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Opacity and risk-taking: Evidence from Norway*

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ABSTRACT

This paper investigates how balance sheet opacity affects banks' risk-taking behavior. We measure bank balance sheet opacity according to two metrics: the ratio of available-for-sale (AFS) securities and the ratio of off-balance sheet items. We show that balance sheet opacity is positively correlated with realized bank risk. Specifically, banks with more AFS securities have lower realized risk, while banks with more off-balance sheet items have higher realized risk. The correlation between opacity and risk depends on both macroeconomic variables and bank characteristics. The positive relationship between bank opacity and bank risk is weaker for better capitalized banks and banks that are subject to more market discipline. The relationship is also weaker during periods of favorable market conditions. Motivated by this analysis, we then investigate how regulation affects bank opacity. We show that higher capital requirements reduce bank opacity and bank risk through a portfolio rebalancing channel.

Keywords: Opacity; Transparency; Available-for-sale securities; Off-balance sheet items; Risk-taking.

JEL Classification: G21, G23, G28

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1 Introduction

Following the 2007-2009 global financial crisis, policy makers across the globe have enacted broad regulatory reforms that aimed at enhancing transparency and resilience in the banking sector. A key pillar of the Basel reform — Pillar 3 — is focused on improving market participants' ability to monitor and discipline banks. Some empirical studies suggest that more transparency is indeed beneficial for financial stability (Demirguc-Kunt et al., 2006) and hence provide support for such policies. Others, however, argue that increasing transparency can have adverse effects on financial intermediation (Chen et al., 2018).[1] Moreover, theoretically, the relationship between transparency and risk-taking is not clear-cut. Conclusions span the whole spectrum. Some studies suggest that more transparency can be stabilizing (Morris and Shin, 1998), for example, through stronger market discipline on banks' behavior (Boot and Schmeits, 2000) or a lower risk of financial panics (Gorton and Huang, 2006; Dang et al., 2017). Other studies, however, suggests that more transparency can be destabilizing, for example through coordinated bank runs (Moreno and Takalo, 2016; Morris and Shin, 2002).[2] In addition, there is also a debate about whether separate measures to enhance transparency are needed, or whether key policy tools such as higher capital requirements are sufficient to induce banks to become more transparent to the extent that the funding of opaque assets requires relatively more capital. Given the current debate on the next generation of financial regulation, understanding the relationship between transparency and risk-taking and how it is shaped by financial regulation is therefore of first-order importance.

In this paper, we use Norwegian supervisory data to focus on two questions. First, what is the empirical relationship between bank balance sheet opacity and bank risk-taking? Second, how do higher capital requirements affect banks choice of transparency and, as a by-product, their risk?

We consider two forms of opacity — opacity arising from the lack of information on the quality of banks' asset holdings, and opacity arising from the fact that existing information on banks' asset holdings is hard to process in order to gauge banks' health. We use a supervisory dataset to create proxies for both measures. Specifically, we measure the amount of off-balance sheet items relative to total assets as a proxy for the first form of opacity, as there typically exists much less information

[1] See Zheng (2020) for empirical evidence suggesting that opacity *adversely* affects lending.

[2] Iachan and Nenov (2015) show how the qualitative impact of transparency on financial stability depends crucially on the underlying set-up in one important class of models.

available for outsiders of banks on the nature and payoff structure of off-balance sheet items. As a proxy for (the inverse of) the second form of opacity, we use the fraction of marked-to-market, available-for-sale (AFS) trading assets relative to total assets, as these assets are priced by market participants and hence more transparent. As for the risk-taking measures, we focus on the log of the realized (inverse) z-score and the standard deviation of the return on assets (RoA).

We investigate the relationship between realized risk and our two opacity measures by running panel regressions for the universe of Norwegian banks over the period 1993-2015. In order to pin down the relationship between our opacity measures and realized risk as precisely as possible, we condition on a wide range of bank-level and macro controls, in addition to including bank and year fixed effects. We start by estimating the average relationship between realized risk and opacity. After having established how opacity and risk correlate on average, we then explore cross-sectional and time-series dimensions. We extend our panel regression setup by including interaction terms that can shed light on the underlying mechanisms behind our findings, such as banks' capital ratio and reliance on market funding, as well as the quarterly GDP growth and the quarterly level of the VIX index. Finally, to investigate how capital requirements affect bank transparency, we exploit the introduction of higher capital requirements in Norway in 2013 as a policy experiment and compare the evolution of bank transparency for more and less affected banks in a difference-in-difference setting.

We present four sets of findings. First, on average, more opaque banks have higher realized risk as measured by the log of the inverse z-score and the standard deviation of RoA. This is consistent with findings from other studies using different opacity measures (Fosu et al., 2017; Demirguc-Kunt et al., 2006). Second, there are substantial cross-sectional and time-series variations. Specifically, the relationship between opacity and risk is muted for banks with higher equity ratios and higher reliance on short-term market funding. These findings are consistent with two potential mechanisms through which opacity affects risk-taking. The first mechanism is that better capitalized banks have more skin in the game and hence less incentives to exploit their opaqueness to take more risk. The second mechanism is that banks that are more reliant on uncollateralized market funding are subject to more market discipline and as a result have more risk-sensitive funding costs. Third, we show that the relationship between opacity and risk-taking is weakened under favorable macroeconomic conditions. Finally, turning to our policy experiment, we find that higher capital requirements enhance bank transparency by inducing banks to shift their portfolios towards relatively more transparent assets. Simulatenously, the realized risk declines.[3] Capital requirements thereby potentially affect bank solvency through a novel, transparency-enhancing channel.

Our paper belongs to an extensive strand of the literature that investigates the implications of bank opacity on bank outcomes.[4] In Section 3.2 we discuss the measurement of opacity in more detail. In Section 2 we discuss how opacity — conditional on its measurement — affects funding costs and the implications of that for bank risk. Here, we focus on outlining our three main contributions to the existing literature. Our first contribution is to consider two new measures of bank opaqueness — off-balance sheet activities and holdings of AFS securities. The advantage with considering these accounting-based measures relative to market-based measures it that they allow us to shed light on the specific balance sheet adjustments banks can make to generate opacity. Much of the literature focuses on market-based measures of transparency, such as stock market responses and disclosure quality of financial statements (for example, Chen et al. (2018) and Fosu et al. (2017), see more details in Section 3.2). Focusing on the balance sheet based measures also allows us to extend the analyses to the universe of banks in Norway, as the relationship between opacity and risk for smaller banks is typically less understood, partly due to lack of (market-based) opacity measures. Second, we provide additional evidence on why there exists a relationship between opacity and risk-taking. Specifically, we provide new evidence on how the relationship between risk-taking and opacity is both bank- and time-dependent. Third, we enrich the limited evidence on how banks' balance sheet opacity responds to banking regulation. We show that higher capital requirement — through a portfolio rebalancing effect — induces banks to shift towards more transparent assets and thereby potentially affects bank risk through a novel, transparency-enhancing channel.

2 Hypothesis development

The purpose of this section is to highlight the theoretical foundations for the hypotheses we test. First, in Section 2.1, we discuss the theoretical underpinnings of the relationship between

[3]Capital requirements could potentially also affect realized risk through other channels.

