How does banking market power affect bank opacity? Evidence from analysts' forecasts

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Abstract: Whilst the ongoing banking regulatory reforms towards a comprehensive Basel III framework emphasise bank transparency, disclosure and a competitive banking market environment, very little is known about the empirical relationship between bank opacity and banking competition. We investigate the impact of competition, as measured by the individual bank's pricing power in the banking market, on bank opacity using a large sample of US bank holding companies over the 1986-2015 period. We uncover new evidence, on the competition-bank opacity nexus, which suggests that banks with higher market power and operating in less competitive banking markets have lower analysts' forecast errors and dispersions and may thus be less opaque. This effect is more pronounced for the 2007-09 global financial crisis period. Our evidence is robust to controlling for analysts' characteristics, bank fixed-effects and endogeneity problems.

Keywords: bank opacity, competition, financial crisis, disclosure and transparency, Basel III framework

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1. Introduction

The ongoing banking regulatory reforms, especially the comprehensive Basel III framework, place major emphasis on disclosure, transparency and competition within the global banking sector.[2] Indeed, interest in bank opacity and competition has arguably become more intense in recent years due to reasons which include the 2007-09 global financial crisis, the increasing complexity of banks' business models and the dynamics of banks' behaviour in response to changes in competitive pressures and regulations (e.g., Verrecchia, 1983, 1990; Shleifer and Vishny 1997; Clinch and Verrecchia 1997; Zhao et al., 2013). In particular, the 2007-09 financial crisis was notably attributed to poor practices relating to lack of disclosure, transparency and fair competition among the major global banks. For instance, the LIBOR (London Interbank Offered Rate) scandal that only emerged recently has been identified as one of the major causes of the 2007-09 financial crisis (Burton, 2018; Vaughan and Finch, 2017). In the main, it shows the extent to which senior bankers and traders of the major global banks colluded and connived to rig the LIBOR in their favour, in blatant disregard for banking and trading rules (Vaughan and Finch, 2017). This and many other opaque banking practices have recently been discovered, often resulting in criminal prosecutions, fines and long-term imprisonments (Burton, 2018; Vaughan and Finch, 2017).

Consequently, the link among disclosure, transparency and competition within the banking system has received considerable attention from regulators, policy makers and practitioners (Anolli et al., 2014; Blau et al., 2017; Boubakri et al., 2015; Bushman et al., 2016). Observably, interest in issues of disclosure, transparency and competition partly stems from the fact that banks remain relatively more opaque than non-bank firms (Morgan, 2002; Flannery et al., 2013; Blau et al., 2017). However, empirical studies examining the association between opacity and competition within the baking sector are rare (Blau et al., 2017; Fosu et al., 2017). The few existing studies also suffer from a number of observable limitations (e.g., Blau et al., 2017; Jiang et al., 2016; Jones et al., 2012). For instance, Blau et al. (2017) examine how changes in competition through

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[2]Specifically, Basel III requires enhanced disclosures on the detail of the components of regulatory capital and their reconciliation to the reported accounts, including a comprehensive explanation of how a bank calculates its regulatory capital ratios. Please see the summary of the key aspects of the Basel framework, especially the market discipline component with the revised pillar 3 disclosure requirements, available at https://www.bis.org/bcbs/basel3/b3summarytable.pdf [last accessed on 03 May 2018].

regulatory reduction of entry barriers influenced the level and tone of voluntary disclosures, but failed to address the competition effect on the quality of information that banks release. Similarly, Jiang et al. (2016) investigated the impact of regulatory reforms that improved banking competition on bank opacity and found that greater competition reduces bank opacity. A major limitation of their analysis, however, is that their measures of bank opacity were restricted to information that is traditionally captured by the financial statements such as loan loss provisions. Thus, bank opacity emanating from other sources, such as the LIBOR scandal, is unlikely to be reflected in their empirical proxies for bank opacity. Of closer relevance to our study is Fosu et al. (2017), who utilised a much broader, market-based (analyst forecast) set of measures of bank opacity to analyse how competition and opacity impact bank stability. They, however, fell short of directly examining how competition affects bank opacity.

Consequently, in this paper, we seek to contribute to the existing literature by providing new evidence on the relationship between competition and bank opacity by invoking the informativeness of analysts' forecast properties (errors and dispersions) and employing a non-structural measure of competition that also directly reveals bank-level market/pricing power. By employing analysts' forecast properties as our opacity measure, we avoid the limitations of the accounting-based measures such as susceptibility to manipulations by managers (Dichev et al., 2013), and being backward-looking (historical), and thus unable to fully reflect current and future asset opacity (Burks et al., 2017). Although private information is generally unavailable to a vast array of capital market participants, analysts can use their expertise to derive private information from public information, as well as use their special access to management to obtain privileged information (Keskek et al., 2017). As a result, analysts' forecast properties such as earnings forecast errors and dispersions can arguably provide a more superior and direct estimate of bank opacity.

We use 'bank opacity' as an encompassing term to refer to the inherent complexities and difficulties that impede the ability of outsiders (e.g., investors) to fully understand, evaluate and monitor the operations and assets of banks (e.g., Dewally and Shao, 2013; Flannery et al., 2013). The challenges to bank monitoring that are associated with opacity may emanate from reasons that include limited transparency and disclosures by banks, as well as the inherently risky nature of banking business. Since financial analysts tend to be industry specialists, who serve as information intermediaries between firms and

market participants (Boubakri et al., 2015; Keskek et al., 2017), we expect analysts of banks to possess an advantage in understanding the complex banking operations. However, if banks are indeed opaque, then, even expert bank analysts may struggle to make accurate predictions about banks' earnings based on the existing public and private information available to them. Hence, we follow Fosu et al. (2017) by relying on the informativeness of analysts' forecast errors and dispersions as our empirical gauge of the extent of bank opacity. Different from Fosu et al. (2017), however, we examine the potential drivers of bank opacity (specifically, the extent of banking competition, as inferred from bank-level pricing power), rather than its consequence on bank stability.

Another important extension that we seek to make to the literature is to consider the role of financial crisis in shaping the competition-opacity nexus. This analysis is motivated by the view that monitoring incentives and information availability on financial firms, and thus bank opacity, may vary over time (i.e., in crisis vs. normal times) (e.g., Flannery et al., 2013; Simkovic, 2013). For example, Flannery et al. (2013) show that, while banks are not unusually more opaque than their non-bank peers in normal periods, they become significantly more opaque during crisis periods. Within the context of the competition effect on bank opacity, Simkovic (2013) contends that competition in the US mortgage securitsation market fuelled the recent financial crisis by undermining securitisers' ability to monitor mortgage originators. This suggests that bank opacity may be considered to be a more serious problem in competitive markets during crisis periods. To the best of our knowledge and based on our extensive review of the literature, we are the first to explore the moderating role of financial crisis in the context of the competition-opacity literature. Jiang et al. (2016), Burks et al. (2017) and Fosu et al. (2017), which are the closest studies to the current paper, all fail to explore how the presence of crisis may moderate or accentuate the impact of competition on bank opacity.

Our results, which are based on a large sample of 610 US bank holding companies over the 1986-2015 period, are as follows. We find that banks with greater market power, and hence operating in less competitive banking markets, are associated with lower bank opacity. In other words, the presence (absence) of intense competition in banking markets seems to increase (decrease) bank opacity. We further find this effect to persist over time, albeit it became more pronounced during the recent 2007-09 financial crisis. These results are robust to controlling for potential endogeneity problems that could arise from the

simultaneity of bank opacity and competition. Further, our findings remain robust to controlling for analysts' characteristics such as firm-specific and general industry experience or knowledge. Finally, our findings remain unchanged when we control for both unobserved firm- and state-quarter fixed-effects, as well as when we utilise a market-level measure of competition.

In the process, we make several new contributions to the existing literature. First, we provide the first evidence of the effect of banking market competition on bank opacity derived from analysts' forecast properties. Second, we depart from the existing literature on the opacity-competition nexus by employing a direct measure of competition at the bank level through individual bank's market power, proxied by *the Lerner Index*, with marginal costs derived from a stochastic cost frontier rather than from accounting numbers in the financial statements. The Lerner index is commonly utilised in the banking literature as a proxy for competition in banking markets (e.g., Beck et al., 2013; Anginer et al., 2014), but has not yet been applied to opacity. Finally, we disentangle the effect of the 2007-09 financial crisis on the relationship between competition and bank opacity by showing that banks behave differently during crisis periods, possibly due to the intense distress imposed by such crises (e.g., Flannery et al., 2013; Blau et al., 2017). This underscores the need to highlight the moderating role of financial crises which has so far been ignored in the literature.

The results of our study are of policy and practical relevance to policy makers, regulators, analysts, and other market participants. For instance, from a policy and regulatory perspective, our key finding implies that, with banking markets across the globe becoming increasingly competitive and innovative, there is the need to vigorously pursue moves to foster increased disclosure and transparency in banks if we are to achieve any meaningful market discipline. In this regard, our findings lend support to the Basel III regulatory framework that seeks to achieve higher levels of market discipline, disclosure and transparency by improving uniformity and full disclosure of banks' capital base and leverage ratios.

The rest of the paper is organised as follows. Section 2 presents a review of the relevant literature. Section 3 discusses the empirical estimation methods, the data and variables used for the study. The empirical results are presented in Section 4, whilst Section 5 concludes

2. Related literature

In this section, we first explore the key reasons as to why banks may be associated with higher opacity. This helps to clarify the concept of bank opacity, as well as highlight the fundamental channels through which banking market competition could potentially impact bank opacity. We also review the literature on the linkage between opacity and competition and derive our hypothesis.

2.1 Why are banks opaque?

Although opacity of balance sheets is a common corporate feature across all industries, banks are generally regarded to be more opaque than other types of firms (e.g., Morgan, 2002; Flannery et al., 2013; Blau et al., 2017). For instance, Flannery et al. (2013) assess the relative opaqueness of banking firms and observe some evidence that suggests that banks are unusually more opaque than a sample of matched non-banking firms, particularly during crisis periods. Similarly, Blau et al. (2017) document that banks exhibit significant stock price delays/inefficiencies relative to matched non-bank firms, suggesting that stock investors are either less informed about bank assets or, perhaps, struggle to fully comprehend banking operations.

