_θ, Φ_θ and Θ_θ are vectors of parameters on competition, bank-controls and macroeconomic controls, respectively; and $\upsilon_{i,t}$ is a vector of i.i.d. residuals. The term Q_θ makes explicit the difference with the standard least squares estimator expressed in Equation (1), which provides information only about the effect of competition at the conditional mean of bank risk. The quantile regression produces multiple coefficient estimates for competition, β_θ, unique to each quantile θ of the conditional distribution of $Risk_{i,t}$, and hence information regarding the variation of the effect of competition on bank risk at different quantiles of the risk distribution.[3] This approach allows us to examine whether the relationship between competition and bank-level risk differs across banks depending on each bank's underlying risk profile. Testing for equality of the coefficient estimates at various quantiles requires estimation of the variance-covariance matrix, which we derive using bootstrapping techniques (Koenker and Hallock, 2001; Buchinsky, 1998). The test statistic is computed by using the variance-covariance matrix of the coefficients of the system of quantile regressions. The null hypothesis is that the coefficient on competition at the θ_s^{th} quantile is statistically the same as the one in the θ_t^{th} quantile (H_0: $\beta_{\theta_s} = \beta_{\theta_t}$). The alternative hypotheis is where the coefficients are not equal (H_0: $\beta_{\theta_s} \neq \beta_{\theta_t}$). This test allows us to investigate if the relationship between risk and competition varies across the conditional risk distribution.

2.1. Dependent variables

We construct the Z-score, the accounting based measure of bank-level risk as:

$$Z_{i,t} = (RoA_{i,t} + k_{i,t})/\sigma_{i,t}^{RoA}, \tag{3}$$

where $RoA_{i,t}$ is the return on assets for deposit-taker i at time t, $k_{i,t}$ is the capital (equity to assets) ratio and $\sigma_{i,t}^{RoA}$ is the standard deviation of the return on assets. The Z-score as a 'distance to default'

[3] These coefficients can be interpreted as the partial derivative of the conditional quantile of Stability with respect to competition, which represents the marginal change in bank-level stability at the θ^{th} conditional quantile due to a change in competition.

metric, measuring the number of standard deviations a bank's return on assets has to decline to entirely deplete its equity. In this sense, the Z-score encompasses risk across a firm's activities. A higher Z-score implies a lower probability of insolvency and hence lower risk. We use a four-year (16 quarter) rolling window of (annualised) returns to calculate $\sigma_{i,t}^{RoA}$, which allows for sufficient variation in the denominator and avoids the Z-score being driven primarily by the fluctuations in the level of the return on assets and the capital ratio. This formulation of the Z-score is common in the existing literature examining the relationship between financial stability and competition (e.g., Schaeck and Čihák, 2014; Cummins et al., 2017).

Figure 1 shows how the distribution of bank-level Z-scores has evolved over time in the UK. In particular, it shows that raw Z-scores are asymmetrically distributed with the Z-scores of those firms above the median showing significantly greater variation than the Z-scores of those firms below the median. To deal with outliers and the highly skewed nature of the data in our sample, we use the logarithm of the Z-score in our estimations.

2.2. Explanatory variables

We use the Boone indicator as our primary measure of competition. The Boone indicator measures the strength of competition from an efficiency perspective. The measure relies on the output-reallocation effect: an increase in competition intensity, either as a result of an endogenous strengthening of competitive effort or from lowering of market barriers to entry, leads to a relative increase in output of the most efficient firms in the market. That is, in more (less) competitive markets,

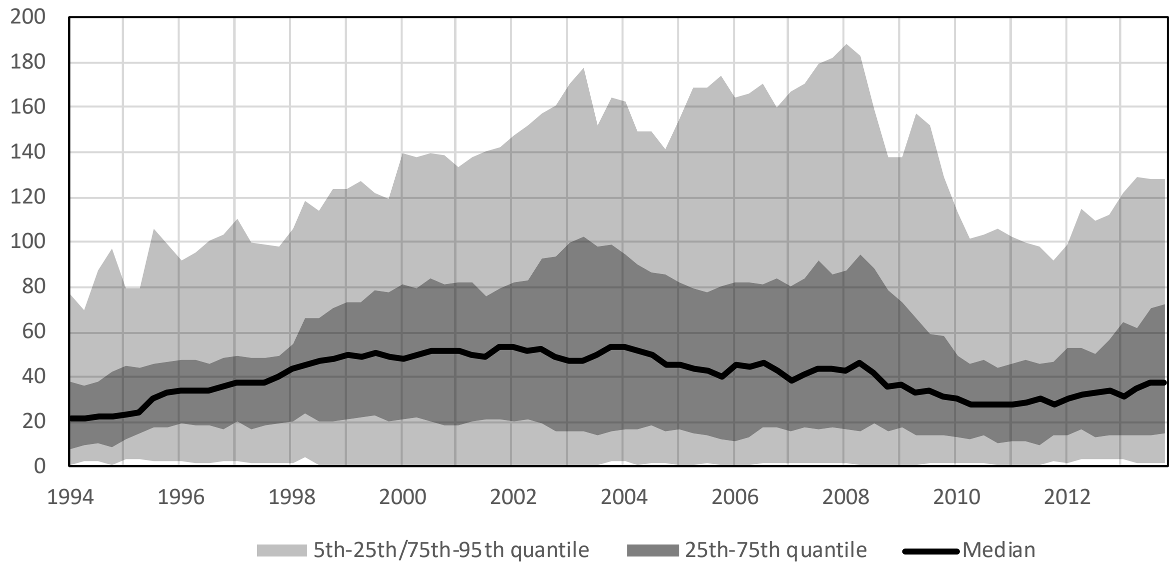

Figure 1. Evolution of bank-level Z-scores (1994 to 2013). The figure shows the evolution of the median, interquartile range and 90% range of the individual bank Z-score estimated according to Equation (3). The horizontal labels show the start of each year.

firms are punished more (less) harshly for being inefficient. (Boone, 2008).[4] Profits should vary more widely for any given change in variable costs when competition intensity is greater, indicated by a larger (negative) profit- to-variable cost elasticity. The Boone Indicator itself is a measure (through time) of the profit-to-variable-cost elasticity. Lower (more negative) values of the Boone indicator imply more intense competition, whereas higher (less negative) values point to less intense competition. This characteristic of the Boone indicator has implication for how we interpret the coefficients on $Competition_{t-2}$ in Equations (1) and (2). A positive value of β (or β_{θ}) suggests that more competition is associated with higher risk (lower Z-scores), consistent with the competition-fragility hypothesis, while finding a negative value implies that more competition is related with lower risk and supports the competition-stability hypothesis.

In our estimate of the Boone indicator, we take into account firm characteristics to account for heterogeneity in business models, in line with the existing literature. We also take account of the strategic behaviour of firms in building deposit market share. In the presence of consumer switching costs, deposit-takers can temporarily increase deposit interest rates to increase their customer base and expand their balance sheets. This strategic behaviour increases average variable costs, and hence the estimate of the elasticity of variable profits, but is not related to changes in the efficiency of the firm. Consequently, without adjusting for this behaviour, estimates of the Boone indicator will be too high (less negative) than that implied by the underlying efficiency of the industry. Appendix A describes this methodology in more detail.

Figure 2 shows the evolution of the adjusted Boone indicator for the period 1993 to 2013. The period 1993-1999 is dominated by banking market liberalisation initiatives in the UK and Europe that result in higher competition (de-Ramon & Straughan 2019). From 1999 to 2007 a general trend towards lower competition was apparent as UK banks experienced significant consolidation (de-Ramon & Straughan, 2019; Vives, 2016). Competition falters during the 2007-2008 financial crisis and its immediate aftermath (Vives, 2016). In 2010 competition begins to recover, but this recovery was contained in part due to the EU sovereign crisis that further fragmentation markets after 2011.

We include a number of bank-level controls to account for other factors that influence bank stability. Our choice of bank-level controls is based on the determinants of bank failure and bank distress literature (e.g., Cole, Cornyn and Gunther, 1995; Cole and White, 2012; Poghosyan and Čihák, 2011). We use bank size (log of total assets) in all of the specifications to consider the possibility that larger banks may be influenced by 'too-big-to fail', moral hazard incentives, although this may be

[4] We follow Schaeck and Čihák (2014) using average variable costs as a proxy for efficiency in empirical estimation of the Boone indicator. We use annualised quarterly profits and variable cost data in the estimation to ensure quarterly volatility does not distort the results. See Appendix A for more detail.