[4]Opacity is generally thought of as a form of *bank complexity.* A large literature focuses on other dimensions of complexity, most prominently geographical complexity (Buch et al., 2011; Cetorelli and Goldberg, 2014; Claessens and van Horen, 2014; Cetorelli and Goldberg, 2016; Goetz et al., 2016; Krause et al., 2017), or the complexities in banks' network or organizational structure (Lumsdaine et al., 2018; Flood et al., 2017).

opacity and risk-taking. We then discuss how capital requirements can affect banks opacity via their portfolio allocation in Section 2.2.

2.1 On the relationship between opacity and risk

A large part of a bank's assets is relatively opaque (Morgan, 2002; Flannery et al., 2004; Fosu et al., 2017). The existing theoretical literature focuses on the consequences of such opacity for bank risk-taking. Several theoretical analyses argue that there is a positive relationship between opacity and risk-taking (see, for instance, Cordella and Yeyati (1998), Boot and Schmeits (2000), Nier (2005) and Moreno and Takalo (2016)). Although different analyses vary across several dimensions, one line of reasoning for the positive relationship between opacity and risk centers around the argument that banks' financing costs are more sensitive to banks' risk-taking when banks are transparent. For instance, consider an extreme case where banks can either be "transparent" or "opaque", as well as of "high" or "low" risk. Outside lenders set a lending rate to reflect the observability and the extent of the bank's risk-taking, as in Froot and Stein (1998). Transparent but riskier banks incur higher costs of funding compared to transparent and less risky banks. Hence, by choosing to be transparent, banks expose themselves to market discipline. By choosing a low-risk portfolio, banks are rewarded by their creditors with lower financing costs. As a result, transparent banks choose to be "safe". If banks choose not to be transparent, however, lenders typically assume that these banks are of higher risk. As a result, opaque banks face a higher cost of funding. This higher cost of funding incentivizes banks to take on more risk. As Moreno and Takalo (2016) show, such intuition carries through to the case where both bank risk and transparency are continuous outcomes. In their setting, the refinancing risk of opaque banks is less sensitive to their portfolio allocation, compared to the case of less opaque banks, hence they have stronger incentives to choose higher risk levels.

Based on this literature, a natural hypothesis (Fosu et al., 2017) is therefore as follows:

Hypothesis 1: *Higher bank opacity leads to higher risk-taking.*

This relationship is not necessarily constant. It may vary with a wide range of bank-level characteristics and macroeconomic environments. For instance, in the case where banks have both insured and uninsured creditors, banks with more uninsured creditors are more subject to market discipline (see for instance Martinez Peria and Schmukler (2001)) and in that case, the marginal impact of bank opacity on risk is muted.

Hypothesis 2: *The marginal impact of bank opacity on risk-taking is lower for banks subject to stronger market discipline.*

Moreover, banks with higher franchise values have — all else equal — less incentives to be engaged in excessive risk-taking due to more skin in the game (see, for instance, Acharya et al. (2017)). Therefore, it is likely that the relationship between opacity and risk is muted for banks with higher equity ratios.

Hypothesis 3: *The marginal impact of bank opacity on risk-taking is lower for banks with higher equity ratios.*

Finally, the franchise value of banks also depends on the economic outlook. Banks, therefore, have lower incentives to engage in risk-shifting behavior when the state of the economy is good (see for instance Baldursson and Portes (2013) or Scharfstein and Stein (2000).)

Hypothesis 4: *The marginal impact of bank opacity on risk-taking is lower when the economic outlook is good.*

2.2 On the relationship between capital requirements and opacity

In Section 6 we investigate the impact of capital requirements on the opacity of banks' balance sheets. In this section, we briefly outline how capital requirements in theory may affect bank opacity.

In general, capital requirements affect the composition of banks' asset holdings both theoretically (Kim and Santomero, 1988; Freixas and Rochet, 2008) and empirically (Gropp et al., 2019; Juelsrud and Wold, 2020). The theoretical underpinnings for why capital requirements affect banks' asset holdings rely on the assumption that equity financing is relatively costly compared to debt financing. Risk weighted capital requirements in such a case impose an equity cost associated with investing in each asset that is proportional to that asset's risk weight. A key result in Kim and Santomero (1988) is that the extent to which changes in capital requirements affect bank portfolio composition depends on whether the risk weight associated with each asset is proportional to the systematic risk and hence the return of that asset. If the risk weight is high relative to the systematic risk of an asset, higher capital requirements induce banks to shift *away* from that asset to save on capital costs. Conversely, if the risk weight is low relative to the systematic risk of an asset, higher capital requirements induce banks to shift *towards* this asset as capital requirements increase.

Hence, theoretically, the impact of capital requirement changes on banks' holdings of opaque assets depends crucially on whether opaque assets have high or low risk weights relative to systematic risk. In general, it is hard to evaluate this ex ante without estimating the systematic risk of each respective asset. The inherent nature of opaque assets makes this especially challenging in our context. However, as argued in Juelsrud and Wold (2020), banks' responses to higher capital requirements are directly informative about the relationship between risk weights and systematic risk. Risk weights are excessively high (low) on opaque assets if we observe that banks shift away from (towards) such assets as capital requirements increase.[5] Therefore, ex ante, higher capital requirements can both reduce or increase banks' holdings of opaque assets. Hence, in Section 6 we test the following two hypotheses.

Hypothesis 5: *Higher capital requirements reduce opacity.*

Hypothesis 6: *Higher capital requirements increase opacity.*

3 Institutional background and data

In this section, we start by providing a brief overview over the structure of Norwegian banking sector. We then move on to discuss what data we use and how we construct our opacity measures.

3.1 The structure of Norwegian banking sector

Norway is a bank-oriented economy where the banking sector (banks and their subsidiaries) accounts for 80% of total domestic credit to households and businesses at the end of 2015. The total assets of the Norwegian banking sector corresponds to approximately 220 % of Norwegian GDP.

[5] See also Fuster and Vickery (2018) for an analysis on how regulation affects bank transparency.

Norwegian banks are classified as either savings banks or commercial banks, although there are in practice limited differences between savings and commercial banks. Market concentration in Norwegian banking sector is comparable with other European countries. The eight largest banks in Norway account for 61% of total loans (Cao et al., 2020) as of 2017Q4; among them, four are subsidiaries/branches of foreign banks.

3.2 Opacity measures

Investigating the relationship between opacity and risk entails measuring both. Measuring the former is not straightforward, especially. In the existing literature, bank opacity is usually measured by market-based indicators. For example, Flannery et al. (2004) and Flannery et al. (2013) measure opaqueness by bank equity trading properties such as bid-ask spread, while Fosu et al. (2017) proxy banks' opacity by analysts' forecast error in bank earnings. Spargoli and Upper (2018) on the other hand investigate bank opacity via the abnormal return from bank insider sales. Moreover, an extensive strand of literature constructs bank opacity measures by the quality of banks' financial statements (for instance, banks' discretionary loan loss provisions (Beatty and Liao (2014), Iannotta and Kwan (2014), Jiang et al. (2016), Kim et al. (2019), and Zheng (2020)) and how much information on its risk profile a bank provides in its financial statements (Nier, 2005; Acharya and Ryan, 2016). Whereas market-based opacity measures are good at capturing market participant's perception of bank risk and as such better predict investors' reaction to banks' behavior, the sources of opacity — often arising from how banks allocate their investments among a wide spectrum of assets with various degrees of opacity — remain less well understood. In addition, market-based measures are only available for a small number of large, listed banks. However, for the rest of the banking sector, i.e., a large number of unlisted banks that often account for a substantial share of a banking system but are subject to much lower information disclosure requirements, the relationship between opacity and bank risk is less understood.