Early research by Morgan (2002) attributes the opacity of the financial sector to the specialty of bank assets and the high leverage that banks employ. He notes that banks' assets (loans and trading assets, in particular) have risks that are hard to observe, but easy to change, resulting in a higher uncertainty over banks. Moreover, the presence of high leverage in banks invites agency problems, thereby compounding the uncertainty over banks' assets. Relating opacity to agency problems (specifically, managerial misbehaviour), Beatty et al. (2002) argue that managers' incentives to extract private rent can cause them to engage in earnings management and, in the process, increase banks' opacity. They further offer empirical evidence to suggest that banks engage in earnings management either to reduce their tax liabilities or to circumvent regulations on capital requirements.

Later studies have also attempted to relate financial innovations to bank opacity. In Wagner's (2007) theoretical model in which managers have the incentive to avoid market discipline, managers use complex financial instruments such as derivatives to make their activities more difficult to monitor. Consistent with the prediction of this model, Dewally and Shao (2013)

find that financial derivatives (specifically, interest rate and foreign exchange derivatives) diminish the transparency of large US bank holding companies' balance sheets, thereby making them more opaque. Overall, it seems that the relatively higher degree of opacity in banks stems from three main sources: (i) the inherently greater risks associated with their balance sheets, particularly their assets; (ii) the higher risk of financial statement manipulation by bank managers, perhaps to circumvent regulatory requirements; and (iii) the complexity of financial innovations, possibly to frustrate market discipline.

Whatever the cause of opacity in the banking sector, there is virtually no disagreement regarding its potential devastating effects on the financial system. Fosu et al. (2017) document that opacity increases insolvency risks among banks. Beyond the effect on individual banks, Jones et al. (2012) suggest that opacity has the potential to threaten the entire banking system because it may cause price contagion in the market which may lead to financial instability and systemic risk. Further, Dewally and Shao (2013) note that, when banks are unusually opaque, market-based discipline may fail as market participants are not able to monitor and discipline banks' risk-taking behaviour. Arguably, the far-reaching consequences of bank opacity provide a justification for tighter regulation of banks. However, the banking sector in most advanced economies, particularly the US, has increasingly been deregulated (Jiang et al., 2016; Burks et al., 2017), with implications for competition and opacity in banks. We, therefore, turn our attention to the literature on the relationship between competition and opacity to further explore this matter.

2.2 Competition and bank opacity

To the extent that competition in the banking market may influence factors such as the nature of assets that banks choose to hold, and managerial incentives to manipulate financial statements, as well as encourage banks to develop complex financial innovations, it is plausible to expect competition (or market power) to be related to bank opacity. Surprisingly, studies on this topic have focused largely on non-bank firms, with mixed conclusions (e.g., Datta, Iskandar-Datta, and Singh, 2013; Markarian and Santalo, 2014; Balakrishnan and Cohen, 2013). Although the literature thus far lacks a clear prediction or conclusion on the effect of competition on firm opacity, it at least points to potential channels through which competition (or individual firm's market power) may increase or decrease bank opacity. Competition can impact on bank opacity mainly through two broad channels: (i) the earnings management and disclosure channel; and (ii) the

innovation channel.

The often-cited channels through which competition impacts opacity are the risk of financial statement manipulation and/or the willingness (or the lack of it) to disclose quality information about the firm to outside stakeholders. Theoretically, competition can improve internal corporate governance (Shleifer and Vishny, 1997), as well as serve as a mechanism for exercising external discipline on management (Nickell, 1996), and thereby reducing discretionary earnings management and improving information disclosure (Leuz et al., 2003). Also, by facilitating market entry, competition can foster effective peer benchmarking, which can help in extracting or verifying information about individual banks within the industry (Darrough and Stoughton, 1990; Holmstrom, 1982; Dichev et al., 2013). Furthermore, Darrough and Stoughton's (1990) model of an entry game suggests that greater competition from potential entrants in an industry leads to greater disclosure by incumbent firms, since the disclosure of 'bad news' by the incumbent can deter potential entrants to the market, whilst the disclosure of positive information would reduce the incumbent firm's cost of capital. Similarly, Wagenhofer (1990) suggests that increased competition can lead to full information disclosure.

Overall, the above theoretical arguments suggest less (more) opacity for banks in competitive (concentrated) markets since competition can reduce earnings management and also improve quality information disclosure. Some existing empirical studies provide evidence to support this position. Balakrishnan and Cohen (2013) find that concentrated (i.e., less competitive) industries tend to have more financial restatements. The authors further show that industries experiencing tariff reductions through exposure to greater foreign competition tend to have fewer restatements. Jiang et al. (2016) relate a deregulation-induced measure of competition to two bank opacity measures (abnormal accrual of loan loss provisions and the frequency of financial statement restatements). They find that intensification of competition following deregulation reduces abnormal accruals of loan loss provisions and the frequency with which banks restate their financial statements. They conclude that competition reduces bank opacity by potentially enhancing the ability of markets to monitor banks.

By contrast, another strand of the literature suggests that competition rather increases opacity by heightening managerial incentives to manipulate financial statements or to withhold quality information from outsiders. Shleifer (2004) argues that intense banking competition could lead to higher uncertainty due to the greater risk of unethical behaviour, including

aggressive earnings manipulations, among managers. Datta et al. (2011) contend that, unlike concentrated industries, where individual firms may have some pricing power, firms in competitive markets have limited pricing power and, thus, a reduced ability to maintain profit margins and absorb exogenous shocks to cost. Consequently, the increased competitive pressure increases the risk of financial statement manipulation, presumably to conceal poor or unfavourable financial results, which can consequently result in higher opacity in competitive markets. Further, greater competition may increase takeover threats (Jones et al., 2012; Jiang et al., 2016), causing job insecurity and, therefore, making managers more inclined to manipulate earnings (Armstrong et al., 2012). On information disclosure by competing firms, Verrecchia (1983) and Clinch and Verrecchia (1997) suggest that firms in industries characterised by intense product market competition tend to disclose less information because the disclosure of more (private) information gives competitors a strategic competitive advantage.

Consistent with the theoretical predictions of the above-mentioned strand of literature, a few scholars (e.g., Bushman et al., 2016; Markarian and Santalo, 2014) report findings that suggest higher (lower) levels of opacity for firms in more competitive (concentrated) markets. For example, using the Lerner and Herfindahl-Hirschman (HHI) indexes to gauge the cross-industry variations in competition, Markarian and Santalo (2014) and Datta et al. (2013) find that competition increases earnings management. Bushman et al. (2016) use a textual analysis of banks' 10-K filings to measure the competitive pressures facing banks and find that banks delay the recognition of expected loan losses when they face stronger competition.

The foregoing discussion points to an ambiguous relationship between competition and bank opacity. We, therefore, next turn to the innovation channel of the relationship to streamline our testable hypothesis. The innovation channel suggests that competition compels firms to be innovative, and thereby making it difficult to accurately assess the quality of their assets. In fact, as Hou and Robinson (2006) highlight, the very need for survival requires firms in competitive industries to innovate. Meanwhile, innovative firms are associated with greater technological discontinuities (i.e., sudden and dramatic changes in the use of a certain technology) and high information complexity, making it more difficult to assess their earnings. Datta et al. (2011) point out that the information complexity associated with innovative firms arises from the difficulty in quantifying

potential success of innovations as well as the deeply complex task of projecting counter responses of rival firms. Interestingly, empirical studies generally find a positive relation between innovative activities and product market competition (e.g., Nickell, 1996; Nerkar and Shane, 2003). For instance, Nerkar and Shane (2003) show that industry concentration inhibits the exploitation of new innovations because such innovations have no compelling strategic survival advantages. To the extent that innovation increases uncertainty about asset quality, this evidence implies that firms in concentrated and, possibly, less competitive markets are less opaque.

Collectively, whilst the earnings management and information disclosure channels offer ambiguous conclusions on the effect of competition (or market power) on firms' opacity, the innovation channel seems to offer an unequivocal positive (negative) relationship between competition (market power) and firms' opacity. Therefore, the crucial role of financial innovations in the banking sector (e.g., Wagner, 2007; Dewally and Shao, 2013) suggests that competition in banking is more likely than not to increase bank opacity. This leads us to hypothesise that *the extent of competition (market power) in the banking market should be positively (negatively) related to bank opacity.*

We test the above hypothesis in ways that differ from the above strands of literature, and thus allowing us to further extend our understanding of the competition-opacity nexus. First, whilst the existing literature focuses mainly on accounting measures of opacity, we measure opacity through analysts' forecast properties. As previously noted, accounting measures are unable to fully reflect the extent of bank opacity because they are: (i) historical in orientation; and (ii) subject to managerial manipulations (Burks et al., 2017; Dichev et al., 2013). In contrast, analysts' forecast properties (errors and dispersions) offer a more direct and superior measure of opacity, as they reflect past, current and future opacity levels by drawing on both publicly and privately available information (Keskek et al., 2017; Ye and Yu, 2017).

By their nature, analysts are important participants in capital markets. They are efficient intermediaries between banks and investors, processing public information efficiently to derive private information useful for market discipline. Further, they provide effective monitoring of banks (Mansi et al., 2011; Boubakri et al., 2015), regularly revising forecasts throughout the year as they update their private information. In fact, the empirical literature suggests that analysts' forecast properties have a first-order causality effect on market

liquidity (Roulstone, 2003; Boubakri et al. 2015). For instance, Roulstone (2003) finds that analysts' forecast dispersion increases the bid-ask spread and its adverse selection component. Similarly, Mansi et al. (2011) and Boubakri et al. (2015) show that analysts' forecast inaccuracies and dispersions are significantly associated with higher credit spreads. Collectively, these studies suggest that analysts' forecast properties (errors and dispersions) may represent a superior measure of opacity with specific reference to broader market discipline. Consequently, our reliance on market-based analysts forecast properties to derive a superior proxy for opacity represents an important contribution to the literature, which may help to resolve the ambiguities in the market structure-bank opacity literature.

Specifically, the errors in the earnings forecasts of analysts, as well as the disagreements among analysts (dispersion of forecasts) that follow a bank, may be strong indicators of opacity. Our approach and rationale in proxying bank opacity is akin to that adopted by Morgan (2002) and Fosu et al. (2017). While Morgan (2002) relies on the disagreements between specialist bond rating agencies (Moody's and Standard & Poor's) as a measure of opacity in banks and insurance companies, Fosu et al. (2017) utilise analyst forecast errors and disagreements among analysts in their forecasts of banks' earnings to measure bank opacity.