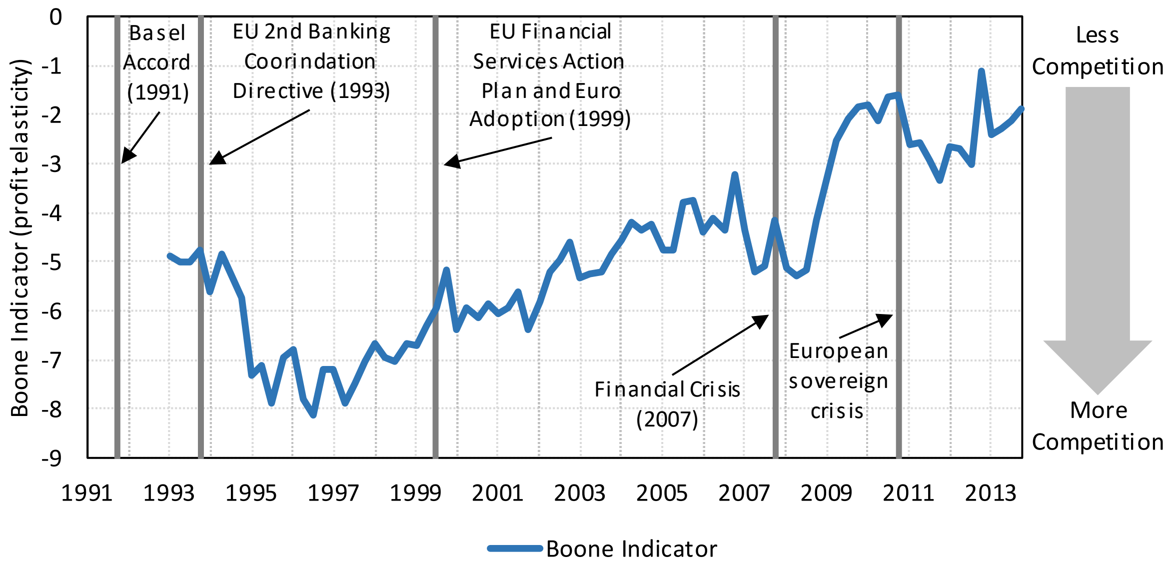

Figure 2. Evolution of the Boone indicator (1993 to 2013). The figure shows the evolution of the Adjusted Boone indicator estimated following the methodology described in Appendix A. The horizontal labels show the start of each year. The arrow on the right hand side indicates the direction of increasing competition intensity.

mitigated by better diversification across geographic regions and asset classes. In addition, we include the ratio of loan loss provisions to assets as a proxy for asset quality, with the idea that higher ratios reflect potentially higher credit risk. To account for business model diversification, we include the ratio of total loans to assets and the ratio of non-interest revenue to total revenue. We also include the ratio of wholesale funding to total liabilities to capture exposure to liquidity risk.[5]

The estimation period encompasses a full economic cycle as well as periods of notable turmoil in the banking sector, including the 2007-09 financial crisis and the UK small banks' crisis of the early 1990s (Balluck et al., 2016). To account for macroeconomic conditions, we incorporate: real economic growth, measured as annualised real GDP growth per quarter from UK Office for National Statistics (ONS), unemployment from Labour Market statistics (ONS), and annualised inflation, measured by the consumer expenditure deflator (ONS). We expect higher bank risk to be negatively related real to GDP growth and positively associated with unemployment and inflation.

3. Data and sample selection

We construct an unbalanced panel dataset using the Bank of England's Historical Banking Regulatory Database (HBRD), which contains detailed balance sheet and income statement information assembled from regulatory reports submitted by UK regulated firms (e.g., see de-Ramon, Francis and

[5] We test for endogeneity of the lagged bank-level and macroeconomic controls with the Z-score due to their possible correlation via a dynamic adjustment of income sources and funding side characteristics. We find that the bank-level controls are exogenous except for non-interest revenue; we use an instrument consisting of two additional lags to adjust.

Milonas, 2017). Our panel dataset includes quarterly information on more than 250 firms (banks, building societies and foreign bank subsidiaries operating in the UK) spanning the period 1989 to 2013.[6]

In defining the relevant banking market for this study, we focus on financial intermediaries that transform deposits into loans in the UK. This focus means that our initial sample includes a broad range of business models that tie together products and services across several financial markets including deposits, loans and payment services offered to different customers (households and businesses).[7] Given the fungible nature of banks' funding and the ability to cross-subsidise activities across the balance sheet, measuring competition in each market would require assigning costs arbitrarily to each activity. Instead, we measure UK banking market competition at an aggregated level and identify prices and costs (or concentration) based on an overall balance sheet-based approach rather than an activity-based approach.

Because of our focus on evaluating the effects of competition on bank-level risk in the UK banking market, we employ a number of filters to ensure we capture information that is most relevant for this market. First, to capture relevant 'banking' firms, we exclude firms that either do not fund their activities significantly with deposits or do not use their funding to provide loans. In particular, we exclude those firms that have a loan-to-assets ratio of less than 10% and a deposit-to-assets ratio less than 20%.[8] Second, to mitigate the influence of non-UK activities, we use data reported at the individual firm level rather than the group level. This approach helps ensure we capture activity booked in the domestic UK market, and not foreign activity booked by large, UK-regulated international groups that have material exposures to non-UK markets. Finally, to reduce the influence of extreme outliers, we follow standard practice in the literature and winsorise all firm-level variables at the top and bottom 1% tails of the distribution.

Table 1 provides summary statistics for the variables used in our empirical analyses.[9] After applying the filtering rules, the total size of the sample available for panel regressions varies between approximately 15,000 and 16,500 observations.[10] At the bottom of Table 1 we include a summary of the data by firm type. The majority of the observations includes small (under £50 billion) UK-owned

[6] Data for building societies cover a shorter timeframe, 1994 to 2013. Our sample excludes data on foreign branches operating in the UK, as we do not have the necessary financial data to estimate their Z-scores.
[7] Foreign branches, which are not included in our data set, do not generally provide these financial intermediary services.
[8] Such firms, tend to be niche institutions that do not compete directly with mainstream firms in the UK banking market. This definition is standard in the literature.
[9] For completeness, the table includes variables used in our robustness checks discussed below.
[10] Appendix C presents simple pairwise correlation coefficients between the variables used in the regression. This analysis shows competition variables are significantly and positively correlated. It also shows that Z-scores are negatively correlated with the Boone indicator and the Lerner index, which we use in robustness checks discussed in Section 5.

Table 1
Summary statistics

Variable	Number of Observations	Mean	Standard Deviation	Median	Minimum	Maximum
Dependent Variables						
Stability measures						
Z-score	15,528	51.381	45.379	37.510	0.431	282.845
Risk-adjusted capital ratio	15,528	46.338	43.028	32.829	0.708	266.316
Risk-adjusted return on assets	15,528	2.956	3.152	2.523	-3.102	17.359
Explanatory Variables						
Competition/concentration indicators						
Boone Indicator (adjusted)	92	-4.897	1.719	-5.049	-8.113	-1.111
Lerner Index (median)	97	0.087	0.020	0.086	0.051	0.145
HHI assets	97	924.7	461.4	645.1	469.2	1791.6
Bank-level controls						
Bank size (Total assets) (£million)	16,628	15,485	89,409	606	0.800	1,694,721
Total loans to assets ratio (%)	16,468	53.293	26.948	61.886	0.000	98.216
Provisions to assets ratio (%)	16,507	1.117	2.896	0.266	0.000	34.462
Non-retail deposit funding (%)	16,598	70.963	34.698	89.636	0.000	117.048
Non-interest revenue to total revenue (%)	16,216	19.450	21.225	12.044	-10.388	95.199
Capital buffer over requirements (%)	15,624	19.224	39.214	5.902	0.000	353.286
Macroeconomic controls						
GDP growth	93	0.019	0.021	0.023	-0.060	0.047
Inflation	97	2.807	1.883	2.409	-0.314	8.158
Unemployment	87	6.863	1.727	6.365	4.684	10.618
Bank type summary						
Z-score Large banks	340	34.381	31.804	23.663	0.764	195.910
Z-score Large Building Societies	828	78.594	60.276	58.971	2.661	282.650
Z-score Medium and Small Banks	4,258	34.222	33.850	24.463	0.431	273.262
Z-score Medium and Small Building Societies	3,569	79.323	45.594	72.815	1.597	282.845
Z-score Foreign	6,533	39.689	39.694	27.221	0.521	281.571

Notes: This table reports summary statistics on variables used in the estimations examining the link between competition and stability. All financial variables are derived from the Bank of England HBRD database (de-Ramon, Francis and Milonas, 2017). The database covers the period from December 1989 to December 2013 at quarterly frequency. Macroeconomic control variables come from the UK Office for National Statistics. The data used in the estimations (and reported here) are winsorised by eliminating observations at the 1st and 99th percentiles.

commercial banks, building societies and foreign-owned bank subsidiaries. Table 1 also shows that building societies tend to have higher average Z-scores.

4. Results

This section compares and contrasts the results of estimating our model of the relationship between competition and bank risk-taking using standard regression and quantile regression techniques. It also discusses results of models augmented to consider how this relationship changes due to the influence of firm type (as characterized by size and ownership) and regulatory pressure (as proxied by proximity to regulatory capital minimums). Finally, it outlines considerations for policymakers when thinking about the relationship between competition and banking sector risk more broadly.

4.1. Main model comparisons

Table 2 presents the results of estimating equation (1) using standard OLS regression with fixed effects (column 2) and equation (2) using quantile regression (in columns 3 to 7). Each model employs the

Table 2

The effect of competition on bank-level stability

Dependent Variable: ln(Z-score)	Standard Regression (2)	Quantile Regression 5th (3)	25th (4)	50th (5)	75th (6)	95th (7)
Boone indicator	0.018**	-0.073***	-0.009	0.033***	0.038***	0.028***
Bank-level controls	(0.007)					
Total assets	-0.065***	-0.075***	-0.084***	-0.080***	-0.068***	-0.043***
	(0.017)	(0.012)	(0.004)	(0.004)	(0.004)	(0.007)
Loans-to-assets ratio	-0.038	0.814***	0.248***	-0.095**	-0.185***	-0.133**
	(0.078)	(0.112)	(0.054)	(0.037)	(0.042)	(0.064)
Provisions-to-assets ratio	-2.207***	-15.251***	-11.991***	-5.070***	-3.333***	-3.073***
	(0.440)	(1.628)	(1.280)	(0.526)	(0.309)	(0.464)
Non-retail deposit funding	-0.157***	-0.513***	-0.488***	-0.545***	-0.443***	-0.268***
	(0.057)	(0.088)	(0.030)	(0.030)	(0.031)	(0.048)
Non-interest revenue	-0.012***	-0.022***	-0.018***	-0.018***	-0.017***	-0.016***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Macroeconomic controls						
GDP growth	3.035***	6.302***	3.132***	3.681***	3.009***	0.642
	(0.350)	(1.434)	(0.647)	(0.451)	(0.411)	(0.650)
Inflation	-0.028***	-0.034	-0.015*	-0.037***	-0.038***	-0.030***
	(0.007)	(0.024)	(0.009)	(0.007)	(0.007)	(0.010)
Unemployment rate	-0.095***	-0.055***	-0.075***	-0.100***	-0.090***	-0.060***
	(0.005)	(0.018)	(0.007)	(0.006)	(0.006)	(0.008)
Constant		2.703***	4.515***	5.588***	5.938***	6.079***
		(0.201)	(0.065)	(0.045)	(0.061)	(0.074)
R-squared	0.085	0.117	0.165	0.177	0.178	0.126
Number of observations	12262	13441				
F-test for equality of coefficient on competition variable across all quantiles				10.558***		
F-tests for equality of coefficient on competition variable between quantiles						
5th quantile			29.477***	40.339***	28.458***	28.162***
25th quantile				7.504***	2.577	3.674*
50th quantile					0.113	0.329
75th quantile						0.722