In this paper, we therefore rely on quarterly, detailed balance sheet information for the *universe* of banks in Norway to measure banks' opacity directly from the holdings of certain specific opaque or transparent assets. We attempt to extract measures of opacity about banks' health, from the perspective of outside investors and lenders. With respect to that, there are two forms of opacity (Damodaran, 2006). First, opacity can arise due to the fact that there simply might not be sufficient information available. This can arise, for instance, if banks have large engagements in off-balance sheet activities. Second, even in the presence of available information, banks can be opaque because the information can only be converted into relevant metrics at a large cognitive and economic cost. This can, for instance, arise when a bank is active in multiple business lines and market segments.

Neither of these two forms of opacity are directly measurable, hence we choose two bank-level proxies. Our first opacity measure is “available-for-sale (AFS) securities”. Under Norwegian accounting standards, security holdings on banks’ balance sheets can be classified in either “AFS securities” — securities that are purchased with the intent of selling before they reach maturity, or “held-to-maturity (HTM) securities” — securities that are purchased with the intent of selling after they reach maturity. The underlying idea of using AFS securities as bank opacity measure is as follows: while HTM securities are accounted for at amortized cost so that their gains and losses are only reported after maturity, AFS securities are marked-to-market so that their (unrealized) gains and losses are reflected immediately in banks’ equity value. As a result, AFS assets are easily valued, based on publicly available and verifiable information. Hence, for banks with more AFS securities, it is essentially easier for market participants to evaluate the health of the institution and banks’ balance sheet opacity is thus lower (Fuster and Vickery, 2018).

Our second opacity measure is the size of banks’ off-balance sheet items, relative to the on-balance sheet total assets. Our dataset contains an overview of off-balance sheet items for a sub-period in our sample (2002-2007). In order to ensure banks’ compliance with capital requirements, banks were obliged to report any off-balance sheet exposure to Norwegian regulatory agency. This includes guarantees, assets transferred with repurchase agreements, unused credit facilities, etc. Although the off-balance sheet items are not observable for investors and depositors, banks are by law obliged to provide an assessment of the value of these items to the regulator. The underlying idea of using off-balance sheet items as a measure of bank opacity is that there is less information available to outsiders about factors which ultimately affect banks’ payoffs on these assets.

3.3 Summary statistics

Our data is an unbalanced panel consisting of quarterly balance sheet reports from Norwegian banks for the period 1993Q1-2015Q4, except the data on off-balance sheet items which is only available from 2002Q1 to 2007Q4. The dataset consists of all Norwegian banks, as well as the subsidiaries and branches of foreign banks. In total, we have at most 148 unique institutions, but the number of banks varies from year to year.[6]

We use two measures of bank risk. The first and primary measure is the (log of) a bank's (inverse) z-score. The z-score is constructed as the sum of 4-quarter return on assets (RoA) and the contemporaneous equity ratio (equity/total assets), divided by the 4-quarter standard deviation of RoA.[7] Our second, supplementary measure of bank risk is the (4-quarter) standard deviation of RoA. Table 1 presents the summary statistics for our sample.[8]

Table 1: Summary statistics

	N	Mean	SD	Min	Max
RoA	12655	.006	.011	-.343	.4662
Equity/assets	12689	.053	.026	-.160	.496
Short-term funding / total assets	1983	.680	.147	.095	.991
Log (total assets)	12689	10.507	1.549	5.024	16.516
AFS securities to total assets	2436	.026	.026	.001	.238
Ratio of off-balance sheet items to total assets	7318	.207	2.077	.001	103.171
Log (1/z-score)	12423	-2.873	.561	-6.510	4.038
Sd(RoA)	12459	0.004	0.008	0.000	0.556

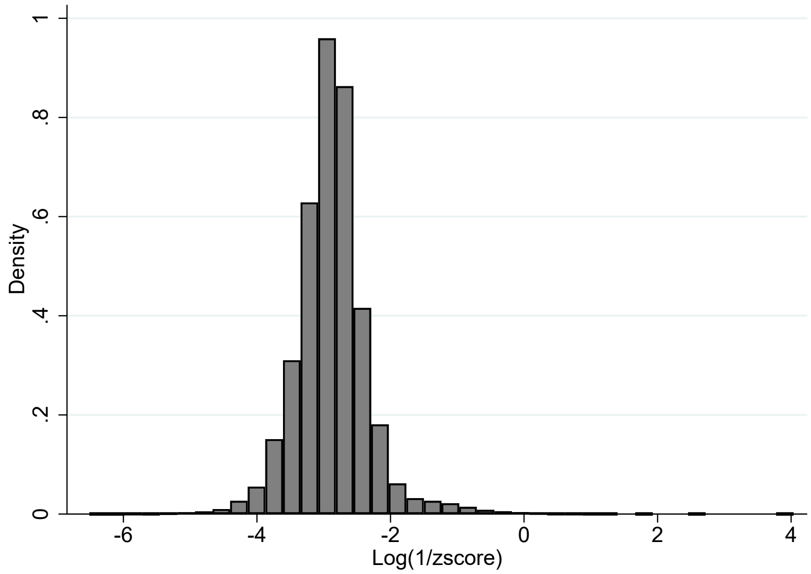
On average, the banks in our sample hold approximately 3 percent AFS securities in their assets. There is a substantial variation across banks, with one bank holding approximately 23 percent of its assets in AFS securities. In terms of off-balance sheet items, the variation is even larger. On average, off-balance sheet items account for roughly 20 percent of total assets. The variation across banks is larger, however, with a few clear outliers.[9]

[6] In most regressions, due to specific control variables that are only available for a subset of banks, the actual number of banks is smaller.

[7] Results are robust to different period lengths, see Appendix A.2.

[8] The summary statistics presented in Table 1 is based on the full sample. In all regressions, we report the relevant summary statistics in the regression table.

[9] Our results are qualitatively robust to considering a truncated sample, excluding the 1st and 99th percentiles of the various risk and opacity measures.