Second, we employ a direct measure of competition at the bank level, the *Lerner index*. Our measure is more intuitive and popular in the banking literature (see Beck et al., 2013; Anginer et al., 2014), as it is more capable of capturing competition arising from the interactions amongst existing banks and new entrants. Unlike other structural measures of competition, such as concentration indices and market share, the Lerner index does not require a precise geographic definition of banking markets (Aghion et al., 2005). This unique feature of the Lerner index is particularly important as banks become increasingly diversified and banking markets become increasingly deregulated, with geographic boundaries between them gradually becoming faint. Further, the Lerner index provides a measure of bank pricing power on both assets and funding cost and reflects the banks' franchise value (Beck et al., 2013; Anginer et al., 2014) upon which the theoretical argument for the competition-opacity relationship partly depends (e.g., Verrecchia, 1983). Thus, the Lerner index which we employ in our study has a sound economic basis and an intuitive appeal to capture salient features of competition different from those used in other existing studies.

In summary, the academic debate on the relationship between competition and opacity in

the banking literature remains largely inconclusive, necessitating further research. We contribute to resolving this puzzle by proposing analyst forecast properties as an alternative measure of opacity in banking in conjunction with an intuitively appealing non-structural measure of competition (i.e., the Lerner index).

3. Data and empirical methodology

3.1 Data description

We obtain consolidated balance sheet and income statement from FR Y-9C quarterly reports filed with the Federal Reserve Bank of Chicago. In addition to this dataset, we obtain the market data for bank holding companies from the Center for Research in Security Prices (CRSP) database. Further, we obtain analysts' forecast and actual earnings per share data from the Detail History file of the Institutional Brokers' Estimate System (I/B/E/S). We link the consolidated balance sheet and income statement with the market data using the CRSP-FRB link table from the Federal Reserve Bank of New York. We then link the resulting dataset with the analysts' earnings forecast data. For consistency, we follow Jones et al. (2012) and present all balance sheet items as end of quarter amounts, whilst income statement variables are annualised quarterly amounts.

Following the existing literature (e.g., Fosu, 2014; Haw et al., 2015), we apply a few exclusion criteria. These include banks with missing values for the main variables. We also exclude banks with negative stock price. Finally, bank holding companies with fewer than three consecutive quarters of data are also excluded. We finally ended up with an unbalanced panel of 610 bank holding companies over the 1986-2015 period.

3.2 Estimation method

In this section, we model the empirical relationship between bank opacity and competition. We follow the existing literature (e.g., Datta et al., 2011; Haw et al., 2015; Jiang et al., 2016) and control for a number of bank-level factors and analysts' characteristics. Specifically, we employ the following econometric framework:

$$Opacity_{i,t} = \alpha + \beta Competition_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{k,i,t-1} + \varepsilon_{i,t-1} \qquad (1)$$

where *Opacity*, *Competition* and *X* are proxies for bank opacity, banking market competition

and other control variables, respectively, all of which are as defined in Section 3.3; α, β and γ are parameters; the subscript i and t indicate the ith bank and the tth time period; and k indices the kth control variable. ε is a composite error term made up of bank-specific fixed-effects (μ_i) and an independent and identically distributed component ($\upsilon_{i,t}$).

As indicated in Section 1, we take the view that banks behave differently during crisis periods than in normal times, as crisis can heighten industry-wide distress, availability of information and incentives to monitor banks (Flannery et al., 2013; Simkovic, 2013). To take account of this difference in bank behaviour over time, we extend Equation (1) to include a crisis dummy variable, taking the value of 1 for the period 2007-2009, representing the recent financial crisis, and 0 otherwise. We thus obtain Eq. (2) as follows:

$$Opacity_{i,t} = \alpha + \beta Competition_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{k,i,t-1} + \left(\eta + \phi Competition_{i,t-1}\right) Crisis_t + \varepsilon_{i,t-1} \quad (2)$$

where *Crisis* is a dummy variable representing the 2007-2009 financial crisis; and η and φ are parameters. We also compare the potential impact of the pre-crisis period on bank opacity by replacing the crisis dummy in Eq. (2) with a pre-crisis dummy taking the value of 1 for the years prior to the 2007-09 crisis, and 0 otherwise.

Eqs. (1) and (2) can be estimated using OLS; however, this approach could lead to biased and inconsistent estimates due to the correlation of the firm fixed-effects with the explanatory variables (Wooldridge, 2009, p. 465). Hence, we estimate these models using the panel fixed-effects approach and use pooled OLS only for robustness check. We control for time fixed-effects by including time dummies in all estimations. Finally, we adjust the standard error using the Huber-White approach and clustering at the firm level.

3.3 Measurements of variables

3.3.1. Competition

The banking literature typically measures competition using the Lerner index, Panzar-Ross H-statistics, Boone indicator and structural measures, such as the Herfindahl-Hirschman Index (HHI). Amongst these measures, however, the Lerner index is the only measure of competition that varies at the bank level, whilst the remaining measures are best suited for measuring cross-country differences in competition. This perhaps explains why the Lerner

index is a popular measure of competition in the banking literature. For instance, Beck et al. (2013) employ the index to investigate whether competition affects bank stability, whereas Anginer et al. (2014) rely on it to explore the link between competition and bank systemic risks.

Since we are particularly interested in individual banks' changes in opacity in response to variations in competition, we follow past studies (Beck et al., 2013; Anginer et al., 2014; Datta et al., 2011; Haw et al., 2015) to infer the extent of banking market competition from the Lerner index – a firm-level measure of competitiveness or market/pricing power. We rely on the classical economic theory that firms in a perfectly competitive market will be price takers and not have much control of prices and profitability (e.g., Mankiw and Whinston, 1986). By contrast, in less competitive markets, individual firms may exercise some control over pricing/profitability, and thus enjoy some level of market power and competitive advantage.

The Lerner index measures the degree of market power exercised by banks, which is proxied by the extent to which banks can charge a higher price above marginal cost. Thus, higher values of the index indicate greater market power, and by extension lower levels of competition in a market, and vice versa. In sum, the Lerner index is a direct measure of banking market power, and, arguably, an indirect measure of banking market competition.[3] The Lerner index is computed as follows:

$$Lerner_{i,t} = \frac{P_{i,t} - MC_{i,t}}{P_{i,t}} \tag{3}$$

where $P_{it,}$ refers to price of total assets of bank i at time t, proxied by the ratio of total revenue to total assets; and $MC_{i,t}$ refers to the marginal cost of bank i at time t. We cannot directly observe marginal cost; hence, we follow the extant literature (e.g., Fernández et al., 2013; Beck et al., 2013) and derive it from a translog cost function (TCF) as in Eq. (6) below:

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[3]We also construct a market-level Lerner index to replace our firm-level index in new sets of regressions reported later, in Section 4.4 (see Table 11). Our conclusions remain robust to this market-level proxy for competition.

$$\ln C_{i,t} = \alpha + \beta_1 \ln Q_{i,t} + \beta_2 \ln Q_{i,t}^2 + \sum_{k=1}^{3} \delta_k \ln W_{k,i,t} + \sum_{k=1}^{3} \sum_{s=1}^{3} \phi_{k,s} \ln W_{k,i,t} \ln W_{s,i,t}$$

$$+ \sum_{k=1}^{3} \gamma_k \ln Q_{i,t} \ln W_{k,i,t} + \lambda_t + \varepsilon_{i,t} \tag{4}$$

where $C_{i,t}$ refers to the total cost of bank i at time t; Q_{it} refers to output, proxied by total assets of bank i at time t; and $W_{k,it}$ is input prices of labour (k=1), capital (k=2) and funding (k=3) for bank i at time t. We apply symmetry and homogeneity of degree one in input prices by scaling the total cost (C) and the price of inputs by the input price of funds. The marginal costs are obtained from Eq. (7) as indicated below:

$$MC_{i,t} = \frac{C_{i,t}}{Q_{i,t}} \left(\beta_1 + \beta_2 \ln Q_{i,t} + \sum_{k=1}^{3} \gamma_k \ln W_{k,i,t} \right) \tag{5}$$

3.3.2 Opacity

As noted earlier, prior literature on the competition-opacity nexus in banking employs mainly accounting measures of bank opacity (e.g., Bushman et al., 2016; Jiang et al., 2017). However, these measures are limited because they are backward looking and fail to incorporate market perspective; and, as a result, they make it difficult to gauge the extent of market discipline (Burks et al., 2017; Dichev et al., 2013). Hence, following Flannery (2004), Ergungor et al. (2015) and Fosu et al. (2017), we derive our measures of opacity mainly from analysts' forecast properties, namely, analyst forecast error, analyst forecast dispersion and opacity score. Our approach broadly relies on the intuition in Morgan (2002) and Fosu et al. (2017) which suggests that disagreements among expert analysts and rating agencies may capture the extent of bank opacity. Before we proceed to derive these measures, we ensure that only the most recent earnings forecast for every analyst who provides more than one forecast is used. Additionally, we adjust earnings forecast using the CRSP cumulative adjustment factor to ensure that actual and forecast earnings per share are based on the same number of shares outstanding (Robinson and Glushkov, 2006).

We measure analysts' forecast error as the absolute value of the difference between mean analysts' forecasts and actual earnings per share scaled by the share price at the beginning of the fiscal quarter. Specifically, we compute analysts' forecast error as below:

$$Forecast\ errror_{i,t} = \left| \frac{FEPS_{i,t} - AEPS_{i,t}}{Pr ice_{i,t-1}} \right| \tag{6}$$

where $FEPS_{it}$ is the average of all earnings forecasts for bank i in fiscal quarter t; $AEPS_{it}$ is the actual earnings per share for bank i in fiscal quarter t; and $Price_{i,t-1}$ is the share price of bank i at the beginning of fiscal quarter t.