Notes: Column (2) reports the estimation of Equation (1) by panel fixed-effects. We use robust standard errors and clustered at the time level. Non-interest revenue use additional lags as instruments. Columns (3) to (7) report the estimation of Equation (2) by quantile regression; Pseudo-R2 are generated for the quantile regressions. The F-stat reported rejects the null hypothesis that all estimated coefficients on the competition parameter are equal across quantiles. The dependent variable in all specifications is the natural log of the Z-score, and the competition measure is the twice-lagged, deposit-adjusted Boone indicator (see Appendix A for details). Common macroeconomic and bank-level controls from the literature are included. The conditional mean and quantile regression estimations use all banks in the sample and quarterly data between 1994 and 2013. All explanatory variables enter with two lags except unemployment which enters with four lags. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parenthesis. For the quantile regression, standard errors are estimated using bootstrap procedures and are consistent across all quantiles.

Boone indicator as our primary measure of competition. The exogeneity test statistic reported at the bottom of Table 9 suggests that we cannot reject the null hypothesis of exogeneity of our lagged competition measure to the dependent variable, ln(Z-score).

Results under standard regression techniques (column 2) show that the coefficient on the Boone indicator is positive and statistically significant at the 1% level which shows that, on average, more competition is associated with higher bank risk (a lower Z-score), consistent with the competition-fragility view. However, we find strikingly different relationships between bank risk and competition across the conditional risk distribution when looking at the results generated using quantile regression (columns 3 to 7). In particular, the coefficient on the Boone indicator is negative for firms in the lower tail (high-risk end) of the distribution, indicating that already fragile institutions reduce risk with heightened competition, consistent with the competition-stability hypothesis.[11] This relationship switches from being negative to positive for firms in the upper tail (low-risk end) of the distribution, indicating that for the relatively low-risk firms within the banking system, risk-taking behaviour increases as competition mounts, consistent with the competition-fragility view and the conclusion under standard regression.

We confirm that the coefficient estimates for the Boone indicator across all quantiles are statistically distinct using F-tests to reject the null hypothesis that the estimates are equal, providing evidence of heterogeneous relationships within the system.[12] This means that the effects of competition can both increase and decrease risk at the same time depending on the underlying risk-profile of the firms in the banking system. Figure 3 illustrates these effects and shows that for the weakest institutions, more intense competition is associated with higher Z-scores (i.e., a negative association), but that the relationship switches for lower-risk institutions. Figure 3 also shows that the quantile estimates are statistically different from the conditional mean estimates (depicted by the dashed line) across a broad range of Z-scores.

Together, these findings imply not only that the relationships between competition and risk may differ depending on the underlying risk of individual institutions, but also that the relationships can potentially be countervailing within banking markets. Such offsetting effects mean there may be trade-offs to weigh, especially on overall system-wide stability, when considering the impacts of competition. While the output from Table 2 can help in gauging the trade-offs, previous research has found evidence that the relationship between competition and risk is sensitive to other features related to size, organizational form and capitalisation (e.g., Tabak, Fazio and Cajueiro, 2012; Liu and Wilson, 2013; Schaeck and Čihák, 2014; Kick and Prieto, 2015) that could potentially have further influences. We explore these other features in more depth below and what they mean for evaluating trade-offs and system-wide financial stability.

Under each approach the coefficients on the macroeconomic and bank-level controls are consistent with expectations. We find that firm-level Z-scores increase, i.e., risk decreases, as inflation and unemployment rates fall and as GDP growth increases as expected. At the firm level, more reliance on relatively more volatile non-retail (wholesale) deposit funding is associated with lower Z-scores,

[11] Schaeck and Čihák (2014) and Kick and Prieto (2015) also find that lower Boone indicators (i.e., more competition) are associated with lower bank risk, supportive of the competition-stability hypothesis.

[12] These results are consistent with Liu and Wilson (2013) who find that the strength of the relationship between competition and risk of Japanese commercial and cooperative banks varies across initial levels of risk. They find that competition reduces risk at the weakest banks in Japan, while at the same time it increases risk at healthier banks.

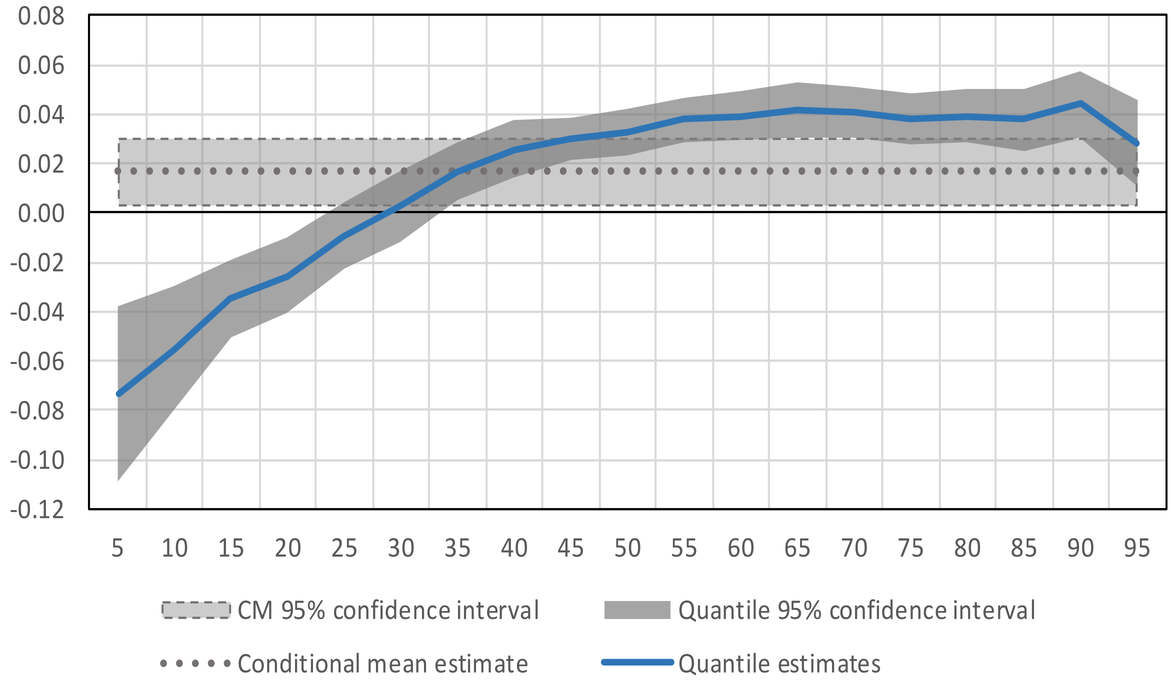

Figure 3. Marginal impact of competition at different points of the conditional risk distribution. The solid line joins 100 values of the quantile regression parameters β_θ from equation (4) while the 95% bands joins 100 individual intervals for each quantile from zero to 100. The conditional mean estimate and confidence interval correspond to the conditional mean estimated parameters and 95% confidence interval. The horizontal scale shows the quantiles from zero to 100. Positive (negative) values on the vertical scale represent less (more) competition.

i.e., higher risk. Overall, Z-scores are lower (i.e., risk is higher) at larger institutions and at institutions with higher measures of credit risk (provisions to assets) and higher sources of non-interest revenue (indicative of a lack of focus on risks associated solely with banking). While the total loan to asset ratio is insignificant in the standard regression estimation, it is significant in the quantile regressions, and suggests that balance sheet composition explains risk heterogeneity across the conditional risk distribution. In particular, the results suggest that higher loan to asset ratios are positively (negatively) associated with lower risk at the low (high) end of the conditional risk distribution.

4.2. Analysis by firm type (asset size and ownership form)

To examine whether our results are driven by particular types of banking firms, we modify our quantile specifications to allow for heterogeneity in the parameters of the competition measure as follows:

$$Q_\theta\left(Risk_{i,t} \middle| FirmType_{f,t}\,, Competition_{t-2}\,, X_{i,t=2}\,, Y_{t-2}\right)$$
$$= \alpha_\theta + \delta\, FirmType_{f,t} + \beta_{\theta f} Competition_{t-2} \times FirmType_{f,t} + \Phi_\theta X_{i,t-2} \qquad (4)$$
$$+ \Theta_\theta Y_{t-2} + \upsilon_{i,t},$$

where $FirmType_{f,t}$ is a dummy variable classifying firms according to asset size and ownership form. The parameter $\beta_{\theta f}$ represents the specific effect of competition on firm type f. We consider size as a differentiating factor using total assets, given that the largest firms are those most capable of achieving higher leverage (lower equity ratios) due, for example, to too-big-to fail perceptions. Allen, Carletti and Marquez (2011) suggests that asset size could be another distinguishing factor: they predict that when small banks are more involved in relationship lending than large banks, they will have larger capital levels, placing them on different parts of the risk distribution. In addition to size, we consider ownership form as a second differentiating characteristic due to previous theoretical arguments and empirical evidence on the effects of organizational form on risk-taking incentives (e.g., Iannotta, Nocera and Sironi, 2007). The ownership form distinction allows us to understand better the different effects that competition may have on risk at firms that are shareholder-owned (commercial banks), mutually-owned (building societies) or foreign-owned (international banks operating as UK subsidiaries).[13] There is also evidence in the literature that finds significant differences in the performance and risk-taking between shareholder-owned banks and mutual building societies in the UK, providing yet further impetus for our added focus on ownership form (Valnek, 1999).