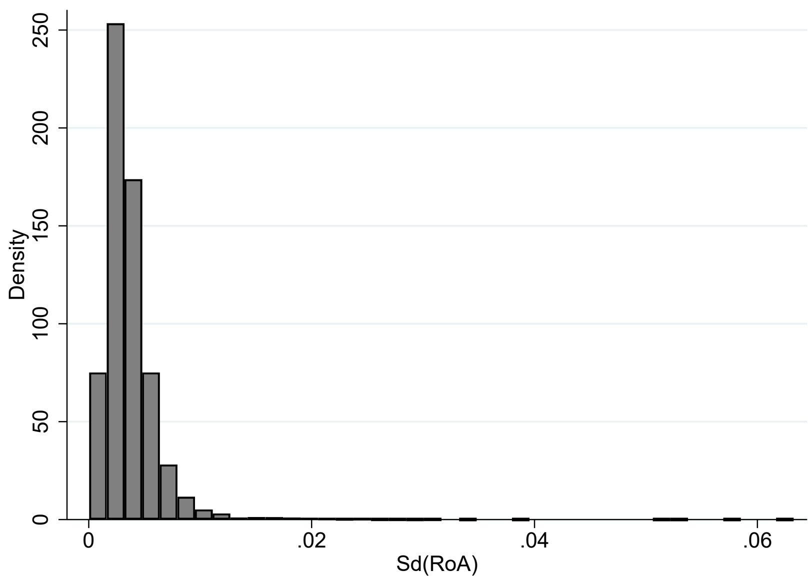


Figure 1: Empirical distribution of log (1/z-score) and (4-quarter) sd(RoA). Z-score is computed as the sum of 4-quarter average of RoA and contemporaneous equity ratio, divided by the standard deviation of RoA over the past 4-quarters. The sd(RoA) distribution is in this plot trunacted at the 7 % level for presentability.

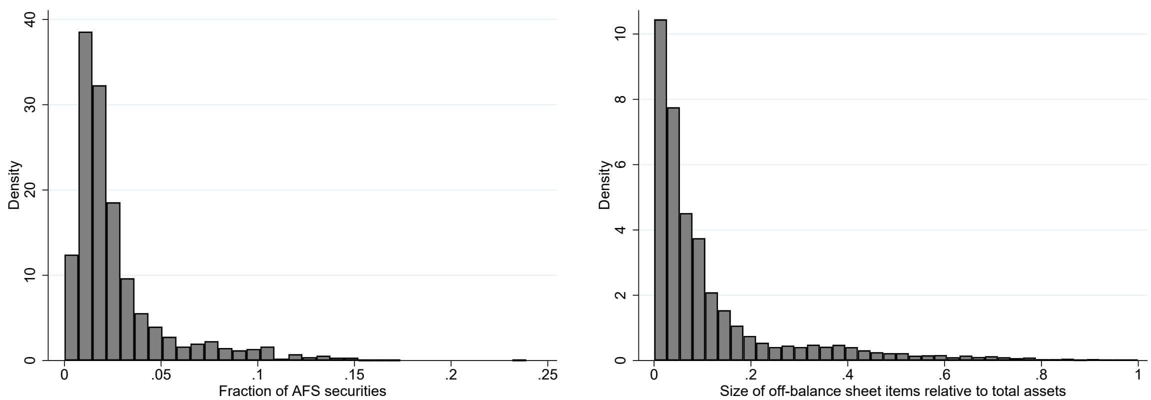


Figure 2: Empirical distribution of the share of AFS securities in total assets (left panel) and off-balance sheet items relative to total assets (right panel). In both plots, we truncate the variable of interest for presentability.

Figure 1 shows the empirical distribution of our two risk metrics. Next, Figure 2 shows the empirical distribution of the ratio of AFS securities (left panel) and the ratio of off-balance sheet items to total assets (right panel). Both measures are approximately log-normal with sizable variations across banks. This variation is crucial in terms of pinning down the conditional correlation between opacity and bank risk in Section 5.

4 Conditional correlation between opacity and risk-taking

4.1 Methodology

In order to investigate the relationship between opacity and risk-taking on average, we estimate the following regression

$$Y_{b,t} = \alpha_b + \beta' \mathbf{d_{b,t-1}} + \theta c_{b,t-1} + \gamma' \mathbf{X_t} + \lambda_t + \epsilon_{b,t} \tag{1}$$

in which $Y_{b,t}$ is the risk measure for bank b in period t. The vector $\mathbf{d_{b,t-1}}$ captures bank-specific determinants of risk, and includes total loans, equity ratio, short-term funding to total assets, log of total assets and return on assets (RoA). The vector $\mathbf{X_t}$ includes macroeconomic controls, i.e., the VIX index and growth rate of GDP, λ_t includes year fixed effect and α_b is a bank-specific intercept. The coefficient of interest is θ, which captures the conditional relationship between the risk measure and a bank-specific opacity measure $c_{b,t-1}$.

4.2 Identification and the causal interpretation of our results

The identification of θ stems from assuming that $\mathbf{d_{b,t-1}}$ captures other confounding factors behind the relationship between opacity and risk. We are aware, however, that the variation we are exploiting in $c_{b,t-1}$ is subject to usual endogeneity concerns and that θ here should be interpreted as an estimate of the conditional correlation between opacity and risk-taking rather than a causal effect.

In order to alleviate some endogeneity concerns, however, we perform several robustness tests in the appendices. There are at least two, major threats to identification.[10]

The first and perhaps the most important threat to identification is the concern that banks that are relatively more opaque have a different business model compared to other banks, that is also correlated with their realized risk. In order to address this concern, we adopt four different strategies.

First, we saturate our estimating equations with bank fixed effects, effectively ensuring that θ is only identified from within-bank variation in opacity and risk. To the extent that opacity and risk are relatively sticky measures, this should alleviate some endogeneity concerns due to different business models.

Second, we conduct a further analysis where we focus on a subsample of smaller banks. Specifically, we exclude the 8 largest banks in our sample. Since the remaining sample (consisting mostly small, regional savings banks that primarily rely on raising deposits from/issuing loans to local firms and households) is much more homogeneous with respect to size and other factors, it strengthens the identification of θ further.

Third, we include several controls for business model. Specifically, we follow Fosu et al. (2017); Köhler (2015); Mergaerts and Vander Vennet (2016) and control for non-deposit funding relative to total assets (to capture banks' business models in funding) as well as non-interest income relative to total income (to capture banks' business models in investments).

Finally, we re-estimate our baseline regression with a sample consisting of foreign branches only. To the extent that foreign branches are less discretionary in terms of their asset allocations, hence

[10] We are very grateful to an anonymous referee for raising these concerns.

changes in their opacity-measures are plausibly more exogenous, it is informative to investigate whether we find similar results for this subsample. A challenge, though, is that this subsample is small.[11]

The second threat to identification is a reverse causality. Banks that are less risky may — as a signaling device — endogenously choose more transparent balance sheets. We address this concern in two ways. First, by lagging our complexity measure by one quarter, we can alleviate some immediate concerns about intra-period reverse causality. Second, by focusing on a smaller sample in Table 10 in Appendix A, we restrict our attention to non-publicly listed banks with primarily insured depositors. For this subsample, the scope for signaling should be less.

4.3 Results

As our point of departure, we plot our two opacity measures against the realized z-score in Figure 3. In the left panel of the figure, we plot the realized z-score against the share of AFS securities. In the right panel of the figure, we plot the realized z-score against the ratio of off-balance sheet items to total assets. Although Figure 3 is only suggestive, it appears to be a downward-sloping relationship between the fraction of AFS securities and the z-score, and an upward-sloping relationship between the ratio of off-balance sheet items and the z-score.