Our second measure of opacity, the dispersion of analyst earnings forecasts, is measured as the standard deviation of analysts' forecasts for the fiscal quarter scaled by the share price at the beginning of the fiscal quarter. We construct our third measure of opacity, opacity score, such that we exploit the informativeness of both forecast error and forecast dispersion. Specifically, we first follow Clement and Tse (2005) and Kim et al. (2011) by applying a transformation that preserves the relative distance of both forecast errors and forecast dispersion as follows:

$$Norm\_Error_{i,t} = \left[\frac{(Forecast\ error_{i,t}) - Min(Forecast\ error_{i,t})}{Max(Forecast\ error_{i,t}) + Min(Forecast\ error_{i,t})} \right] \tag{7}$$

$$Norm\_Dispersion_{i,t} = \left[\frac{(Forecast\ dispersion_{i,t}) - Min(Forecast\ dispersion_{i,t})}{Max(Forecast\ dispersion_{i,t}) + Min(Forecast\ dispersion_{i,t})} \right] \tag{8}$$

The transformed variables range from 0 to 1. We then develop *Opacity Score* as the sum of the transformed forecast error $(Norm\_Error)$ and the transformed forecast dispersion $(Norm\_Dispersion)$:

$$Opacity\_Score = Norm\_Error + Norm\_Dispersion \tag{9}$$

3.3.3 Control variables

To gauge the relationship between competition and opacity, we follow the existing literature (e.g., Li, 2010; Datta et al., 2011; Haw et al., 2015; Huyghebaert and Xu, 2016) and control for several variables in our econometric models. We include bank size (*Size*, the natural logarithm of each bank's total assets) to account for the possibility that large banks have more stable earnings and do disclose more information (Huyghebaert and Xu, 2016). Larger banks may also be followed by a larger number of analysts, which subsequently impacts forecast accuracy

(Ye and Yu, 2017). Hence, we also account for the number of analysts (*Analyst*) following each bank in each quarter.

We acknowledge that each of these analysts may have differing levels of general forecast experience (*Experience*) and firm-specific experience (*Length*), measured as the average number of days since the analysts first forecast for any firm or for the covered firm, respectively (Clement, 1999; Ergungor et al., 2015). Further, each following analyst may have a different breadth of coverage, which may influence their forecast accuracy; hence, we include the number of firms followed by each covered analyst in each quarter, *Scope* (Ergungor et al., 2015). The marginal benefits of analyst's experience and breadth of coverage may diminish over time; hence, we express these variables as 1 plus their natural logarithm.

Moreover, we account for bank business model by including variables capturing funding and income structure. Bank funding structure is the proportion of core deposits to total liabilities (*Deposits*), whilst income structure is the proportion of non-interest income to total income (*Non-interest*). Banks with core deposits have stable funding (Huang and Ratnovski, 2011), but they are subject to less stringent monitoring (Calomiris, 1999). Banks with higher non-interest income could be complex, making their earnings difficult to forecast (Thomas, 2002).

Additionally, we control for bank capital (*Capital*), the ratio of book value of equity to total assets, as a bank's level of capitalisation is associated with its level of stability or risk-taking, with consequences for its level of opacity. Also, more volatile earnings make bank assets difficult to value; hence, we control for earnings volatility (*Volatility*) as in Datta et al. (2011) and Haw et al. (2015). We measure *Volatility* as the annual standard deviation of return on equity. Likewise, we control for earnings surprise (*Surprise*), defined as the absolute difference between current and prior quarter earnings per share (Haw et al., 2015). Finally, we include the ratio of bank loans to total assets (*Loans*) and loan loss provisions to total assets (*Provisions*) to capture banks' lending specialisation and credit risk, respectively. Table 1 presents a detailed list and definitions of all variables used.

[Table 1 about here]

3.4. Descriptive statistics and bivariate correlations

In Table 2, we present the descriptive statistics of the variables for our empirical analysis. We report our three measures of opacity: (i) analyst forecast error, (ii) analyst forecast dispersion

and (iii) opacity score. The mean values of these measures are 0.44, 0.20 and 0.26, respectively. These variables also have a standard deviation of 0.90, 0.37 and 0.36, respectively. This implies that, among these three measures, analyst forecast error has the highest mean value and degree of variability. In general, our measures of opacity exhibit high levels of variability. Further, the mean value of our competition variable (*Lerne*r) is 0.64 with a standard deviation of 0.16. This variable rises from a minimum of 0.35 to a maximum of 0.87, suggesting a high degree of heterogeneity across the banks investigated.

With respect to the control variables, a few findings are worth noting. First, we observe that the mean value of *Size* is 15.55 with a standard deviation of 1.47. This variable has a minimum and maximum value of 13.45 and 18.70, respectively, signifying a fair degree of heterogeneity. Also, the average value of the number of analysts following is 6.33, with a standard deviation of 6.22. It also has a minimum value of 1 and a maximum value of 39, suggesting high levels of heterogeneity in the number of analysts following the sample banks. The mean value of general experience (*Experience*) is 7.60 with a standard deviation of 0.87, a minimum value of 0 and a maximum value of 9.22, thus exhibiting a high level of heterogeneity. We also note that Length and Scope have mean values of 6.28 and 2.77, respectively. These variables have standard deviations of 1.54 and 0.34 and minimum (maximum) values of 0.00 (8.71) and 0.69 (4.93), respectively. These figures show a moderate degree of variability and a high degree of heterogeneity in the characteristics of analysts following the banks investigated.

[Table 2 about here]

Turning our attention to Table 3, we present the correlation between the variables used in our study. We first note that the correlations between our measures of opacity (i.e., analyst forecast error, analyst forecast dispersion and opacity score) are very high. This suggests that all the three dependent variables are capturing similar information (i.e., opacity). A preliminary insight into the relationship between opacity and competition (*Lerner*) is also illustrated by the correlation matrix. We observe that the correlation (but not necessarily causal relationship) between our measures of opacity (i.e., analyst forecast error, analyst forecast dispersion and opacity score) and *Lerner* is negative.

In general, the evidence emerging from the correlation matrix, as well as the descriptive statistics, suggests that our sample does not seem to suffer from serious issues such as limited variation and heterogeneity or large outliers.

[Table 3 about here]

4. Results and Discussion

In this study, we set out to investigate the banking competition-opacity relationship by using three different but related measures of opacity. We observe a slight variation in the sample size depending on the choice of dependent variables; that is, (i) analyst forecast error, (ii) analyst forecast dispersion or (iii) opacity score. In the sections that follow, we look at the impact of banking competition on each of these measures of opacity.

4.1 Banking competition and bank opacity – analysts' forecast error

In Table 4, we present the empirical results of Eq. (1) by testing the effect of competition on bank opacity derived from analysts' forecast error. Models 1 to 5 are based on OLS estimation and 6 to 10 present panel fixed-effects estimation.

[Insert Table 4 about here]

We start our discussion with Models 1 and 6 where bank opacity is explained by competition (*Lerner index*) only. In both models, the coefficient on Lerner index is negative and statistically significant at the 1% level, suggesting that greater banking market power reduces bank opacity. This implies that intense competition in banking markets may increase bank opacity. We extend Models 1 and 6 by including control variables for bank size, lending specialisation, the level of capitalisation, earnings surprise, loan loss provisions, volatility of returns on equity and analysts following in Models 2 and 7. We further control for bank business model, proxied by the ratio of non-interest income to total income and the ratio of core deposits to total deposits alternatively in Models 3-4 and Models 8-9, and jointly in Models 5 and 10. The coefficient on *Lerner index* remains negative and statistically significant at the 1% level throughout all specifications, supporting the negative (positive) relationship between market power (competition) and opacity. The economic impact of banking market power is also very large. Based on our fully specified models, a one standard deviation increase in the *Lerner index* is associated with a 14.81–17.23 basis point decrease in analysts' forecast error, our measure of opacity. This represents 33.55%–39.05% of the mean bank opacity. Overall, our finding suggests that, in a competitive banking environment, banks are less likely to disclose sensitive information, to prevent rivals from capitalising on the information (Verrecchia, 1983).

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Although our finding is in stark contrast to Jiang et al. (2016), we exercise a fair amount of caution in our comparison, as our measures of opacity and competition differ from theirs. Our results, however, support the evidence in Bushman, Hendricks and Williams (2016) showing that greater competition is associated with higher opacity, as measured by less timely loan loss recognitions. Our finding suggests that the recent Basel III regulatory framework, which promotes market discipline through bank transparency, could yield more benefits in countries with a relatively higher degree of banking market competition.

With respect to the control variables, notable observations are that larger firms have larger analysts' forecast errors. This finding suggests that larger banks are more opaque than their smaller counterpart banks, and it is consistent with the evidence that larger banks exercise more discretion on loan loss provisions (Jiang et al., 2016) and on asset valuation (Huizinga and Laeven, 2012). This finding is also consistent with the evidence for non-financial firms, suggesting that larger firms have larger analysts' forecast errors (Datta et al., 2011; Haw et al., 2015). Also, banks with large outstanding loans, and hence higher lending specialisation, have higher forecast errors. Similarly, banks with a larger share of loan loss provisions, signifying exposure to credit risk, exhibit larger forecast errors. Moreover, in line with Anolli et al. (2014), Datta et al. (2011) and Haw et al. (2015), we find that volatility of return on equity increases forecast errors. Banks with higher earnings surprise have larger forecast errors, whilst banks followed by a larger number of analysts have lower analysts' forecast errors. These findings are also largely consistent with the evidence for non-financial firms (e.g., Datta et al., 2011; Haw et al., 2015). Further, non-interest income capturing earnings diversification is positively associated with forecast errors. This finding is consistent with the view that income diversification makes earnings less predictable (Thomas, 2002). Finally, dependence on core deposit funding is positively associated with analysts' forecast errors. This finding is consistent with the view that deposit funding is associated with less monitoring (Calomiris, 1999). In contrast, banks with higher levels of capital have lower forecast error.

4.2 Banking competition and bank opacity – other related measures of opacity

In this section, we demonstrate that our results are robust to using other analyst forecast-related measures of opacity. First, we follow Krishnaswami and Subramaniam (1999) and Fosu et al. (2016) and employ analysts' forecast dispersion as our measure of opacity. Forecast dispersion captures the disagreement amongst analysts that follow a bank (Krishnaswami and Subramaniam, 1999); hence, it represents a good measure of opacity. We present the results in

Table 5. As before, we follow the sequential approach where we first model forecast dispersion as a function of competition (Models 1 and 5) only and extend the model to include bank-specific control variables (Models 2 and 6) as well as the bank business model variables (Models 3-5 and 8-10). The results show that the coefficient on Lerner index is negative and statistically significant at the 1% level. The impact of *Lerner index* on analysts' forecast dispersion is also economically significant – a one standard deviation increase in the *Lerner index* is associated with a 29.97%–32.08% decrease in the mean forecast dispersion of the average bank. This finding suggests that banking market power (competition) significantly decreases (increases) bank opacity, which is in line with our earlier results.