With size-ownership criteria in mind, we construct firm type dummies for large banks (the top seven largest shareholder-owned commercial banks each period which capture roughly 80% of the commercial banking sector's assets), large building societies (the top twelve mutually-owned building societies each period which capture 40% of the building society sector's assets), small commercial banks, small building societies, and foreign-owned banks operating as UK subsidiaries of non-UK domiciled banking groups.[14] When estimating Equation (4), we exclude the large-bank dummy variable and treat these institutions as the reference firm type. The interaction terms in this setup reveal, conditional on the underlying risk of the firm, the relationship between competition and risk for each firm type separately. Other studies have followed a similar approach to investigate for different relationships between competition and risk across various firm types in traditional regression setups (Liu and Wilson, 2013; Kick and Prieto, 2015). These studies, however, do not consider whether the effect of firm type differs across the conditional risk distribution. This aspect of our analysis offers a multi-dimensional perspective of the relationship between competition and risk (at the individual level) that, to our knowledge, has not featured in previous research.

[13] This distinction between shareholder-owned and mutually-owned institutions may also capture differences in the business models and legal constraints between banks and building societies which may affect the way that these firms respond to competition. For example, de-Ramon and Straughan (2019) show that building societies had systematically less market power than banks over the period 1994 to 2013 and attribute this to building societies' mutual ownership structure and regulatory constraints which limit the types of loans they extend (retail and small business) and their funding sources (predominantly retail deposits).

[14] Foreign-owned banks generally have a much smaller presence than domestic banks in UK retail deposit and lending markets. No foreign banks meet the definition for being a large bank using this process.

Table 3 reports the results from this analysis. As with the previous table, column 2 reports estimates from standard regression while columns 3 to 7 include those from quantile regression. We report only the relevant parameter estimates for the interaction terms, which reflects the relationship between competition and risk for each firm type separately, conditional on the underlying risk-profile of the firm.[15] Results using standard regression provide some first clues as to how additional heterogeneity in firm size and ownership influences the association. In particular, it shows that the coefficient on the interaction term is negative for large banks, suggesting that the Z-scores of these firms improve (i.e., risk falls) as competition intensity increases, which contrasts with the average outcome for all firms (reported in Table 2). For all other institutions, the coefficient is positive, indicating that Z-scores are adversely associated with competition (i.e., risk increases) at these firms, although the association is not significant for foreign banks.

Quantile regression results provide even greater nuance and suggest that the relationship with competition at different points across the conditional risk distribution varies depending on the types of firm. Table 3 shows that, with the exception of foreign-owned banks, the risk-reducing effects of competition are most evident in the most fragile domestic banks (columns 3 to 5) and building societies (column 3). For large banks, the interaction term is always negative (albeit not statistically significant for some quantiles), implying that greater competition is generally risk-reducing. This relationship is also evident for relatively risky, small UK banks (columns 4 and 5). The destabilising effects of competition are most pronounced for relatively low-risk, small building societies (columns 4 to 7), large building societies (columns 5 and 6) and all foreign bank subsidiaries. F-tests (reported at the bottom of Table 3) reject the hypothesis of the equality of coefficients across quantiles, supporting the idea that the relationship between competition and risk is different across the conditional-risk distribution, even after considering the possible additional influence that firm type has on risk-taking.

Taken together, the results show that there is significant variation in the competition-risk relationship, both between and within firm types, which could have implications for assessing the links between banking sector stability and competition. This issue seems especially acute when comparing the large versus small firm effects, where the results indicate that competition has a generally risk-reducing impact on all large banks and small, more risky banks, but a risk-increasing influence on building societies that are already low risk and foreign subsidiaries. Two recent papers offer possible explanations for these findings. First, Wagner (2010) considers a model of competition with endogenous bank-risk taking where banks choose their risk depending on the competition level they

[15] The coefficients on the macro and bank-level control variables are similar to those reported in Table 2. The full set of results is available upon request.

Table 3

Regression of ln (Z-score) on competition: influence of firm type on the effect of competition

	Standard	Quantile Regression				
	Regression	5th	25th	50th	75th	95th
Dependent variable: ln (Z-score)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Interaction terms with Boone indicator:						
Large UK banks	-0.0389**	-0.3224***	-0.0281	-0.0236	-0.0227	-0.0603**
	(0.0155)	(0.0322)	(0.0316)	(0.0231)	(0.0372)	(0.0304)
Large building societies	0.0133	-0.0731***	-0.0138	0.0697***	0.0675***	-0.0477
	(0.0182)	(0.0197)	(0.0138)	(0.0224)	(0.0179)	(0.0434)
Small building societies	0.0296***	-0.0472***	0.0535***	0.0725***	0.0892***	0.0661***
	(0.0102)	(0.0113)	(0.0068)	(0.0069)	(0.0099)	(0.0118)
Small UK banks	0.0179**	-0.0426	-0.0509***	-0.0475***	-0.0150	0.0224
	(0.0079)	(0.0262)	(0.0155)	(0.0136)	(0.0120)	(0.0208)
Foreign banks	0.0088	0.0613*	0.0354***	0.0126	0.0023	0.0299*
	(0.0098)	(0.0323)	(0.0110)	(0.0092)	(0.0106)	(0.0163)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes					
Constant		Yes	Yes	Yes	Yes	Yes
R-squared	0.0859	0.1883	0.1999	0.2065	0.2047	0.2050
Number of observations	12,262	13,441				
F-test for equality of coefficient on interaction terms across quantiles p > F(4,13423):						
Large UK banks		19.840***				
Large building societies		10.933***				
Small building societies		30.424***				
Small UK banks		4.143***				
Foreign banks		2.509**				

Notes: Column (2) reports the estimation of Equation (1) by panel fixed-effects instrumental variables. We use robust standard errors and clustered at the time level. Columns (3) to (7) report the estimation of Equation (5) by quantile regression; Pseudo-R2 are generated for the quantile regressions. The F-stat reported rejects the null hypothesis that all estimated coefficients on the competition parameter are equal across quantiles. The dependent variable in all specifications is the natural log of the Z-score, and the competition measure is the twice-lagged, deposit-adjusted Boone indicator (see Annexe A for details). The interaction terms measure the effects of competition for (i) large, shareholder-owned institutions (large UK banks); (ii) small, shareholder-owned institutions (small UK banks); (iii) large, depositor-owned institutions (large building societies); (iv) small, depositor-owned institutions (small building societies); and (v) foreign-owned banks. Common macroeconomic and bank-level controls from the literature are included. The conditional mean and quantile regression estimations use all institutions in the sample and quarterly data between 1994 and 2013. All explanatory variables enter with two lags except unemployment which enters with four lags. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parenthesis. For the quantile regression, standard errors are estimated using bootstrap procedures and are consistent across all quantiles.

face. When competition increases, portfolio risk falls because borrowers choose lower levels of risk as in Boyd and De-Nicoló (2005). However, this effect can be reversed because, as borrowers become safer and the bank's franchise value falls (due to lower profit margins), a bank takes on more lending risk to maintain profits. Wagner goes on to show that the increase in risk depends on the intensity of competition, its impact on margins and the characteristics of the bank. The ultimate impact on solvency can be positive or negative and depends on the balance between benefits from greater risk taking and losses. Second, Freixas and Ma (2015) develop a model that considers how banks set leverage endogenously in the face of stronger competition and how such movements interact with the Boyd and de-Nicolo (2005) asset side risk-shifting effect. They find that when banks that rely on less stable, wholesale funding coexist with banks that rely on more stable, retail deposits, in the face of higher competition, the Boyd and de-Nicolo (2005) risk-shifting effect dominates for the former, improving stability, while leverage increases at the latter banks, reducing stability.

Our results imply that bank regulators and policymakers may need to consider trading off reducing risk for the riskiest firms with increasing the riskiness of the least risky firms when evaluating measures that may have an effect on competition. Such trade-offs may also have important implications for gauging and assessing the effects of competition on sector-wide stability, which we highlight in more detail in Section 4.4 below.

4.3. Analysis of regulatory pressure

Research shows that regulatory capital requirements influence banks' choice of capital ratios and balance sheet activities and that such effects can depend on how close a bank is to regulatory minima (Hancock and Wilcox, 1994; Ediz, Michael and Perraudin, 1998; Alfon, Argimon and Bascuñana-Ambros, 2004; Berrospide and Edge, 2010; Francis and Osborne, 2012). These results suggest that the trade-offs highlighted above might depend on how regulatory capital requirements influence firm risk as competition changes.[16] This sub-section examines whether and how regulatory pressure influences the relationship between competition and risk. To characterize regulatory pressure, we construct a dummy variable equal to one if a firm's regulatory capital buffer (the firm's actual capital ratio above its required minimum capital ratio) is in the lowest decile, and zero otherwise. We modify Equation (2) to include this dummy variable and an interaction term with the Boone indicator as follows:

$$\begin{aligned} Q_\theta\left(Risk_{i,t}\middle|Competition_t, RegPressure_{i,t-2}, X_{i,t-2}, Y_{t-2}\right) \\ = \alpha_\theta + \delta_\theta RegPressure_{i,t-2} + \beta_\theta Competition_{t-2} \\ + \lambda_\theta Competition_{t-2} \times RegPressure_{i,t-2} + \Phi_\theta X_{i,t-2} + \Theta_\theta Y_{t-2} \\ + \upsilon_{i,t}. \end{aligned} \tag{5}$$

The coefficient on the interaction term in this setup provides a measure of the marginal effect on risk of competition at banks that are close to their regulatory minimum and, thus, under regulatory pressure. Finding a negative coefficient on the interaction term would be consistent with the idea that regulatory pressure reduces risk-taking incentives at these firms.