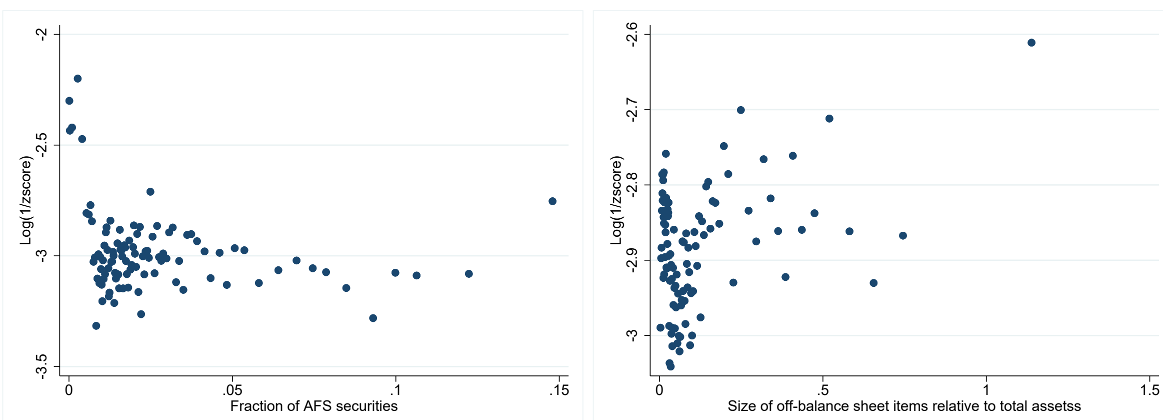


Figure 3: Correlation between log (1/z-score) and the share of AFS securities (left panel) / the share off-balance sheet items (right panel). Binned scatterplot.

Next, in Figure 4 we plot our two opacity measures against the bank-level sd(RoA). Again,

[11]Relative to the full sample, the branch × year-quarter subsample constitutes roughly 2% of our total number of observations.

especially AFS securities relative to total assets appears weakly positively correlated with this risk metric. The unconditional relationship between off-balance sheet items and sd(RoA) is downward-sloping. This relationship, however, changes once we add bank-level and macro controls.

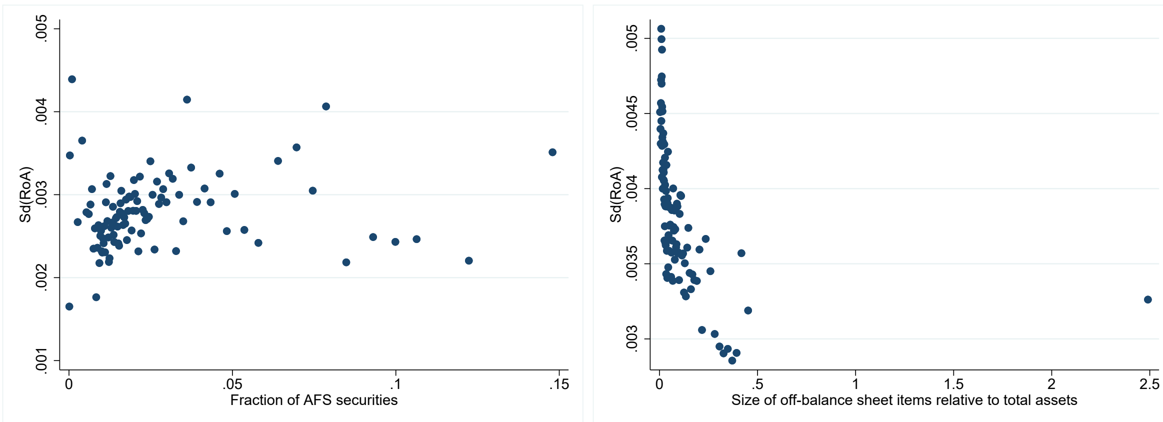


Figure 4: Correlation between sd(RoA) to total assets and the share of AFS securities (left panel) / the share off-balance sheet items (right panel). Binned scatterplot.

In order to statistically test whether our two opacity measures are significantly correlated with our risk metrics, we proceed by estimating equation (1). These results are shown in Table 2.

Starting with column (1), we show that the conditional correlation between the share of AFS securities and the z-score. There is a negative and statistically significant relationship. The same is true when we include sd(RoA), as shown in column (2).

Moving to columns (3) and (4), we focus on the ratio of off-balance sheet items to total assets as our opacity measure. The coefficient is positive and statistically significant when focusing on the z-score. For sd(RoA), there is a positive but imprecise conditional correlation (column 4) and we can not reject the null hypothesis.

To sum up, Table 2 documents statistically significant, albeit imprecise relationships between our two opacity measures and our risk measures. Higher share of AFS securities tends to be negatively associated with bank risk, while more off-balance sheet items tend to be positively associated with bank risk, at least according to the z-score. As we show in Appendix A, these results are largely robust to a series of tests that we propose in Section 4.2, namely[12]

[12]The major difference between the results from the robustness tests and here is that for some specifications the relationship between opacity and risk becomes insignificant. This is especially true for off-balance sheet items as opacity measure. Our interpretation is that this is primarily due to lower sample sizes - coefficient estimates are largely unchanged with few exceptions.

Table 2: Conditional correlation

	(1) Risk	(2) Risk	(3) Risk	(4) Risk
AFS securities to total assets, lagged	-3.3222*	-0.0121**		
	(1.8151)	(0.0047)		
Off balance sheet items to total assets, lagged			0.1196**	0.0003
			(0.0570)	(0.0002)
Risk measure	Z-score	Sd(RoA)	Z-score	Sd(RoA)
N	701	701	811	811
No. of clusters	25	25	28	28
Mean of dependent variable	-2.7641	0.0029	-2.7110	0.0034
SD of dependent variable	0.5450	0.0015	0.4656	0.0015
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: * $p<0.1$, ** $p<0.05$, ***$p<0.01$. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include the ratio of short-term funding to total assets, log(assets), loans to total assets, return on assets, equity to total assets, the growth rate of GDP and the VIX. All bank-level control variables are lagged.

1. Excluding large banks (see results in Table 10);
2. Controlling for time-varying proxies of business model following Fosu et al. (2017) (see results in Table 11);
3. Focusing exclusively on foreign branches (see results in Appendix A.3).

Discussion Although the results only reflect conditional correlations, they do suggest that the impact of AFS securities on bank risk differs from that of off-balance sheet items. AFS security holdings plausibly reduce the opacity in banks' balance sheets, as their losses and gains are easily observable for outsiders in real time. This allows investors and lenders to price banks' risk-taking better and hence make bank funding costs more sensitive to risk-taking. Simultaneously, as the losses and gains in AFS securities are immediately reflected through the value of banks' equity, AFS security holdings make banks' regulatory capital more volatile. To reduce the volatility in regulatory capital, banks need to reduce risk-taking in AFS assets and / or hold more capital buffers to cushion the losses, which also leads to lower realized risk.[13]

However, for off-balance sheet items, the implication is totally different. The components and payoff structure of off-balance sheet items are usually non-observable, or, opaque, for outsiders, and their losses and gains are not disclosed in real time. This makes it hard for investors and lenders to correctly price the risks.