The coefficients on the control variables are also consistently signed. Larger banks have higher forecast dispersion, as they are banks with higher levels of lending specialisation, earnings surprise, loan loss provisions, volatility of returns and non-interest income. In contrast, and consistent with the previous results, banks with higher levels of capital have lower forecast dispersion.

[Insert Table 5 about here]

Second, we develop a measure of opacity that is based on the normalised values of analysts' forecast errors and forecast dispersion. Specifically, we normalise both analysts' forecast errors and forecast dispersion so that each of them ranges between 0 and 1. We then sum up the normalised values of these variables and derive our third measure of opacity, *Opacity Score*. In Table 6, we present the estimation results based on this measure of opacity. We note that the coefficient on *Opacity Score* is negative and statistically significant at the 1% level across all models, suggesting that banking market power (competition) increases bank opacity. The impact of market power (competition) is also noteworthy – a one standard deviation increase in competition is associated with a 29.97%–35.34% decrease (increase) in bank opacity. On the control variables, we find that bank size, lending specialisation, earnings surprise, provisions for loan losses, volatility of returns on equity and non-interest income increase bank opacity, whilst higher levels of bank capital decrease bank opacity.

[Insert Table 6 about here]

Overall, the results obtained from using alternative measures of bank opacity suggest that intense banking competition increases bank opacity; the effect is both statistically significant and economically significant.

4.3 Banking competition and bank opacity – addressing potential endogeneity

We acknowledge the concern that bank opacity and the levels of banking competition may be simultaneously determined, leading to potential endogeneity issues, which can bias our findings. This issue is of less concern since we lag our independent variables. In this section, however, we take extra steps to address the potential endogeneity issues and show that our findings remain robust.

We re-estimate our main models using a two-stage estimation approach. We employ bank inefficiency, measured as the ratio of bank overheads to income (i.e., cost-income ratio), and the second lag of the *Lerner index* as instruments for the *Lerner index*. Hence, in the first stage, we model the *Lerner index*, as a function of its second lag, of cost-income ratio, and all the other exogenous variables. In the second stage, we model our measures of bank opacity (forecast error, forecast dispersion and opacity scores) alternately, as a function of the predicted values of the *Lerner index*, derived from the first-stage regressions, and all the other control variables. We present the results in Table 7.

[Insert Table 7 about here]

In Models 1, 3 and 5 of Table 6, we present the results of the first-stage regression. The coefficient on cost-income ratio and the lagged *Lerner index* are positive and significant at the 1% level across all the models. This suggests that the instruments are relevant. The diagnostic tests presented also confirm the relevance and validity of the instruments.[4] In Models 2, 4 and 6, we present the second-stage regression results. The coefficient on the *Lerner index* remains negative and significant across these models. The results corroborate our earlier finding suggesting that a higher degree of market power (intense banking competition) decreases (increases) bank opacity. Overall, the results suggest that the findings are not plagued by endogeneity problems.

4.4. Other robustness checks and further analysis

In this section, we present the results of a battery of robustness tests by: (i) controlling for analyst characteristics; (ii) disentangling the effect of crisis; (iii) using state-quarter mean-

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[4]The Hansen *J*-statistics *p*-values are all in excess of 0.1. This suggests that the over-identifying restrictions are valid (e.g., Baum, Schaffer and Stillman, 2003). Also, the Kleibergen-Paap *rk* Wald *F* statistic, compared with the Stock-Yogo IV critical values, rules out weak instrument problems; they are all larger than the rule-of-thumb minimum of 10 (Baum, 2006).

adjusted measure of competition; and (iv) utilising a market-level competition measure. We present the results in Tables 8-11. In all cases, we confirm our results suggesting that banking market power (competition) decreases (increases) bank opacity.

First, the analyst forecast literature suggests that analysts' experience gained by covering a particular bank (firm-specific experience) or several banks (general experience) over time impacts their forecast ability (e.g., Clement, 1999; Mikhail, Walther, and Willis, 1997; Ergungor et al., 2015). To this end, we re-estimate our models again by controlling for analysts' firm-specific experience, general level of experience and scope of coverage, alternately and jointly. We present the results in Table 8. The coefficient on the *Lerner index* remains negative and statistically significant at the 1% level across all models in Table 8, confirming our main finding that banking market power (competition) decreases (increases) bank opacity. The importance of analysts' experience is, however, mixed: analysts' general experience is negatively and significantly related to all of our opacity measures, but the scope of analysts' coverage seems to reduce forecast error only when we do not control for analysts' bank-specific and general level of experience. Contrary to our expectations, we find that the bank-specific experience seems to increase opacity derived from forecast error and opacity score.

[Insert Table 8 about here]

Second, we address the concern that our finding may be plagued by the confounding effect of the recent financial crisis. Our sample period covers the 2007-09 financial crisis. The crisis could affect analysts' optimism and pessimism, as it increases industry-wide distress (Easterwood and Nutt, 1999; Flannery et al., 2013). Moreover, the crisis could affect banks' incentives to release accurate information about themselves (Flannery et al., 2013), as well as the incentives of key stakeholders in competitive markets to monitor banks (Simkovic, 2013). Thus, the impact of competition on bank opacity may vary across normal and crisis periods. To examine this issue, we include dummy variables for the pre-crisis (1986-2006) and acute crisis (2007-2009) periods in our regression. The post-crisis period (2010-2015) effectively becomes the reference period. This approach permits us to observe whether the crisis sub-periods shift the regression line. Further, we include the interaction terms between these dummy variables and the *Lerner index*, thus permitting us to assess the moderating role of the crisis on the opacity-competition nexus.

In Models 1-3 of Table 9, we present the results where forecast error is our measure of opacity.

The coefficient on the *Lerner index* remains negative and significant. The coefficient on the interaction term between the *Lerner index* and pre-crisis dummy variable is, however, positive across all models, suggesting that competition decreases bank opacity, albeit by a lower margin in the period prior to financial crisis. However, the coefficient on the interaction term between the *Lerner index* and the crisis dummy variables is negative and statistically significant, suggesting that competition increases bank opacity by a larger margin during a crisis period. We obtain qualitatively similar results in Models 4-6 and Models 7-9 where forecast dispersion and opacity score are used, respectively, as the measure of opacity. These results are generally in line with the view that banks become more opaque during a crisis period than in normal periods (e.g., Flannery et al., 2013).

[Insert Table 9 about here]

Third, we address the concern that the bank-level competition measure that we use may be driven by state-specific attributes, such as regulatory and institutional differences, that may bias the opacity-competition nexus. We address this concern in two main ways. Firstly, we adjust our competition measure by subtracting from the bank-level measure of competition the state-mean competition, thereby arriving at a state-quarter mean-adjusted measure of competition. Similarly, we adjust our measures of opacity and obtain state-quarter mean-adjusted opacity. We then re-estimate our models using these state-quarter mean-adjusted measures of competition and opacity. This approach effectively controls for state-quarter fixed effects, which helps to identify systematic differences in competition and opacity (see Clement, 1999). We report our findings in Table 10. The results support our main finding that market power (competition) decreases (increases) bank opacity.

[Insert Table 10 about here]

Finally, we acknowledge the concern that the Lerner index, which measures bank market power, may not capture competition at the banking market level. To address this concern, we obtain an aggregate banking market-level measure of competition by taking the average of the Lerner index across banks for each state-quarter (e.g., Hainz et al., 2013; Calderon and Schaeck, 2016). We report the findings in Table 11. The coefficient on the mean Lerner index remains negative and statistically significant across all models. Overall, the results are consistent with our main finding that competition increases bank opacity.

[Insert Table 11 about here]

5. Conclusion

Bank opacity remains a key element in regulatory framework, especially in the wave of banking system deregulation. In particular, the 2007-09 financial crisis has partly been attributed to poor practices relating to lack of disclosure, transparency and fair competition within the global banking system. This has resulted in a considerable amount of reforms relating to disclosure, transparency and competition in the banking sector. In this case, the comprehensive Basel III accord is at the apex of such efforts. For example, Basel III requires enhanced disclosures with respect to the details of the components of regulatory capital and their reconciliation to the reported accounts, including transparency on how banks calculate their regulatory capital ratios. Such comprehensive banking reforms have also appealed to a renewed empirical interest in the nexus between bank opacity and several banking market outcomes, such as risk-taking and performance, with little attention paid to banking competition. In fact, the existing empirical literature focuses mainly on analysing deregulatory and textual-analysis measures of competition on accounting measures of opacity.

We, therefore, have departed from much of the existing literature by utilising the traditional competition measure (the Lerner index) and a market-based measure of opacity to provide robust first-hand evidence that banking market competition increases analysts' forecast error, dispersion and score. Our findings, thus, show that banking market competition (market power) increases (decreases) bank opacity. This finding is consistent with Bushman et al. (2016) who show that greater competition is associated with higher bank risks and less timely loan loss recognitions. However, our finding is at odds with that of Jiang et al. (2016) who find increased levels of competition through deregulation to be associated with quality bank reporting (i.e., low bank opacity). Further, we show that the effect of banking market competition on opacity persists over time but is more pronounced during crisis. This finding is novel in the competition-opacity literature. All our results are robust to controlling for traditional analyst characteristics, such as experience and scope, and to alternative estimation approaches.

The findings from this study do not only deepen our understanding of the relationships between competition and opacity, but they also provide salient policy implications for the Basel III policy initiatives emphasising the need for transparency and market discipline. For instance, as market discipline (emphasised in Basel III) encompasses the ability of financial markets and

regulators to penalise banks for excessive risk-taking, transparency across the full operations of banks is essential. This drives home Basel III's call for uniform and full disclosure of capital base and liquidity ratios, especially for countries with more competitive banking markets. In other words, the clarity offered by Basel III for the definitions of Tier 1 and Tier 2 capital, as well as the total exposure of banks used in computing leverage ratios, could reduce room for abuse, enhance transparency and consequently reduce opacity that often plagues banks in competitive markets. For the Basel III disclosure and transparency accord to be effective, however, the development, implementation and enforcement of a uniform standard of reporting and disclosure framework akin to the international financial reporting standards framework by the Basel Committee on Banking Supervision will be crucial.

Notwithstanding the importance and robustness of our findings, it is useful to acknowledge the limitations of our paper. For example, similar to all archival-based studies of this nature, our proxies for opacity, competition and bank attributes may or may not reflect practice. In this case, future research may be able to offer further insights by conducting in-depth interviews with analysts, bankers, policymakers and regulators. Similarly, our study focuses on US banks; future studies may be able to enrich our findings by extending our analysis using a sample of banks from a number of countries, comprising both developed and developing countries. Also, as more data becomes available, future studies can extend our analysis by using greater post-2007-09 financial crisis period datasets.