Table 4 reports the results of this estimation under both standard regression (column 2) and quantile regression (columns 3 to 7). We report only the relevant results for the coefficients on the Boone indicator, the interaction term and the regulatory pressure dummy variable. Results under

[16] This idea is in line with Fischer and Grout (2014) who suggest that a proactive approach to competition is most likely to reduce bank risk. Although there may be an optimal point of competition in banking due to fixed entry costs, the authors explain that the optimal competition level may be an academic question rather than practical one. A prudential regulator can always push banks to the right level of risk (undoing moral hazard) regardless of the amount of competition in the system.

Table 4

Regression of ln (Z-score) on competition: influence of regulatory pressure

Dependent variable: ln (Z-score)	Standard Regression (2)	Quantile Regression 5th (3)	25th (4)	50th (5)	75th (6)	95th (7)
Boone indicator	0.031***	-0.0776***	-0.0035	0.0358***	0.0435***	0.0337***
	(0.0088)	(0.0182)	(0.0068)	(0.0055)	(0.0054)	(0.0082)
Boone indicator × Regulatory pressure	-0.192***	0.0250	-0.0331**	-0.0532***	-0.0548***	-0.0672**
	(0.0461)	(0.0786)	(0.0168)	(0.0188)	(0.0142)	(0.0295)
Regulatory pressure	-0.947***	0.1151	-0.3351***	-0.4424***	-0.4495***	-0.5612***
	(0.2754)	(0.4579)	(0.0960)	(0.1134)	(0.0736)	(0.1340)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	–	–	–	–	–
Constant	-	Yes	Yes	Yes	Yes	Yes
R-squared	0.077	0.1174	0.1618	0.1714	0.1787	0.1847
Number of observations	12,262	13,441				
F-test for equality of quantile coefficients p>F(4,12521)						
Boone indicator		7.362***				
Boone indicator × Regulator pressure		2.745***				

Notes: Column (2) reports the estimation of Equation (1) by panel fixed-effects instrumental variables. We use robust standard errors and clustered at the time level. Columns (3) to (7) report the estimation of Equation (6) by quantile regression; Pseudo-R2 are generated for the quantile regressions. The F-stat reported rejects the null hypothesis that all estimated coefficients on the competition parameter are equal across quantiles. The dependent variable in all specifications is the natural log of the Z-score, and the competition measure is the twice-lagged, deposit-adjusted Boone indicator (see Annexe A for details). The regulatory pressure dummy variable is one if a firm has a capital buffer in the smallest decile and zero otherwise. Common macroeconomic and bank-level controls from the literature are included. The conditional mean and quantile regression estimations use all banks in the sample and quarterly data between 1994 and 2013. All explanatory variables enter with two lags except unemployment which enters with four lags. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parenthesis. For the quantile regression, standard errors are estimated using bootstrap procedures and are consistent across all quantiles.

standard regression (column 2) indicate that competition is associated with higher risk (lower Z-scores), but that regulatory pressure mitigates this destabilising relationship on average. Similar results are evident in the quantile regression results for the relatively less risky institutions (in the 50th, 75th and 95th quantiles) that also face such pressure. These results are consistent with the idea that regulatory discipline may make the capital-at-risk effect greater than the franchise-value effect (in the spirit of Hellman, Murdoch and Stiglitz, 2000), thereby reducing incentives to take risks. These result support the idea that it may be possible to address the trade-offs between competition and stability through regulation to some extent (Vives, 2016).

4.4. Implications for system-wide bank stability

The results presented so far suggest that there may be real differences in the relationship between risk and competition within the system. Results from the conditional mean regression in Table 2 indicate that, on average, competition increases risk at the individual bank level which, by extension, might also imply a similar relationship for the banking system overall. At the same time, however, results from the quantile regression indicate that this relationship is evident only for institutions that are relatively less risky (i.e., have higher Z-scores) to begin with, while for more fragile firms competition reduces risk. These varied relationships at the firm level mean that the relationship at the system-wide level is not obvious and will depend on how the individual relationships aggregate across the system.

In this subsection we undertake a simple exercise to illustrate the implications for evaluating the relationship between competition and broader financial stability. More specifically, we trace the distribution of Z-scores in the UK banking sector over our sample period and then show how this distribution changes in response to an increase in competition, i.e., moving the Boone indicator to bring it into line with the relatively higher levels of competition intensity characterizing the mid-1990s in the UK (see Figure 2). The motivation for this exercise comes from the literature, where previous papers have used measures of the central tendency of the distribution of bank-level Z-scores to proxy system risk of the entire banking sector. For example, Beck, Demirgüç-Kunt and Levine (2010) uses the median Z-score to proxy banking sector risk within countries (or groups of countries).[17] In addition, Houston et al. (2010) employs the asset-weighted average of bank-level Z-scores to measure system-wide insolvency risk, although Strobel (2011) shows that the weighted average Z-score provides a downwardly-biased measure of the weighted average probability of insolvency, raising questions about its use as a measure of system soundness. Nevertheless, Strobel goes on to demonstrate that the weighted nth percentile of Z-scores gives an unbiased measure of the weighted nth percentile of probabilities of insolvency.

Taking the lead from these papers, we simulate the change in the distribution of Z-scores, first using the parameter from the standard regression (reflecting the average relationship) and second using the parameters from the quantile regression (reflecting differences in underlying risk). We then examine how the different central tendency measures of the Z-score distribution noted above compare. We calculate the two alternative Z-scores for each bank-time data point by increasing competition by two standard deviations, which is approximately a 3½ point reduction in the Boone indicator, or roughly the equivalent of a return to the more dynamic competition conditions of the mid-1990s from the immediate pre-crisis levels in 2006-2007 (see Figure 2). Table 5 reports the results of this counterfactual exercise focusing on institutions in the bottom quintile of the Z-score (the riskiest 20 per cent of firms) and compares the impact on comparable measures for those institutions in the least risky quintile (safest 20 per cent of firms) in our sample.

The simulation for the riskiest quintile of firms using the standard regression parameter shows that the competition-fragility hypothesis dominates, with the Z-score reduced by 6% in response to a 3½ point reduction in the Boone indicator (column 2). In contrast, the simulation for the riskiest firms

[17] This method underlies the Z-scores reported by the World Bank in its database of financial measures (e.g., see Beck, Demirgüç-Kunt and Levine, 2010).

Table 5

Impact of increasing competition on aggregate solvency risk measured using Z-scores

	Impact on Z-score (Riskiest Firms)[(1)]		Impact on Z-score (Safest Firms)[(2)]		Impact on Z-score (All Firms)	
	(2)	(3)	(4)	(5)	(6)	(7)
Regression methodology	Standard	Quantile	Standard	Quantile	Standard	Quantile
Impacts of competition on:						
Unweighted average	-6%	17%	-6%	-10%	-6%	-9%
Asset-weighted average	-6%	15%	-6%	-11%	-6%	-7%
Unweighted median	-6%	18%	-6%	-12%	-6%	-10%
Asset-weighted median	-6%	13%	-6%	-13%	-6%	-4%
Suggested impact on systemic soundness	Fragility	Stability	Fragility	Fragility	Fragility	Fragility
Share of total assets	22.2%		5.9%		100.0%	

Notes: This table reports the percentage change in the simple (unweighted) average, asset-weighted average, simple median and asset-weighted median of bank-level Z-scores for all firms and for firms in the first and fifth risk quintiles. (1) data between 0th and 20th percentiles; (2) data between 80th and 100th percentiles.

using parameters from the quantile regression suggests that the competition-stability effect dominates, with a favourable impact on the central tendency measures of Z-scores, showing increases of 13% to 18% (column 3). Table 5 also shows that the firms in the riskiest quintile are also some of the largest firms, comprising over 22% of total system assets.

The simulation results for the safest quintile of firms are shown in columns 4 and 5. The result using the standard regression parameters is identical to that of the riskiest firms as there is no allowance for heterogeneity in firm-specific risk. The unfavourable impact of increased competition on firm-specific risk using the quantile regression estimates is higher than the effect using the standard regression parameters for all Z-score measures. At the same time, these firms tend to be some of the smallest, holding roughly 6% of system assets, making them potentially less important for system soundness overall. The range of negative results for the Z-score central tendency measures for the safest firms of between 10% and 13% are therefore smaller than the improvements for the riskiest firms. Together, these disparate results mean that policymakers, when evaluating the consequences of competition on banking system stability more widely, may need to consider trading off an increase in risk for the least risky firms with a reduction in risk for the most risky firms. Columns 6 and 7 show the effects for the full sample (12,265 observations). Again, the results for the standard regression parameters are the same as for the riskiest and safest firms, while the quantile regression simulation suggests that the overall competition-fragility relationship is not dissimilar, with the decline in the central tendency measures ranging between 4% and 10%.

This exercise shows how using the conditional regression results alone could lead one to conclude that competition could undermine the stability of all firms and the system overall. Supplementing such analysis with quantile regression can help uncover heterogeneous effects within the system that might lead one to infer differently. Combining the conditional mean and quantile regression results may identify important trade-offs between the effects on the most risky, least stable banks and the least risky, most stable banks, that can help inform the need for and design of regulatory measures.

5. Robustness checks

We subjected the above findings to a number of robustness checks which show that the standard and quantile regression results are robust to: (i) using alternative measures of bank risk; (ii) using alternative measures of competition; and (iii) excluding crisis periods from our estimation sample. We discuss results from each of these checks in turn below.