5 Heterogeneous effects

We proceed by augmenting our baseline setup by interacting the opacity measures with bank characteristics. Specifically, we estimate

$$Y_{b,t} = \alpha_b + \beta' \mathbf{d_{b,t-1}} + \theta c_{b,t-1} + \psi' \left(c_{b,t-1} \times \mathbf{d_{b,t-1}}\right) + \chi' \left(c_{b,t-1} \times \mathbf{X_t}\right) + \gamma' \mathbf{X_t} + \lambda_t + \epsilon_{b,t} \qquad (2)$$

where $Y_{b,t}$ is a risk measure, ψ is a vector of coefficient estimates of the interactions between our opacity measures and the vector of bank characteristics, and χ' is a vector of coefficient estimates of the interactions between our opacity measures and the vector of macro controls. Estimating

[13] See Fuster and Vickery (2018) for a further discussion on the empirical relevance on this in the context of US banks.

equation (2) has the advantage of revealing whether the relationship between opacity and risk is stronger for some moments in the data. If that is the case, it may help unveil the underlying mechanisms.

In this section we focus on four different moments in the data. We focus on the moments that can shed light on two different channels:

1. Excessive risk taking: limited liability banks tend to take excess risk, as long as the downside risk, or, bankruptcy risk is small. However, better capitalized banks have more skin in the game (or, higher bankruptcy cost to incur) and should, all else equal, engage less in such risk-taking. In addition, the charter value of banks is likely to be higher when economic prospects are good (Scharfstein and Stein, 2000). We therefore also consider how the impact of opacity and risk depends on the state of the macro economy.[14]

2. Market discipline: we also investigate whether the relationship varies with uncollateralized market funding. Banks with more uncollateralized market funding are likely to be subject to more refinancing risk which ultimately affects risk-taking, as explained in Section 2.1. If market participants discipline banks, these banks should, to a larger extent, be punished for engaging in excess risk-taking behavior.[15]

We start by estimating (2), using AFS securities as our opacity measure. The results are reported in Table 3.[16]

[14]We use VIX and GDP growth as macro interaction variables. Using VIX as an interaction term is our attempt to investigate whether the relationship between opacity and risk varies across different financial market conditions. Moreover, the purpose of investigating whether it varies with GDP growth is to analyze whether there are similar interactions with the state of the real economy, since recent literature (for example, Zheng (2020)) documented that the positive relationship between opacity and bank lending is weakened under higher GDP growth.

[15]One concern is that market funding in general does not capture market discipline due to creditors' perception of implicit government guarantees, that developed from crisis resolution. During the most recent, 1988-1992 Norwegian banking crisis, the state promptly stepped in at an early stage and nationalized several failing banks so that all non-bank depositors were fully compensated, while other bank creditors suffered from losses (see details in Moe et al. (2004), Chapter 3); therefore, bank creditors should have much lower expectation on public guarantees and higher incentive to discipline borrowing banks. As a robustness exercise, we therefore measure exposure to market discipline by bank's reliance on interbank funding. The results are reported in Appendix C.2.

[16]In appendix C, we report all coefficient estimates. Here, for brevity, we only report the interaction terms in addition to the θ.

Table 3: Conditional correlation and heterogeneity, using AFS as opacity measure

	(1) Risk	(2) Risk	(3) Risk	(4) Risk	(5) Risk	(6) Risk	(7) Risk	(8) Risk
AFS securities to total assets, lagged	-11.5039*	3.6761	-2.4143	-1.8622	-0.0193	0.0140	-0.0090	-0.0069
	(6.2109)	(4.9919)	(2.8590)	(1.5994)	(0.0143)	(0.0150)	(0.0081)	(0.0052)
AFS securities to total assets, lagged×Equity to total assets	190.6706*				0.1684			
	(107.5491)				(0.2403)			
AFS securities to total assets, lagged×Short-term funding to total assets		-11.3440				-0.0413**		
		(6.8207)				(0.0176)		
AFS securities to total assets, lagged×GDP growth			-0.3109				-0.0011	
			(0.5028)				(0.0017)	
AFS securities to total assets, lagged×VIX				-0.0732				-0.0003
				(0.0757)				(0.0002)
Risk measure	Z-score	Z-score	Z-score	Z-score	Sd(RoA)	Sd(RoA)	Sd(RoA)	Sd(RoA)
N	701	701	701	701	701	701	701	701
No. of clusters	25	25	25	25	25	25	25	25
Mean of dependent variable	-2.7641	-2.7641	-2.7641	-2.7641	0.0029	0.0029	0.0029	0.0029
SD of dependent variable	0.5450	0.5450	0.5450	0.5450	0.0015	0.0015	0.0015	0.0015
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p<0.1, ** p<0.05, ***p<0.01. Mean and standard deviations are taken over the full sample period (1993-2015). Standard errors clustered at the bank level. Controls include the ratio of short-term funding to total assets, log(assets), loans to total assets, return on assets, equity to total assets, the growth rate of GDP and the VIX. All bank-level control variables are lagged.

Most of the interaction terms in Table 3 are statistically insignificant, with the exception of an imprecise result regarding the interaction term with bank equity ratios and short-term funding. The coefficients are significant for different risk metrics, and hence whether the association between bank risk and AFS securities varies according to the interaction terms is somewhat inconclusive.

Next, we move on to analyze whether the relationship between off-balance sheet items and realized risk varies in our data. The results are reported in Table 4.

Table 4: Conditional correlation and heterogeneity, using off-balance sheet as opacity measure

	(1) Risk	(2) Risk	(3) Risk	(4) Risk	(5) Risk	(6) Risk	(7) Risk	(8) Risk
Off balance sheet items to total assets, lagged	0.0371***	0.1057***	0.0426***	-0.0877***	0.0001	0.0002	0.0001**	-0.0001
	(0.0131)	(0.0275)	(0.0077)	(0.0136)	(0.0001)	(0.0002)	(0.0000)	(0.0001)
Off balance sheet items to total assets, lagged×Equity to total assets	-0.7817***				-0.0013**			
	(0.1192)				(0.0005)			
Off balance sheet items to total assets, lagged×Short-term funding to total assets		-0.1522***				-0.0003*		
		(0.0297)				(0.0002)		
Off balance sheet items to total assets, lagged×GDP growth			-0.0068***				-0.0000***	
			(0.0005)				(0.0000)	
Off balance sheet items to total assets, lagged×VIX				0.0057***				0.0000***
				(0.0006)				(0.0000)
Risk measure	Z-score	Z-score	Z-score	Z-score	Sd(RoA)	Sd(RoA)	Sd(RoA)	Sd(RoA)
N	878	878	878	878	878	878	878	878
No. of clusters	29	29	29	29	29	29	29	29
Mean of dependent variable	-2.6978	-2.6978	-2.6978	-2.6978	0.0034	0.0034	0.0034	0.0034
SD of dependent variable	0.4728	0.4728	0.4728	0.4728	0.0015	0.0015	0.0015	0.0015
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p<0.1, ** p<0.05, ***p<0.01. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include the ratio of short-term funding to total assets, log(assets), loans to total assets, return on assets, equity to total assets, the growth rate of GDP and the VIX. All bank-level control variables are lagged.