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Table 1: Description of variables

Variable	Description
Dependent variables	
Forecast error	Measure of opacity, measured as the absolute value of the difference between mean analysts' forecasts and actual earnings per share scaled by the share price at the beginning of the fiscal quarter.
Forecast dispersion	Alternative measure of opacity, measured as the standard deviation of analysts' forecasts for the fiscal quarter scaled by the share price at the beginning of the fiscal quarter.
Opacity score	Opacity index measured as the sum of the normalised values of analysts' forecast errors and forecast.
Independent variables	
Lerner	Lerner index, a measure of competition at the bank level derived from Eq. 3. A higher value of the index indicates lower competition.
Size	Bank size, measured as the natural logarithm of total assets.
Loans	The ratio of bank loans to total assets.
Capital	The ratio of book value of equity to total assets.
Surprise	Earnings surprise, defined as the absolute value of the difference between current earnings per share and the prior quarter earnings per share deflated by stock price at the beginning of the fiscal quarter.
Provisions	The ratio of loan loss provisions to total loans.
Volatility	Standard deviation of return on equity.
Analysts	The number of analysts following.
Non-interest	The ratio of non-interest income to total income.
Deposits	The ratio of core deposits to total liabilities.
Experience	General experience: the log of one plus the total days since the analyst first issued a forecast for any bank they are following.
Length	Firm-specific experience: the log of one plus average number of days since the analysts covering a bank first issued a forecast for the bank.
Scope	Scope of coverage: the log of one plus the average number of banks covered by the analysts following a bank in the fiscal quarter.

The table presents the mnemonics and description of each dependent and independent variable used in this paper.

Table 2: Descriptive statistics

	Mean	Std. Dev.	Min.	Max.	Obs.
Absolute forecast error	0.44	0.90	0.00	3.75	18632.00
Forecast dispersion	0.20	0.38	0.00	1.57	15255.00
Opacity score	0.26	0.46	0.00	2.00	15255.00
Lerner	0.64	0.16	0.35	0.87	18632.00
Size	15.55	1.47	13.45	18.70	18632.00
Loans	0.87	0.15	0.56	1.16	18631.00
Capital	0.09	0.02	0.06	0.14	18632.00
Surprise	0.01	0.02	0.00	0.08	17502.00
Provisions	0.02	0.01	0.01	0.03	18631.00
Volatility	0.02	0.03	0.00	0.12	18338.00
Analysts	6.33	6.22	1.00	39.00	18632.00
Non-interest	0.80	0.10	0.54	0.94	18632.00
Deposits	0.67	0.14	0.32	0.87	18065.00
Experience	7.60	0.87	0.00	9.22	18632.00
Length	6.28	1.54	0.00	8.71	18632.00
Scope	2.77	0.34	0.69	4.93	18632.00

The table presents the descriptive statistics for all variables used in this study. The sample comprises 610 US bank holding companies over the period 1986-2015. All variables are as defined in Table 1.

Table 3: Correlations matrix

	Error	Dispersion	score	Lerner	Size	Loans	Capital	Surprise	Provisions	Volatility	Analysts	Non-interest	Deposits	Experience	Length	Scope
Forecast error	1.00															
Forecast dispersion	0.77*	1.00														
Opacity score	0.93*	0.93*	1.00													
Lerner	-0.04*	-0.04*	-0.03*	1.00												
Size	-0.06*	-0.01	-0.02*	0.09*	1.00											
Loans	0.09*	0.12*	0.10*	0.01	0.08*	1.00										
Capital	-0.07*	-0.04*	-0.07*	0.13*	-0.09*	0.08*	1.00									
Surprise	0.66*	0.72*	0.72*	-0.05*	-0.03*	0.09*	-0.07*	1.00								
Provisions	0.28*	0.31*	0.33*	0.02	0.22*	-0.17*	-0.10*	0.32*	1.00							
Volatility	0.52*	0.51*	0.54*	-0.02	0.06*	0.10*	-0.14*	0.55*	0.25*	1.00						
Analysts	-0.06*	0.01	-0.02	0.11*	0.81*	0.11*	0.09*	-0.03*	0.17*	0.03*	1.00					
Non-interest	0.10*	0.07*	0.09*	-0.12*	-0.48*	0.11*	-0.13*	0.07*	-0.05*	0.01	-0.49*	1.00				
Deposits	-0.07*	-0.09*	-0.08*	0.03*	-0.38*	-0.30*	0.21*	-0.08*	-0.02*	-0.15*	-0.29*	0.25*	1.00			
Experience	0.01	0.05*	0.04*	0.08*	0.23*	0.07*	0.19*	0.03*	0.02	0.02	0.30*	-0.22*	-0.06*	1.00		
Length	0.03*	0.07*	0.05*	0.08*	0.38*	0.03*	0.08*	0.04*	0.12*	0.04*	0.39*	-0.26*	-0.10*	0.53*	1.00	
Scope	-0.04*	-0.04*	-0.02*	-0.01	0.08*	-0.02	-0.02*	-0.04*	0.06*	-0.04*	0.06*	-0.01	0.07*	0.25*	0.18*	1.00

The table presents the unconditional correlation coefficient between any pair of variables. All variables are as described in Table 1. * indicates significance at 5%.

Table 4: Banking competition and bank opacity – analysts' forecast error

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) FE	(7) FE	(8) FE	(9) FE	(10) FE
Lerner	-2.181***	-1.102***	-1.090***	-1.091***	-1.051***	-1.592***	-1.021***	-0.863***	-1.068***	-0.904***
	(0.492)	(0.264)	(0.258)	(0.274)	(0.266)	(0.343)	(0.253)	(0.238)	(0.254)	(0.236)
Size		-0.005	0.007	-0.004	0.005		0.078***	0.053*	0.088***	0.062**
		(0.015)	(0.015)	(0.014)	(0.015)		(0.027)	(0.027)	(0.028)	(0.028)
Loans		0.266***	0.220***	0.269***	0.211***		0.282***	0.251***	0.344***	0.312***
		(0.057)	(0.062)	(0.056)	(0.060)		(0.091)	(0.090)	(0.102)	(0.101)
Capital		-2.068***	-2.004***	-2.117***	-1.996***		-3.240***	-3.017***	-3.433***	-3.232***
		(0.553)	(0.546)	(0.601)	(0.590)		(0.717)	(0.711)	(0.733)	(0.726)
Surprise		22.640***	22.545***	22.909***	22.810***		12.415***	12.415***	12.611***	12.625***
		(1.643)	(1.683)	(1.644)	(1.677)		(1.056)	(1.050)	(1.049)	(1.044)
Provisions		13.377***	12.979***	13.520***	13.090***		16.468***	15.755***	16.495***	15.796***
		(2.134)	(2.092)	(2.201)	(2.163)		(2.254)	(2.207)	(2.309)	(2.275)
Volatility		5.795***	5.860***	5.817***	5.873***		6.356***	6.449***	6.387***	6.478***
		(0.591)	(0.594)	(0.604)	(0.606)		(0.465)	(0.469)	(0.474)	(0.476)
Analysts		-0.008**	-0.007**	-0.008**	-0.007**		-0.002	-0.002	-0.003	-0.003
		(0.003)	(0.003)	(0.003)	(0.003)		(0.003)	(0.002)	(0.002)	(0.002)
Non-interest			0.377***		0.402***			0.828***		0.830***
			(0.127)		(0.127)			(0.237)		(0.215)
Deposits				0.009	-0.046				0.243*	0.234*
				(0.095)	(0.094)				(0.140)	(0.140)
Constant	1.332***	1.416***	0.932**	1.311***	0.860**	1.253***	-0.610	-0.891**	-0.983**	-1.249***
	(0.247)	(0.364)	(0.368)	(0.343)	(0.355)	(0.238)	(0.448)	(0.442)	(0.482)	(0.482)
Observations	17321	16215	16215	15745	15745	17321	16215	16215	15745	15745
Adjusted R^2	0.213	0.521	0.522	0.527	0.529	0.237	0.399	0.401	0.406	0.408
Number of banks	596	592	592	590	590	596	592	592	590	590

This table presents the OLS and fixed-effects estimation results of the effects of competition on analysts' forecast error. Models 2-5 present the OLS estimation results, whilst Models 6-10 include bank fixed-effects. Time dummies are included in all estimations. Standard error robust to heteroscedasticity and clustering within banks are given in parentheses. The sample and variable definitions are as described in Table 1. *, **, *** indicate significance at 1%, 5% and 10% respectively.

Table 5: Banking competition and bank opacity – analysts' forecast dispersion

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) FE	(7) FE	(8) FE	(9) FE	(10) FE
Lerner	-0.661***	-0.410***	-0.407***	-0.405***	-0.392***	-0.661***	-0.414***	-0.357***	-0.424***	-0.366***
	(0.218)	(0.105)	(0.104)	(0.108)	(0.106)	(0.123)	(0.085)	(0.091)	(0.085)	(0.088)
Size		0.006	0.010	0.006	0.009		0.025**	0.015	0.026**	0.017
		(0.007)	(0.007)	(0.007)	(0.007)		(0.012)	(0.013)	(0.013)	(0.013)
Loans		0.126***	0.109***	0.124***	0.104***		0.078**	0.068*	0.087**	0.076*
		(0.024)	(0.026)	(0.025)	(0.027)		(0.039)	(0.038)	(0.042)	(0.042)
Capital		-0.724***	-0.701***	-0.755***	-0.712***		-0.835***	-0.752**	-0.858***	-0.792**
		(0.235)	(0.233)	(0.252)	(0.248)		(0.305)	(0.306)	(0.314)	(0.314)
Surprise		11.156***	11.122***	11.232***	11.198***		7.020***	7.021***	7.042***	7.048***
		(0.636)	(0.644)	(0.639)	(0.644)		(0.399)	(0.396)	(0.402)	(0.400)
Provisions		6.262***	6.109***	6.096***	5.935***		7.950***	7.661***	7.848***	7.576***
		(0.911)	(0.904)	(0.928)	(0.922)		(0.905)	(0.895)	(0.892)	(0.889)
Volatility		1.680***	1.705***	1.695***	1.715***		1.830***	1.864***	1.838***	1.870***
		(0.231)	(0.231)	(0.237)	(0.236)		(0.176)	(0.178)	(0.179)	(0.181)
Analysts		-0.001	-0.000	-0.001	-0.000		0.001	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Non-interest			0.129***		0.133**			0.308**		0.297***
			(0.050)		(0.054)			(0.120)		(0.100)
Deposits				0.004	-0.015				0.037	0.036
				(0.041)	(0.042)				(0.065)	(0.064)
Constant	0.417***	0.030	-0.138	0.396**	0.245	0.545***	-0.167	-0.265	-0.221	-0.311
	(0.092)	(0.119)	(0.133)	(0.162)	(0.168)	(0.086)	(0.198)	(0.208)	(0.238)	(0.249)
Observations	14601	14032	14032	13599	13599	14601	14032	14032	13599	13599
Adjusted R^2	0.237	0.589	0.590	0.592	0.593	0.301	0.488	0.490	0.491	0.493
Number of banks	519	511	511	508	508	519	511	511	508	508

This table presents the OLS and fixed-effects estimation results of the effects of competition on analysts' forecast dispersion. Models 2-5 present the OLS estimation results, whilst Models 6-10 include bank fixed effect. Time dummies are included in all estimations. Standard error robust to heteroscedasticity and clustering within banks are given in parentheses. The sample and variable definitions are as described in Table 1. *, **, *** indicate significance at 1%, 5% and 10% respectively.