5.1. Alternative measures of bank risk

We employ two alternative measures of bank risk to estimate equations (1) and (2): (i) risk-adjusted profitability, $RoA_{i,t}/\sigma_{i,t}^{RoA}$, and (ii) risk-adjusted leverage, $k_{i,t}/\sigma_{i,t}^{RoA}$.[18] As each of these measures is an additive component of the Z-score, examining the relationship with competition separately can shed light on the dominant factors underlying the competition-risk nexus. The coefficients on the competition indicators in specifications employing the leverage measure, $k_{i,t}/\sigma_{i,t}^{RoA}$, can provide indirect evidence on the *franchise-value effect*. Positive values for β_θ in equation (2) imply that, as competition increases, risk-adjusted capital ratios decrease, supporting the franchise value effect and the competition-fragility hypothesis. Estimates using profitability as the dependent variable can provide evidence of the risk-shifting effects posited by Boyd and De Nicoló (2005). Negative values of β_θ would imply that as competition increases, risk-adjusted profitability increases, consistent with the risk-shifting paradigm and the competition-stability hypothesis.

Table 6 reports the relevant coefficient estimates for the Boone indicator using risk-adjusted leverage (Panel A) and risk-adjusted profitability (Panel B). Column 2 in Panel A shows that the coefficient on competition is positive under the standard regression approach, implying that capital ratios decline as competition mounts, consistent with competition-fragility. This finding supports the results of our main model using this regression technique. The coefficient estimates on competition under the quantile regressions are similar in sign and significance across the five quantiles to those reported in our main model. These results provide further evidence that the relationship between competition and bank-risk are different across the conditional risk distribution. In this case, the negative coefficients found at the 5th and 25th quantiles (columns 3 and 4) indicate that risk-adjusted leverage improves as competition increases for the riskiest 25% of firms, while the positive coefficients reported across the remaining quantiles (columns 5 to 7) indicate that risk-adjusted leverage worsens

[18] Other studies have evaluated the impact of competition on components of Z-scores (e.g., Beck, De Jonghe and Schepens, 2013 and Schaeck and Čihák, 2014 for banks; Cummins, Rubio-Misas and Vencappa, 2017 for European life insurers).

Table 6

Robustness tests: alternative measures of bank stability

	Standard Regression (2)	Quantile Regression 5th (3)	25th (4)	50th (5)	75th (6)	95th (7)
Panel A: Dependent variable: Risk-adjusted leverage ratio						
Competition (Boone Indicator)	2.204***	-0.504***	-0.293**	1.536***	3.289***	4.307***
	(0.392)	(0.106)	(0.133)	(0.180)	(0.265)	(0.723)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes					
Constant		Yes	Yes	Yes	Yes	Yes
R-squared	0.103	0.037	0.107	0.153	0.193	0.175
Number of observations	12248	13423				
F-test for competition parameter equality, $p > F(4,13414)$			34.306***			
Panel B: Dependent variable: Risk-adjusted returns						
Competition (Boone Indicator)	-0.285***	-0.311***	-0.244***	-0.221***	-0.283***	-0.539***
	(0.036)	(0.020)	(0.014)	(0.014)	(0.022)	(0.055)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes					
Constant		Yes	Yes	Yes	Yes	Yes
R-squared	0.107	0.095	0.102	0.096	0.093	0.129
Number of observations	12223	13414				
F-test for competition parameter equality, $p > F(4,13414)$			12.779***			

Notes: Column (2) reports the estimation of Equation (1) by panel fixed-effects instrumental variables. We use robust standard errors and clustered at the time level. Columns (3) to (7) report the estimation of Equation (2) by quantile regression; Pseudo-R2 are generated for the quantile regressions. The F-stat reported rejects the null hypothesis that all estimated coefficients on the competition parameter are equal across quantiles. The dependent variable in Panel A is the risk-adjusted leverage ratio, while in Panel B, the dependent variable is the risk-adjusted return on assets. In all specifications the competition measure is the twice-lagged, deposit-adjusted Boone indicator (see Annexe A for details). Common macroeconomic and bank-level controls from the literature are included. The conditional mean and quantile regression estimations use all banks in the sample and quarterly data between 1994 and 2013. All explanatory variables enter with two lags except unemployment which enters with four lags. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parenthesis. For the quantile regression, standard errors are estimated using bootstrap procedures and are consistent across all quantiles.

as competition intensifies. The F-test rejects the null hypothesis of coefficient equality on the competition measure, consistent with the findings from the main model.

Panel B shows that the coefficients on competition are consistently negative and statistically significant for the standard regression (column 2) and across all quantiles, suggesting that heightened competition improves risk-adjusted returns for all banks. The negative association is consistent with an outcome implied by mechanisms underlying Boyd and De Nicoló (2005): more competition decreases the credit risk of bank borrowers, which lowers credit losses and increases earnings overall. These results align better with the competition-stability hypothesis which, together with the results on risk-adjusted capitalisation discussed above, imply that the two main competing theories on the effects of competition hold concurrently depending on how measures of risk are defined. The combined results also indicate that the primary way in which relatively stable firms increase their risk profile in response to higher competition is by lowering capital (de-Ramon, Francis and Straughan, 2018).

5.2. Alternative measures of competition

We employed different measures of competition, replacing the Boone indicator with measures of the Lerner index (market power) and the Herfindahl Hirschman index (HHI) (concentration). Table 7 reports the results and shows that, in general, the findings are similar to those of the benchmark specifications in Table 2. The signs on coefficient estimates on the Lerner index (Panel A) and HHI (Panel B) are similar to those on the Boone indicator for the conditional mean and quantile regressions and should be interpreted in the same way. In addition, Table 7 shows that equality of coefficient estimates across the quantiles can be rejected, providing further support that the findings using the Boone are robust.

5.3. Exclusion of crisis periods

Our estimation period spans both the 2007-09 financial crisis as well as the UK small banks crisis of the early 1990s. We excluded both of these crisis periods from our estimation sample to see if crisis periods distort our results. Table 8 reports the results of this exercise and shows that the signs of the coefficients on competition under the conditional mean and quantile regressions are similar to those of our main model reported in Table 2. The coefficient on competition under conditional mean regression (column 2) is positive, consistent with competition-fragility. Under quantile regression, the signs move from being negative at the lower quantiles, suggestive of competition-stability for relatively risky firms, and positive at the higher quantiles, implying competition-fragility for the relatively least risky firms. Table 8 also indicates we can reject the equality of these coefficients across quantiles, further confirming the results when using the full sample period.[19]

5.4. Testing exogeneity of competition measure

To ensure the relationship between competition and stability is not biased, we re-estimated equation (1) and performed formal exogeneity tests on our measures of competition using instruments for competition. In particular, we formally evaluate the null hypothesis that the suspect regressor, competition, can be treated as exogenous. The exogeneity test is the difference between two Sargan-Hansen statistics: one generated for an equation with a smaller set of instruments where the suspect regressors are treated as endogenous, and one for an equation with the larger set of instruments, where the suspect regressors are treated as exogenous (see Hayashi, 2000, pp. 233-34). The test statistic is distributed as chi-squared with degrees of freedom equal to the number of regressors tested.

[19] Given our long estimation period (1994 to 2013), the possibility of other structural changes beyond those set out in Table 8 could exist. We plan to explore this issue in future work.

Table 7

Robustness tests: alternative measures of competition

Dependent variable: ln (Z-score)	Standard Regression (2)	Quantile Regression 5th (3)	25th (4)	50th (5)	75th (6)	95th (7)
Panel A: Lerner Index	2.160***	-1.365	0.683	2.329***	1.960***	3.670***
	(0.385)	(1.766)	(0.641)	(0.482)	(0.386)	(0.712)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes					
Constant		Yes	Yes	Yes	Yes	Yes
R-squared	0.086	0.114	0.165	0.176	0.176	0.127
Number of observations	12262	13441				
F-test for competition parameter equality, $p > F(4, 13441)$			3.298**			
Panel B: HHI - assets	0.076**	-0.325***	-0.022	0.116***	0.165***	0.145***
	(0.031)	(0.084)	(0.029)	(0.021)	(0.022)	(0.033)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes					
Constant		Yes	Yes	Yes	Yes	Yes
R-squared	0.085	0.117	0.165	0.176	0.177	0.127
Number of observations	12262	13441				
F-test for competition parameter equality, $p > F(4, 13441)$			9.706***			

Notes: Column (2) reports the estimation of Equation (1) by panel fixed-effects instrumental variables. We use robust standard errors and clustered at the time level. Columns (3) to (7) report the estimation of Equation (2) by quantile regression; Pseudo-R2 are generated for the quantile regressions. The F-stat reported rejects the null hypothesis that all estimated coefficients on the competition parameter are equal across quantiles. The dependent variable in all specifications is the natural log of the Z-score, and the competition measure is the twice-lagged, Lerner index (Panel A) and the HHI for assets (Panel B). Common macroeconomic and bank-level controls from the literature are included. The conditional mean and quantile regression estimations use all banks in the sample and quarterly data between 1994 and 2013. All explanatory variables enter with two lags except unemployment which enters with four lags. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parenthesis. For the quantile regression, standard errors are estimated using bootstrap procedures and are consistent across all quantiles.

Table 8

Robustness tests: Sample excluding crisis periods (prior to 1994 and after 2007)

Dependent variable: ln (Z-score)	Standard Regression (2)	Quantile Regression 5th (3)	25th (4)	50th (5)	75th (6)	95th (7)
Competition (Boone Indicator)	0.012	-0.038	-0.022	0.003	0.024*	0.054**
	(0.010)	(0.034)	(0.017)	(0.013)	(0.013)	(0.022)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes					
Constant		Yes	Yes	Yes	Yes	Yes
R-squared	0.080	0.187	0.207	0.200	0.187	0.123
Number of observations	8105	8699				
F-test for competition parameter equality, $p > F(4,8699)$			2.820**			

Notes: Column (2) reports the estimation of Equation (1) by panel fixed-effects instrumental variables. We use robust standard errors and clustered at the time level. Columns (3) to (7) report the estimation of Equation (2) by quantile regression; Pseudo-R2 are generated for the quantile regressions. The F-stat reported rejects the null hypothesis that all estimated coefficients on the competition parameter are equal across quantiles. The dependent variable in all specifications is the natural log of the Z-score, and the competition measure is the twice-lagged, deposit-adjusted Boone indicator (see Annexe A for details). Common macroeconomic and bank-level controls from the literature are included. The conditional mean and quantile regression estimations use all banks in the sample and quarterly data between 1994:Q1 to 2007:Q2 (excluding data from before 1994, during the UK small banks crisis, and after the start of the 2007-09 financial crisis). All explanatory variables enter with two lags except unemployment which enters with four lags. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parenthesis. For the quantile regression, standard errors are estimated using bootstrap procedures and are consistent across all quantiles.