When focusing on the z-score, several of the interaction terms are significant. Focusing on columns (1) and (2), the relationship between risk and opacity is muted for better capitalized banks and banks with a higher degree of short-term funding.

Columns (3) and (4) focus on whether the effects depend on the state of the macro economy. The coefficient estimates suggest that the relationship between opacity and risk is muted when macroeconomic conditions are favorable, i.e., during high growth (column (3)) or low financial uncertainty (column (4)). Similar findings are present when we focus on sd(RoA) as the dependent variable (columns (5)-(8)).

We explore further the implications of heterogeneity in Appendix B. Specifically, we compute the marginal effects of changes in AFS securities and off-balance sheet items evaluated at different levels of the interaction terms. Using off-balance sheet items as opacity measure and z-score as risk metric, we show that the relationship between opacity and risk is statistically significantly weaker for high-capitalized banks relative to low-capitalized banks, and similarly for banks with a high relative to low dependence on short-term funding.[17] The magnitudes are relatively large. For instance, moving from the 25th percentile in the equity ratio distribution to the 75th percentile, the impact of a 1 standard deviation change in off-balance sheet items on realized risk is lowered by approximately 50 percent.

Discussion Insignificant results in Table 3 can either reflect statistical imprecision or reflect two opposite effects of AFS security holdings on banks' realized risks. On one hand, since the losses and gains from AFS securities are reflected in banks' equity value in real time, more holdings of AFS securities increase the volatility in banks' equity value, hence realized risks. On the other hand, lower opacity in AFS securities makes banks more disciplined by investors and lenders. This restricts banks' risk-taking behavior and induces banks to build more loss-absorbing buffers, lowering banks' realized risks. These two diverting effects may apply to all banks, independent on their own characteristics.

Table 4 provides more sharp evidence that the impact of off-balance sheet items depends on bank- and macro-characteristics. The positive impact of off-balance sheet items on realized risk is lower for better capitalized banks. When banks have more skin in the game, shareholders have to absorb more realized losses and this reduces banks' incentive to take excessive risks. Second, the impact is also lower for banks that rely more in short-term, uncollateralized funding. Since

[17] "High" is defined as the 75th percentile and "low" is defined as the 25th percentile in the distributions of equity ratio and the ratio of short-term funding.

opaque banks with more off-balance sheet items are more likely to experience funding runs from short-term, uncollateralized creditors once the banks' true status of financial health is revealed, banks that rely more on such creditors will discipline themselves *ex ante* and choose to reduce their risk-taking.

6 Higher capital requirements and opacity

Given that opacity in banks' investments has a non-negligible impact on banks' realized risk and that there are not yet regulatory rules in the Basel III framework that *directly* restrict banks' opacity, the natural question is whether current regulatory requirements affect banks' choices on opacity more indirectly. One candidate regulatory policy is capital requirement. Higher capital requirements may affect bank opacity through a portfolio rebalancing effect, as discussed in section 2.2.

However, a key challenge to understand the impact of higher capital requirements on bank transparency is that banks' portfolio decisions and the changes in regulatory tools such as capital requirements are driven by common, unobservable factors. To address such challenge to identification, in this section, we use a policy experiment to identify the effect of increasing capital requirements.

6.1 Policy experiment

In order to test how higher capital requirements affect bank opacity, we follow Juelsrud and Wold (2020) and exploit the 2013 increase in capital requirements in Norway. Following the global financial crisis of 2007-2009, the Basel III accord was put forward by the Basel Committee on Banking Supervision (Basel Committee on Banking Supervision, 2010). One of the prominent features of the Basel III accord was to increase the lower bound on banks' capital ratios. As a member of the European Economic Area, Norway implemented the directive into its own legislation.

In Figure 5, we plot the capital requirements for Norwegian banks over time. The increase in capital requirements for Norwegian banks was proposed in late March 2013, passed through legislation in late June and adopted on the 1st of July of the same year. It entailed an increase in both the minimum requirement for banks CET1 capital, and also a substantial increase in

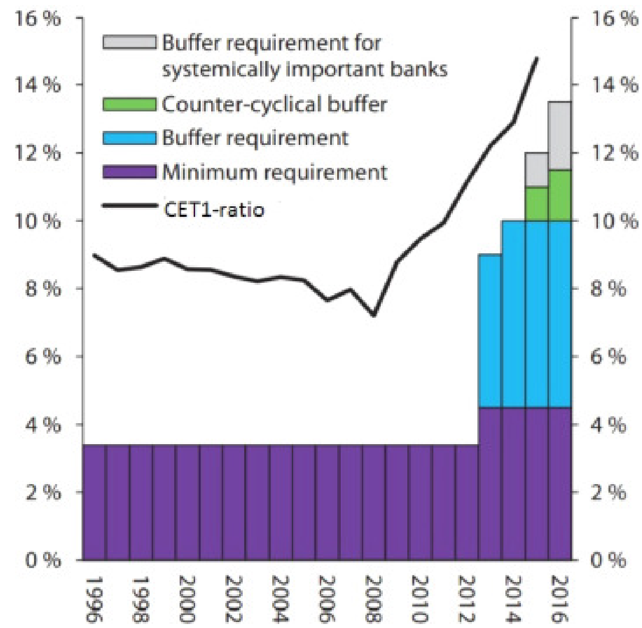


Figure 5: Capital requirement and CET-ratio for Norwegian banks. Source: Ministry of Finance, Norway.

buffer requirements. The buffer requirements were phased in over two years, and as a result, non-systemically important banks were facing a total CET1 capital requirement of 12.5 % by mid 2016. Systemically important banks faced an additional surcharge of 2 percentage points.

Juelsrud and Wold (2020) use the 2013 new capital requirements as a natural experiment to document how banks respond to higher capital requirements. They show that the increase in capital requirements is well suited for identification purposes for two reasons. First, due to the fact that Norway was not a member of the European Union, Norwegian authorities did not participate in designing the rules. Hence, it is unlikely that the specifics of the regulation — as well as the timing — were tied to the specifics of the Norwegian banking sector. Second, they show that Norwegian banks did not adjust, to a large extent, before the reform was put in place. Hence, it is unlikely that anticipatory effect invalidates the policy reform as a quasi-natural experiment.

The reform comprised of first and foremost an increase in capital requirements. Hence, risk-weights remained constant. The increase in capital requirements therefore made assets with high risk weights relatively more costly compared to assets with relatively low risk weights. In the Norwegian regulation of risk weights, marked-to-market assets — including AFS — are typically given relatively low risk weights.

Table 5: AFS and capital requirements

	(1) Log(AFS securities to total assets)	(2) Log(AFS securities to total assets)
Post×Debt to total assets, 2012	0.0431*	0.0389**
	(0.0251)	(0.0192)
N	1335	1331
No. of clusters	102	98
Mean of dependent variable	-3.9001	-3.9013
SD of dependent variable	0.8001	0.7982
Bank FE	No	Yes
Year FE	No	Yes

Notes: * p<0.1, ** p<0.05, ***p<0.01. Mean and standard deviations are taken over the full sample period (2011q1-2015q4). *Post* = 1 for 2013, 2014 and 2015 and zero otherwise. Standard errors clustered at the bank-firm level.