Table 6: Banking competition and bank opacity – opacity score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	OLS	FE	FE	FE	FE	FE
Lerner	-0.993***	-0.608***	-0.604***	-0.586***	-0.568***	-0.821***	-0.548***	-0.475***	-0.556***	-0.481***
	(0.285)	(0.139)	(0.136)	(0.142)	(0.138)	(0.162)	(0.111)	(0.108)	(0.111)	(0.106)
Size		0.003	0.009	0.001	0.006		0.030**	0.018	0.032**	0.020
		(0.009)	(0.009)	(0.009)	(0.009)		(0.013)	(0.014)	(0.014)	(0.014)
Loans		0.148***	0.125***	0.141***	0.113***		0.100**	0.087*	0.110**	0.097*
		(0.033)	(0.035)	(0.034)	(0.036)		(0.047)	(0.046)	(0.052)	(0.052)
Capital		-1.016***	-0.987***	-1.025***	-0.966***		-1.137***	-1.033***	-1.165***	-1.078***
		(0.308)	(0.304)	(0.331)	(0.324)		(0.375)	(0.375)	(0.385)	(0.385)
Surprise		13.006***	12.961***	13.168***	13.121***		7.479***	7.481***	7.607***	7.616***
		(0.826)	(0.838)	(0.818)	(0.828)		(0.516)	(0.513)	(0.507)	(0.506)
Provisions		8.788***	8.589***	8.529***	8.306***		9.807***	9.441***	9.675***	9.320***
		(1.172)	(1.161)	(1.187)	(1.174)		(1.089)	(1.066)	(1.085)	(1.068)
Volatility		2.773***	2.806***	2.761***	2.789***		2.976***	3.019***	2.963***	3.004***
		(0.298)	(0.298)	(0.303)	(0.303)		(0.228)	(0.230)	(0.230)	(0.231)
Analysts		-0.002	-0.002	-0.002	-0.002		-0.000	-0.000	-0.000	-0.000
		(0.002)	(0.002)	(0.002)	(0.002)		(0.001)	(0.001)	(0.001)	(0.001)
Non-interest			0.168**		0.184***			0.389***		0.388***
			(0.065)		(0.070)			(0.136)		(0.117)
Deposits				-0.016	-0.044				0.040	0.039
				(0.056)	(0.056)				(0.079)	(0.078)
Constant	0.521***	0.095	-0.124	0.637***	0.428**	0.663***	-0.170	-0.294	-0.246	-0.364
	(0.109)	(0.152)	(0.168)	(0.199)	(0.207)	(0.113)	(0.220)	(0.223)	(0.247)	(0.255)
Observations	14601	14032	14032	13599	13599	14601	14032	14032	13599	13599
Adjusted R^2	0.225	0.597	0.598	0.602	0.603	0.292	0.493	0.494	0.499	0.501
Number of banks	519	511	511	508	508	519	511	511	508	508

This table presents the OLS and fixed-effects estimation results of the effects of competition on opacity score. Models 2-5 present the OLS estimation results, whilst Models 6-10 include bank fixed effect. Time dummies are included in all estimations. Standard error robust to heteroscedasticity and clustering within banks are given in parentheses. The sample and variable definitions are as described in Table 1. *, **, *** indicate significance at 1%, 5% and 10% respectively.
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Table 7: Banking competition and bank opacity – two-stage least square

	(1)	(2)	(3)	(4)	(5)	(6)
	Forecast error		Forecast dispersion		Opacity score	
	First-stage	Second-stage	First-stage	Second-stage	First-stage	Second-stage
Dependent variable	Lerner	Forecast error	Lerner	Forecast dispersion	Lerner	Forecast score
Inefficiency$_{t-1}$	-0.863***		-0.857***		-0.857***	
	(0.048)		(0.053)		(0.053)	
Lerner$_{t-2}$	0.079***		0.085***		0.085***	
	(0.025)		(0.027)		(0.027)	
Lerner		-1.135***		-0.402***		-0.573***
		(0.266)		(0.099)		(0.121)
Size	0.013***	0.064**	0.014***	0.017	0.014***	0.020
	(0.002)	(0.028)	(0.002)	(0.013)	(0.002)	(0.015)
Loans	0.014**	0.326***	0.015**	0.076*	0.015**	0.100*
	(0.007)	(0.102)	(0.007)	(0.042)	(0.007)	(0.052)
Capital	-0.030	-3.161***	-0.029	-0.772**	-0.029	-1.046***
	(0.025)	(0.727)	(0.027)	(0.314)	(0.027)	(0.384)
Surprise	0.002	12.549***	0.002	7.029***	0.002	7.587***
	(0.011)	(1.043)	(0.013)	(0.398)	(0.013)	(0.504)
Provisions	-0.033	15.938***	-0.052	7.610***	-0.052	9.388***
	(0.053)	(2.315)	(0.058)	(0.901)	(0.058)	(1.087)
Volatility	0.006	6.478***	0.008	1.873***	0.008	3.009***
	(0.005)	(0.475)	(0.005)	(0.180)	(0.005)	(0.230)
Analysts	-0.000**	-0.003	-0.000**	0.001	-0.000**	-0.000
	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)
Non-interest	-0.013	0.821***	-0.014	0.298***	-0.014	0.384***
	(0.013)	(0.215)	(0.014)	(0.100)	(0.014)	(0.117)
Deposits	0.008	0.277**	0.009	0.043	0.009	0.057
	(0.008)	(0.137)	(0.008)	(0.065)	(0.008)	(0.078)
Observations	15599	15599	13487	13487	13487	13487
Adjusted R^2		0.385		0.473		0.482
Number of banks	551	551	477	477	477	477
Kleibergen-Paap F stat.		374.527		305.438		305.438
Hansen J p-value		0.605		0.161		0.353

This table presents the two-stage estimation results of the effects of competition on analysts' forecast error, forecast dispersion and opacity score. Models 1, 3 and 5 present the results of the first-stage regressions, whilst Models 2, 4 and 6 present the results of the corresponding second-stage regressions. Time dummies are included in all estimations. Standard error robust to heteroscedasticity and clustering within banks are given in parentheses. Inefficiency is the ratio of overheads to income. The sample and variable definitions are as described in Table 1. *, **, *** indicate significance at 1%, 5% and 10% respectively.

Table 8: Banking competition and bank opacity – Controlling for analysts' characteristics

Dependent variable	(1) Forecast error	(2) Forecast error	(3) Forecast error	(4) Forecast error	(5) Forecast dispersion	(6) Forecast dispersion	(7) Forecast dispersion	(8) Forecast dispersion	(9) Opacity score	(10) Opacity score	(11) Opacity score	(12) Opacity score
Lerner	-0.898***	-0.904***	-0.906***	-0.898***	-0.366***	-0.366***	-0.366***	-0.365***	-0.481***	-0.481***	-0.481***	-0.480***
	(0.236)	(0.235)	(0.236)	(0.235)	(0.089)	(0.088)	(0.088)	(0.088)	(0.106)	(0.106)	(0.106)	(0.106)
Size	0.065**	0.061**	0.064**	0.062**	0.018	0.017	0.017	0.016	0.021	0.020	0.020	0.019
	(0.028)	(0.028)	(0.028)	(0.028)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Loans	0.315***	0.311***	0.316***	0.312***	0.078*	0.077*	0.077*	0.077*	0.098*	0.097*	0.098*	0.097*
	(0.100)	(0.101)	(0.101)	(0.100)	(0.042)	(0.042)	(0.042)	(0.042)	(0.052)	(0.052)	(0.052)	(0.052)
Capital	-3.248***	-3.221***	-3.223***	-3.203***	-0.801**	-0.792**	-0.792**	-0.794**	-1.091***	-1.077***	-1.078***	-1.078***
	(0.727)	(0.725)	(0.725)	(0.724)	(0.314)	(0.314)	(0.314)	(0.314)	(0.386)	(0.385)	(0.385)	(0.385)
Surprise	12.631***	12.614***	12.633***	12.600***	7.052***	7.049***	7.050***	7.045***	7.620***	7.615***	7.620***	7.612***
	(1.045)	(1.044)	(1.044)	(1.044)	(0.400)	(0.400)	(0.400)	(0.400)	(0.505)	(0.505)	(0.505)	(0.505)
Provisions	15.905***	15.761***	15.781***	15.788***	7.609***	7.577***	7.573***	7.595***	9.366***	9.317***	9.309***	9.331***
	(2.272)	(2.274)	(2.276)	(2.271)	(0.888)	(0.889)	(0.889)	(0.888)	(1.065)	(1.066)	(1.068)	(1.065)
Volatility	6.472***	6.478***	6.462***	6.460***	1.867***	1.870***	1.869***	1.868***	3.000***	3.004***	3.000***	2.998***
	(0.476)	(0.476)	(0.475)	(0.474)	(0.180)	(0.181)	(0.181)	(0.180)	(0.231)	(0.231)	(0.231)	(0.231)
Analysts	-0.003	-0.003	-0.003	-0.003	0.001	0.001	0.001	0.001	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non-interest	0.819***	0.831***	0.838***	0.823***	0.293***	0.297***	0.297***	0.292***	0.383***	0.388***	0.389***	0.382***
	(0.214)	(0.215)	(0.214)	(0.214)	(0.100)	(0.100)	(0.100)	(0.100)	(0.117)	(0.117)	(0.117)	(0.117)
Deposits	0.223	0.236*	0.239*	0.234*	0.035	0.036	0.037	0.036	0.037	0.040	0.041	0.040
	(0.140)	(0.140)	(0.140)	(0.140)	(0.064)	(0.065)	(0.065)	(0.065)	(0.078)	(0.079)	(0.078)	(0.079)
Experience	-0.029***			-0.035***	-0.010***			-0.013***	-0.014***			-0.018***
	(0.009)			(0.009)	(0.004)			(0.005)	(0.005)			(0.005)
Length		0.004		0.014***		-0.000		0.003		0.000		0.005*
		(0.005)		(0.005)		(0.002)		(0.002)		(0.003)		(0.003)
Scope			-0.050**	-0.035			-0.003	0.003			-0.011	-0.003
			(0.022)	(0.023)			(0.008)	(0.009)			(0.010)	(0.011)
Constant	-1.047**	-1.257***	-1.147**	-0.962**	-0.236	-0.311	-0.304	-0.227	-0.257	-0.364	-0.341	-0.234
	(0.491)	(0.483)	(0.486)	(0.488)	(0.251)	(0.249)	(0.250)	(0.252)	(0.259)	(0.255)	(0.256)	(0.258)
Observations	15745	15745	15745	15745	13599	13599	13599	13599	13599	13599	13599	13599
Adjusted R^2	0.408	0.408	0.408	0.408	0.493	0.493	0.493	0.493	0.501	0.500	0.501	0.501
Number of banks	590	590	590	590	508	508	508	508	508	508	508	508