There are two possible sources of endogeneity that could affect accuracy of our estimates: (i) reverse casualty that may invalidate our lagged competition measure in a dynamic setup with long lags and (ii) a missing factor that drives both competition and individual bank stability. To address (i), we estimate the baseline model using further lags of competition. To address (ii), we estimate the baseline model using well-known material (exogenous) changes that occurred in the structure and legal environment of the UK banking markets during our estimation period.[20] Table 9, column 2 presents results when using additional lags of competition as instruments, while column 3 uses large (exogenous) changes to the UK banking markets. The *p*-values of the exogeneity tests suggests that the Boone indicator is exogenous. In addition, the estimated parameters are very similar to the conditional mean estimates of Table 2, column 2.

Table 9

Robustness tests : Using instruments for competition

Dependent Variable: ln(Z-score)	**Additional Lags of Competition (2)**	**Lifting Entry Barrier and Consolidation (3)**
Boone indicator	0.017*	0.020**
	(0.009)	(0.009)
Bank-level controls		
Total assets	-0.063***	-0.068***
	(0.018)	(0.019)
Loans-to-assets ratio	-0.035	-0.041
	(0.079)	(0.077)
Provisions-to-assets ratio	-2.208***	-2.206***
	(0.440)	(0.441)
Non-retail deposit funding	-0.158***	-0.156***
	(0.057)	(0.057)
Non-interest revenue	-0.012***	-0.012***
	(0.001)	(0.001)
Macroeconomic controls		
GDP growth	3.011***	3.067***
	(0.351)	(0.348)
Inflation	-0.028***	-0.028***
	(0.007)	(0.007)
Unemployment rate	-0.094***	-0.095***
	(0.005)	(0.005)
R-squared	0.085	0.085
Number of observations	12,262	12,262
Exogeneity test for competition p > Chi-square (1)	0.760	0.095

Notes: Columns (2) and (3) report the estimation of Equation (1) by panel fixed-effects instrumental variables. Column (2) uses additional lags as instruments. Column (3) uses several step variables signalling points of time when changes in entry legislation and market consolidation occurred. We use robust standard errors clustered at the time level. The exogeneity test statistic does not reject the null that the competition measure is exogenous. The dependent variable in all specifications is the natural log of the Z-score, and the competition measure is the twice-lagged Boone indicator. The estimations use all banks in the sample and quarterly data between 1994 and 2013. All explanatory variables enter with two lags except unemployment which enters with four lags. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parenthesis.

[20] This approach follows Angelini and Cetorelli (2003) who investigate competition in the Italian banking market. We rely on de-Ramon and Straughan (2018), which describes several significant changes, to construct four step variables that we use as instruments: the implementation of the EU banking directive in 1993; the conversion of most building societies into banks completed in 1997; the end of a wave of bank consolidations at end-2000; and the entry of Santander UK (formed by the merger of several UK institutions) in 2004.

6. Conclusions

This paper contributes to the ongoing debate regarding the relationship between bank competition and risk. We estimate the relationship between bank-level risk and competition using two techniques: standard regression, which features in most of the research and provides an estimate of the conditional mean effect, and quantile regression, which permits a finer view of the potential heterogeneous effects across the conditional risk distribution. We then compare results produced using these techniques, providing insights into the relationship between bank-level risk and competition that help reconcile mixed findings in the existing empirical literature and highlight implications for assessing the association between competition and banking system stability.

Using data on all banks and building societies in the United Kingdom from 1994 to 2013, we find that the relationship between bank competition and risk is, on average, destabilising based on standard regression techniques. We find more nuanced results under quantile regression. For the most risky firms, we find that the relationship is favourable, consistent with the idea that competition sharpens incentives at these firms to improve efficiency and increase capital ratios. The destabilising relationship is most evident within institutions that are already relatively more stable (i.e., less risky). The more refined results under quantile regression suggest that the two competing views on the relationship between competition and stability can hold simultaneously, in line with the conclusions reached by Berger, Klapper and Turk-Ariss, (2009).

The results are robust to different measures of risk and competition, as well as the exclusion of relevant crisis periods in the UK marked by significant government intervention that could give rise to competitive distortions (such as government bail-outs of large banks). These results support the idea that, when data sets have significant unobserved heterogeneity, substantial information gains can be realized by employing techniques that allow a thorough analysis at different points of the conditional risk distribution. This paper not only establishes the relationship between solvency risk and competition, but also provides insights into its relative variation along the conditional risk distribution.

Our results have implications for policymakers and regulators. Findings from quantile regression shed light on other dimensions of firm heterogeneity that may be important to consider when designing rules and policies that alter competition in banking markets. In contrast to the results under standard regression which imply that competition-enhancing regulations may worsen the stability of individual banks on average, the quantile regression results suggest that this outcome may not necessarily be relevant for all banks. Instead, our results show such measures may be associated with lower risk-taking of already risky banks and higher risk-taking at healthy banks in the system. These results highlight that there may be real differences in the competition-stability nexus at the individual level.

While our study has not looked directly at the relationship between competition and overall financial stability, it highlights some lessons for ongoing research on this issue. First, the impacts of competition on firm-level stability can differ within a banking system. Our evidence using quantile regression is consistent with findings of previous researchers who also document disparate relationships at different points of the conditional solvency distribution. Such evidence may help in reconciling mixed results reported in previous studies examining the relationship between competition and stability. Second, we find evidence consistent with the idea that that promoting competition encourages already less efficient, less stable institutions to operate more efficiently, reducing and lowering the likelihood of failure. Put another way, our results indicate that a lack of competition can foster inefficiencies, which can increase risk and the likelihood of failure. Third, we find that a higher degree of regulatory pressure reduces the adverse effects of higher competition on bank risk-taking behaviour as posited under the franchise value paradigm. This result is consistent with the idea that, regardless of the degree of competition in the banking market, adjustments to regulatory tools such as prudential capital requirements may play a role in mitigating risk-taking incentives that derive from competition.

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Appendix A: Constructing measures of competition

This appendix describes in more detail the three measures of competition used in this study and how we estimated each of them. The measures are constructed from balance sheet, income and expenditure data reported by individual (i.e., non-group) banking entities (commercial banks and building societies) operating in the United Kingdom that are authorised and directly regulated by the UK Prudential Regulation Authority. Non-group data represent more closely activities undertaken within the domestic UK banking markets. We also include UK incorporated subsidiaries of international banks operating in the UK loan and deposit markets.

The Boone Indicator

The Boone indicator measures competition from an efficiency perspective. The measure relies on the output-reallocation effect: any increase (decrease) in competition intensity will lead to a relative increase (decrease) in output by the most efficient firms (e.g., see de-Ramon and Straughan, 2019 for more detail). Typically for the deposit-taking sector, output is proxied by a measure of variable profits, and efficiency is proxied by a measure of average variable costs. The Boone indicator is estimated as the time-varying coefficient on the (log of) average variable cost from an equation with variable profit as the dependent variable and average variable cost as a regressor, after controlling for other factors that influence variable profits. The estimated coefficient on the average cost is effectively a measure of the elasticity of variable profits to average variable cost. The estimated equation is of the form:

$$\pi_{i,t} = \alpha_t + \beta_t \ln\left(c_{i,t}\right) + \Phi X_{i,t} + \eta_{i,t} \,, \tag{A.1}$$

where $\pi_{i,t}$ is variable profits for firm i and time t, $c_{i,t}$ is average variable costs, $X_{i,t}$ are other control variables and $\eta_{i,t}$ is the error term. The Boone indicator is given by β_t, which is estimated for each time period t using interactions between average variable costs and a time-fixed effects dummy variable.

To estimate Equation A.1, we measure variable profits as the ratio of total revenue less variable costs (i.e., interest paid, staff expenditure, other variable costs including occupancy) to total assets. Average variable costs are measured as variable costs scaled by variable revenue derived directly from current activity (i.e., interest received, foreign exchange receipts, investment income, fees and other charges). We use a number of bank-level variables common in the literature in addition to variable profit and average variable cost as a control for heterogeneity in firm's business models. These control variables include average risk on balance sheet, provisions, Tier 1 capital, the loans-to-assets ratio, the proportion of retail funding, other non-interest earning assets and balance sheet size. To eliminate the effects of outliers, we winsorise all variables at the first and 99th percentiles.

One issue to address with the estimation is the co-variance of the deposit-to-assets ratio and other bank controls with the measure of average variable cost. Firms' deposit-to-assets ratios are raised by increasing variable funding costs (through higher deposit interest rates), which also influences average variable cost. Moreover, average variable costs will be influenced by the structure of firms' balance sheets included in the bank-level controls. To address any potential endogeneity between average variable cost, the deposit-to-assets ratio and the other controls, we include one-quarter-lagged average variable cost as an instrument and use a two-stage least squares process to estimate the two series. As we use average variable cost as a proxy for the efficiency of a firm, the Boone indicator in this case will be negative (higher costs / efficiency reduce profits / output) and bounded by zero, with competition intensity diminishing as the Boone indicator approaches zero.

We also consider an extension to the standard estimate of the Boone indicator to take account of the 'competition for market share' phenomenon which tends to distort the measure of competition. The modification is based on insights from Klemperer (1995) which looks at the implications for firm profits in the presence of customer switching costs. Customers for bank deposits from the UK deposit-taking sector are 'sticky' which is consistent with the presence of switching costs for consumers. If the market for deposit takers has switching costs, firms have two strategies: one is to raise deposit interest rates now (i.e. increase variable costs) to attract additional customers that increase future profits; the other is to maximise profits from existing customers (and risk losing them in future to other banks). The first strategy distorts the measurement of competition as the firm's average variable cost rises although the efficiency of the firm may not have changed – hence the Boone indicator will suggest that competition is weaker (the Boone indicator is less negative) than efficiency would imply.

The strategy any firm takes will depend on which actions maximise the value of both current and future profits: $V_t = \pi_t + \delta V_{t+1}(\sigma_t)$ where V_t is the total value of current (time t) profits (π_t) and discounted future profits (δV_{t+1}), and where future profits depend positively on current market share (σ_t). Rearranging, we note that current profit π_t is a negative function of the change in market share: $\pi_t = \delta V_{t+1}(\sigma_t) - V_t(\sigma_{t-1}) \approx f(-\Delta\sigma_t)$ where $\Delta\sigma_t$ is the change in market share. Subsequently, we add the change in the deposits-to-assets ratio for each firm as a proxy for the change in market share when estimating the adjusted Boone indicator, β_t^a:

$$\pi_{i,t} = \alpha_t + \beta_t^a \ln(c_{i,t}) + \Phi X_{i,t} + \sum_{j=0}^{4} \gamma \Delta d_{i,t-j} + \eta_{i,t} \tag{A.2}$$

The addition of this control does not violate any of the conditions for the Boone indicator to be a sufficient measure of competition, as set out in Boone (2008). We expect that the coefficient on the change in the deposits-to-assets ratio to be negative in our estimated equation, providing a test as to whether the adjustment is valid.

The Lerner index

The Lerner index measures the price-cost margin for individual firms over time and a central tendency measure (the average or median) across all firms in a market or industry is used as a proxy for market power and competition. The values of the index reflect theoretical outcomes from the competitive process: under perfect competition the index is zero as the output price (marginal revenue) equals marginal cost, and economic profits are zero. The Lerner index is positive as a firm's market power increase and price rises above marginal cost in a Cournot static (quantity-setting) oligopoly model.

We follow a well-established approach to estimating the index (e.g., Berger, Klapper and Turk-Ariss, 2009; Fernández de Guevara, Maudos and Perez, 2007). The Lerner index ($L_{i,t}$) is computed as the ratio of the difference in the output price (P) and marginal cost ($MC_{i,t}$) to the output price: $L_{i,t} = \left(P_{i,t} - MC_{i,t}\right)/P_{i,t}$. The output price is calculated as interest and non-interest revenue per unit of total output (proxied by total assets). The marginal cost $MC_{i,t}$ is not directly observable, either for the firm or for a particular product supplied by the firm. The marginal cost is derived empirically from the parameters of an estimated total cost function which is generally of the form:

$$\begin{aligned}\ln\left(c_{i,t}\right) = {} & \alpha_0 + \alpha_1 \ln Q_{i,t} + ½\alpha_2\left(\ln Q_{i,t}\right)^2 + \sum_{j=1}^{3} \beta_j \ln\left(w_{j,i,t}\right) \\ & + ½\sum_{k=1}^{3}\sum_{j=1}^{3} \alpha_{kj} \ln\left(w_{k,i,t}\right) \ln\left(w_{j,i,t}\right) + \sum_{j=1}^{3} \delta_j \ln\left(w_{j,i,t}\right) \ln Q_{i,t} \\ & + \lambda_1 E_{i,t} + ½\lambda_2 E_{i,t}^2 + \theta_1 T + \theta_2 T^2 + \sum_{j=1}^{3} \lambda_j T \ln\left(w_{j,i,t}\right) + \Phi' X_{i,t} \\ & + \varepsilon_{i,t}\end{aligned} \tag{A.3}$$

where $c_{i,t}$ is the total cost for firm i at time t, $Q_{i,t}$ is total output, the $w_{j,i,t}$ are input costs, $E_{i,t}$ is equity capital, T is a time trend, $X_{i,t}$ contains other relevant control variables and $\varepsilon_{i,t}$ is the error term. We identify three input costs common to the literature for the financial sector: staff (labour) costs, physical capital (buildings and other business costs) and funding (interest paid on deposits). The marginal cost is then calculated as the derivative of total cost with respect to output:

$$MC_{i,t} = \frac{\partial c_{i,t}}{\partial Q_{i,t}} = \left(\alpha_1 + \alpha_2 \ln Q_{i,t} + \sum_{j=1}^{3} \delta_j \ln w_{j,i,t}\right) \frac{c_{i,t}}{Q_{i,t}} \tag{A.4}$$

The Lerner index calculated for each bank i ranges from 0 to 1, with values approaching 1 indicating increasing levels of market power (wider margins) on the part of the firm. We derive the Lerner index from estimates of the total cost function shown in equation A.3. Variables used in the specifications have been winsorised at the first and 99th percentiles to reduce the impact of outliers. We also impose homogeneity of inputs so that the elasticity of all cost inputs sum to one by using funding costs as a numeraire. The estimated model parameters are robust to the inclusion of different controls.

The Herfindahl-Hirschman Index

As an additional measure, we employ the Herfindahl-Hirschman Index (HHI). The HHI is a relative measure of concentration, calculated as the sum of the each banks' share in a market squared: $HHI = \sum_{i=1}^{N} s_i^2$ where s is the market share of the bank in a particular market and N is the total number of firms in the industry. Bank shares are calculated on a scale between zero and 100 such that a monopoly industry will have an HHI of 10,000 while increasingly atomised industry will have an HHI approaching zero. We follow other papers from the literature (e.g. Beck, Demirgüç-Kunt and Levine, 2010; Berger, Klapper and Turk-Ariss, 2009; Anginer, Demirgüç-Kunt and Zhu, 2014) and compute the HHI for UK assets of UK deposit takers. We recognise that the HHI is not a direct proxy for competition but it is useful in providing comparisons with previous studies and in helping evaluate the results from the other competition measures.

Appendix B: Variable definitions

Variable	Definition	Source
Measures of stability:		
Z-score	(Core capital ratio + RoA)/standard deviation of RoA	Bank HBRD and authors' calculations
Core capital to assets ratio	Total equity/total assets	Bank HBRD and authors' calculations
Risk-adjusted return on assets	Return on assets/standard deviation of RoA	Bank HBRD and authors' calculations
Risk-adjusted capital ratio	Core capital to assets ratio/standard deviation of RoA	Bank HBRD and authors' calculations
Measures of competition:		
Boone Indicator	Elasticity of profits to variable costs (estimated)	Bank HBRD and authors' calculations
Lerner Index	Price-cost markup (estimated)	Bank HBRD and authors' calculations
HHI assets	Sum of squared market shares in assets of all UK banks	Bank HBRD and authors' calculations
Bank-level controls:		
Bank size (Total assets)	Log of total assets	Bank HBRD and authors' calculations
Provisions to assets ratio (%)	Stock of loan loss reserves/total assets	Bank HBRD and authors' calculations
Total loans to assets ratio (%)	Total loans/total assets	Bank HBRD and authors' calculations
Non-retail deposit funding (%)	Wholesale funding (i.e., non-Retail deposits)/total deposits	Bank HBRD and authors' calculations
Non-interest rev to total rev (%)	(Trading, fees and other non-interest revenue)/total revenue	Bank HBRD and authors' calculations
Capital buffer to RWA (%)	Total capital minus capital requirement/risk weighted assets	Bank HBRD and authors' calculations
Macroeconomic controls:		
UK GDP growth	Annual rate of real GDP growth	UK Office for National Statistics
UK Inflation	Annual rate of inflation	UK Office for National Statistics
UK Unemployment rate	Unemployment rate	UK Office for National Statistics

Notes: This table shows the definitions of the variables used in the regression and other quantitative results and their sources. Bank HBRD is the Bank of England's Historical Regulatory Database (e.g., see de-Ramon, Francis and Milonas, 2017).

Appendix C: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	log Z-score	1.0000										
(2)	Boone Indicator (adjusted)	-0.0102	1.0000									
(3)	Lerner Index (median)	-0.0704*	0.5088*	1.0000								
(4)	log HHI (assets)	0.0047	0.8590*	0.3759*	1.0000							
(5)	GDP growth	0.0316*	-0.4323*	-0.0246	-0.4833*	1.0000						
(6)	Inflation	-0.0792*	0.2125	0.1407	0.4121*	-0.1934	1.0000					
(7)	Unemployment rate	-0.1800*	0.1239	0.3658*	-0.0275	-0.2132	0.3032*	1.0000				
(8)	Non-interest revenue to total rev	-0.3813*	0.1847*	0.1264*	0.1532*	-0.0537*	0.0436*	0.0508*	1.0000			
(9)	Bank Size (log assets)	-0.1711*	0.0958*	-0.0008	0.1165*	-0.0504*	0.0082	-0.0830*	-0.0019	1.0000		
(10)	Provisions to assets ratio	-0.1867*	-0.1123*	0.0132	-0.1372*	0.0719*	-0.0158*	0.0909*	0.0575*	-0.1046*	1.0000	
(11)	Total loans to assets ratio	0.2586*	-0.0411*	-0.0257*	-0.0425*	0.0059	-0.0192*	-0.0152*	-0.4596*	0.1130*	0.0484*	1.0000
(12)	Wholesale to total deposits ratio	-0.2503*	-0.0726*	-0.0122	-0.0726*	0.0422*	0.0081	0.0409*	0.1851*	0.1410*	0.0974*	-0.2811*