This table presents the fixed-effects estimation results of the effects of competition on analysts' forecast error, forecast dispersion and opacity score. Models 2-5 present the OLS estimation results, whilst Models 6-10 include bank fixed effect. Time dummies are included in all estimations. Standard error robust to heteroscedasticity and clustering within banks are given in parentheses. The sample and variable definitions are as described in Table 1. *, **, *** indicate significance at 1%, 5% and 10% respectively.

Table 9: Banking competition and bank opacity – Crisis subsamples

	(1) Forecast error	(2) Forecast error	(3) Forecast error	(4) Forecast dispersion	(5) Forecast dispersion	(6) Forecast dispersion	(7) Opacity score	(8) Opacity score	(9) Opacity score
Lerner	-1.534***	-0.496**	-0.854***	-0.467***	-0.268***	-0.288**	-0.686***	-0.315***	-0.393***
	(0.350)	(0.200)	(0.311)	(0.127)	(0.090)	(0.131)	(0.152)	(0.096)	(0.139)
Size	0.059**	0.057**	0.056**	0.016	0.015	0.015	0.018	0.017	0.017
	(0.027)	(0.028)	(0.028)	(0.013)	(0.013)	(0.013)	(0.014)	(0.015)	(0.015)
Loans	0.299***	0.276***	0.274***	0.074*	0.068	0.068	0.091*	0.082	0.081
	(0.099)	(0.100)	(0.099)	(0.042)	(0.042)	(0.042)	(0.052)	(0.052)	(0.052)
Capital	-3.172***	-3.184***	-3.171***	-0.794**	-0.799**	-0.799**	-1.079***	-1.087***	-1.087***
	(0.710)	(0.709)	(0.704)	(0.313)	(0.312)	(0.312)	(0.381)	(0.380)	(0.379)
Surprise	12.465***	12.315***	12.288***	7.025***	6.981***	6.979***	7.571***	7.503***	7.497***
	(1.046)	(1.041)	(1.043)	(0.397)	(0.398)	(0.398)	(0.503)	(0.502)	(0.501)
Provisions	15.399***	15.958***	15.749***	7.539***	7.647***	7.637***	9.218***	9.420***	9.378***
	(2.248)	(2.231)	(2.219)	(0.883)	(0.881)	(0.880)	(1.060)	(1.049)	(1.050)
Volatility	6.442***	6.438***	6.433***	1.863***	1.862***	1.861***	2.989***	2.988***	2.986***
	(0.471)	(0.469)	(0.468)	(0.181)	(0.180)	(0.180)	(0.230)	(0.229)	(0.229)
Analysts	-0.002	-0.002	-0.002	0.001	0.001	0.001	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non-interest	0.830***	0.774***	0.784***	0.295***	0.282***	0.283***	0.387***	0.365***	0.368***
	(0.212)	(0.213)	(0.212)	(0.100)	(0.101)	(0.100)	(0.116)	(0.117)	(0.117)
Deposits	0.222	0.197	0.196	0.033	0.027	0.027	0.034	0.026	0.025
	(0.136)	(0.137)	(0.136)	(0.065)	(0.065)	(0.065)	(0.078)	(0.079)	(0.079)
Experience	-0.034***	-0.034***	-0.034***	-0.013***	-0.013***	-0.013***	-0.018***	-0.018***	-0.018***
	(0.009)	(0.009)	(0.009)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Length	0.013**	0.013**	0.013**	0.003	0.003	0.003	0.005*	0.005	0.005
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Scope	-0.032	-0.035	-0.034	0.004	0.003	0.003	-0.002	-0.003	-0.003
	(0.023)	(0.023)	(0.023)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)
Lerner x Pre-crisis	1.392***		0.666*	0.230		0.037	0.464**		0.151
	(0.383)		(0.363)	(0.152)		(0.145)	(0.187)		(0.173)
Pre-crisis	-1.000***		-0.540**	-0.238**		-0.116	-0.387***		-0.187*
	(0.255)		(0.239)	(0.096)		(0.093)	(0.118)		(0.109)
Lerner x crisis		-2.451***	-2.128***		-0.588**	-0.570**		-1.001***	-0.929***
		(0.602)	(0.606)		(0.253)	(0.261)		(0.313)	(0.315)
Crisis		1.504***	1.291***		0.426***	0.414***		0.665***	0.618***
		(0.297)	(0.309)		(0.131)	(0.140)		(0.159)	(0.163)
Constant	-0.496	-1.053**	-0.818	-0.148	-0.247	-0.234	-0.076	-0.268	-0.215
	(0.519)	(0.485)	(0.512)	(0.260)	(0.256)	(0.267)	(0.270)	(0.262)	(0.273)
Observations	15745	15745	15745	13599	13599	13599	13599	13599	13599
Adjusted R^2	0.410	0.412	0.412	0.493	0.494	0.494	0.502	0.503	0.503
Number of banks	590	590	590	508	508	508	508	508	508

This table presents the fixed-effects estimation results of the effects of competition on analysts' forecast error, forecast dispersion and opacity score. Models 2-5 present the OLS estimation results, whilst Models 6-10 include bank fixed effect. Time dummies are included in all estimations. Standard error robust to heteroscedasticity and clustering within banks are given in parentheses. The sample and variable definitions are as described in Table 1. *, **, *** indicate significance at 1%, 5% and 10% respectively.

Table 10: Banking competition and bank opacity – addressing state-quarter fixed effects

	(1)	(2)	(3)
	AFE	FDISP	Score
Lerner	-1.126***	-0.369***	-0.528***
	(0.268)	(0.088)	(0.119)
Size	0.048	0.015	0.020
	(0.033)	(0.015)	(0.018)
Loans	0.163	0.030	0.033
	(0.105)	(0.046)	(0.061)
Capital	-1.900***	-0.550*	-0.681*
	(0.730)	(0.330)	(0.406)
Surprise	8.333***	4.663***	5.062***
	(0.909)	(0.341)	(0.441)
Provisions	5.651**	2.458***	2.774**
	(2.244)	(0.852)	(1.115)
Volatility	4.391***	1.081***	1.884***
	(0.414)	(0.145)	(0.189)
Analysts	-0.006**	-0.002*	-0.003*
	(0.003)	(0.001)	(0.001)
Non-interest	0.800***	0.313***	0.419***
	(0.183)	(0.073)	(0.088)
Deposits	0.150	-0.042	-0.036
	(0.160)	(0.076)	(0.095)
Constant	-1.533***	-0.454*	-0.624**
	(0.558)	(0.263)	(0.317)
Observations	15748	13601	13601
Adjusted R^2	0.125	0.147	0.162
Number of banks	590	508	508

This table presents the fixed-effect estimation results of the effects of competition on analysts' forecast error, forecast dispersion and opacity score. Lerner index and opacity are state-quarter mean-adjusted in all models. Standard error robust to heteroscedasticity and clustering within bank are given in parentheses. The sample and variable definitions are as described in Table 1. *, **, *** indicate significance at 1%, 5% and 10% respectively.

Table 11: Banking competition and bank opacity – using a measure of competition at the banking market level

	(1) AFE	(2) FDISP	(3) SCORE
Lerner	-0.887***	-0.450**	-0.513***
	(0.332)	(0.176)	(0.184)
Size	0.044	0.009	0.010
	(0.028)	(0.013)	(0.014)
Loans	0.282***	0.066	0.082
	(0.101)	(0.042)	(0.052)
Capital	-3.387***	-0.850***	-1.159***
	(0.715)	(0.312)	(0.380)
Surprise	12.705***	7.074***	7.653***
	(1.044)	(0.400)	(0.504)
Provisions	15.920***	7.618***	9.386***
	(2.286)	(0.892)	(1.069)
Volatility	6.480***	1.867***	3.000***
	(0.478)	(0.181)	(0.232)
Analysts	-0.002	0.001	-0.000
	(0.002)	(0.001)	(0.001)
Non-interest	0.928***	0.332***	0.438***
	(0.219)	(0.099)	(0.119)
Deposits	0.184	0.018	0.013
	(0.139)	(0.065)	(0.078)
Constant	-0.960*	-0.134	-0.178
	(0.527)	(0.287)	(0.289)
Observations	15745	13599	13599
Adjusted R^2	0.406	0.492	0.499
Number of banks	590	508	508

This table presents the fixed-effects estimation results of the effects of competition on analysts' forecast error, forecast dispersion and opacity score. Lerner index is measured at the state level for each year-quarter in all models. Standard error robust to heteroscedasticity and clustering within banks are given in parentheses. The sample and variable definitions are as described in Table 1. *, **, *** indicate significance at 1%, 5% and 10% respectively.