6.2 Identification

In order to exploit the 2013 policy experiment on capital requirement, we follow Juelsrud and Wold (2020) and compare the evolution of bank outcomes among banks with different initial capital ratios. Due to data availability, we focus on the evolution of the share of AFS securities only, as our data on off-balance sheet items are not available for the reform period. Specifically, our treatment intensity measure $T_b \equiv \left(\frac{\text{Debt}}{\text{Total assets}}\right)_{b,t}$ is the 2012 debt ratio of a bank b.

We estimate the following equation

$$\log\left(\text{AFS securities/Total assets}\right) = \alpha_b + \delta \text{Post}_t + \beta \text{Post}_t \times T_b + \epsilon_{b,t} \tag{3}$$

where α_b is a bank fixed effect and δ_t is a time fixed effect. Post_t is a dummy equal to 1 for the period 2013-2015 and zero otherwise. The coefficient β is our coefficient of interest, and it measures whether that the (log) portfolio share of AFS securities during the capital requirement changes relative to the pre-period depends significantly on banks' initial capitalization.

The results from estimating equation (3) are shown in Table 5. Overall, the results in Table 5 suggest that low-capitalized banks (banks with a high debt relative to overall total assets) expand their holdings of AFS securities relative to other banks after the capital requirement increase. The results suggest that a 10 percentage point increase in debt to total assets, increases the portfolio share of AFS securities by approximately 0.4 percent.

Table 6: AFS and capital requirements

	(1) Risk	(2) Risk
Post×Debt to total assets, 2012	0.0007	-0.0001*
	(0.0036)	(0.0000)
Risk-metric	z-score	Sd(RoA)
N	2078	2135
No. of clusters	134	135
Mean of dependent variable	-3.0198	0.0029
SD of dependent variable	0.4702	0.0025
Bank FE	Yes	Yes
Year FE	Yes	Yes

Notes: * p<0.1, ** p<0.05, ***p<0.01. Mean and standard deviations are taken over the full sample period (2011q1-2015q4). $Post = 1$ for 2013, 2014 and 2015 and zero otherwise. Standard errors clustered at the bank-firm level.

Hence, higher capital requirements shift banks' portfolios towards more AFS securities, *decreasing* overall bank opacity. Thus, capital requirements can potentially affect bank solvency through a more indirect channel compared to the direct effect of higher capital ratios, namely by increasing banks' holdings of transparent, less opaque assets.

A natural question is whether this increase in AFS securities is associated with a decrease in risk. In Table 6, we redo our estimation using the two risk metrics as outcome variables. The point estimate for sd(RoA) suggests an imprecise but statistically significant decline in risk for low-capitalized banks. It is challenging, however, to pin-point how much of this decline in risk that can be attributed to a shift towards more transparent assets, as banks' adjustments to higher capital requirements affect risk through several channels.

Our results complement the evidence documented by Fuster and Vickery (2018). Fuster and Vickery (2018) find that after a change on the accounting rule regarding AFS security holdings in US, — which is equivalent to increasing capital requirements specifically on AFS assets, — banks in general became more opaque by shifting other assets towards HTM assets. As a comparison, when the rise in capital requirements is applied to *all* asset classes instead of just AFS assets, our results show that weaker, under-capitalized banks actually choose to reduce their opacity through increasing AFS security holdings.[18]

7 Conclusion

In this paper, we investigate the relationship between bank transparency and realized risk, and how bank transparency is affected by capital regulation. Our results confirm previous empirical studies which document a positive relationship between opacity and risk, such as Fosu et al. (2017), and we further show how the relationship varies with bank-level characteristics and macroeconomic variables. Next, we investigate how higher capital requirements affect bank transparency. Our findings suggest that higher capital requirements improve bank transparency by inducing banks to invest in less opaque assets.

Our paper raises several further questions for both policy makers and researchers. First, how can effective reforms targeted at improving market discipline affect the relationship between opacity and risk-taking? The “Third Pillar” in Basel III emphasizes the role of market discipline through developing disclosure requirements that allow market participants to assess banks’ capital adequacy. How these recent regulatory reforms affect banks’ opacity in balance sheets and their risk-taking largely remains an open question. Second, and more fundamentally, how should transparency regulation be designed to complement other regulatory rules? Although in this paper we find that capital adequacy rules reduces bank opacity through portfolio rebalancing, we do believe that separate, properly designed transparency rules are needed — as a kind of “Tinbergen Rule” — not only because other rules may not be sufficient to achieve optimal transparency, but also because other regulatory rules may even have reverse impact on transparency. For example, the new Net Stable Funding Ratio (NSFR) requirement discourages banks’ short-term money market funding, and this may reduce the market discipline on bank opacity. We leave these questions for future research.

[18] There are no indications that banks offset the increase in AFS securities by simulatenously increasing in HTMs. More generally, the shares of AFS and HTM securities are relatively stable prior to the policy experiment.

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Appendix

A Robustness

A.1 Alternative specification of baseline regression

In equation (1), we included both a set of (quarterly) macro controls and year fixed effects. This leads to a potential concern of multicollinearity. To investigate whether multicollinearity affects our results, we redo the estimation of equation (1) while dropping the quarterly macro controls. The results are shown in Table 1. Reassuringly, the coefficient estimates remain overall roughly unchanged, especially when considering z-score as risk metric. The coefficient of sd(RoA) on AFS securities remains qualitatively similar but less precisely estimated, while the coefficient of sd(RoA) changes sign. We note, however, that the coefficient is essentially zero.

Table 7: Conditional correlation, dropping controls.

	(1) Risk	(2) Risk	(3) Risk	(4) Risk
AFS securities to total assets, lagged	-2.7204***	-0.0023		
	(0.9905)	(0.0037)		
Off balance sheet items to total assets, lagged			0.0097***	-0.0001***
			(0.0012)	(0.0000)
Risk measure	Z-score	Sd(RoA)	Z-score	Sd(RoA)
N	2383	2383	7098	7098
No. of clusters	112	22	157	157
Mean of dependent variable	-2.9864	0.0028	-2.8834	0.0038
SD of dependent variable	0.5207	0.0017	0.4575	0.0019
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	No	No	No	No

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Mean and standard deviations are taken over the full sample period (1993q1-2015q4). Standard errors clustered at the bank level.

A.2 Alternative measure of risk

Table 8: Conditional correlation, alternative definitions of risk metrics

	(1) Risk	(2) Risk	(3) Risk	(4) Risk
AFS securities to total assets, lagged	-7.2841**		-0.0112*	
	(2.6789)		(0.0058)	
Off balance sheet items to total assets, lagged		0.2162**		0.0000
		(0.0803)		(0.0002)
Risk measure	Z-score	Z-score	Sd(RoA)	Sd(RoA)
N	701	811	701	811
No. of clusters	25	28	25	28
Mean of dependent variable	-3.2408	-3.2035	0.0023	0.0026
SD of dependent variable	0.9739	0.9401	0.0021	0.0023
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: * $p<0.1$, ** $p<0.05$, ***$p<0.01$. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include the ratio of short-term funding to total assets, log(assets), loans to total assets, return on assets, equity to total assets, the growth rate of GDP and the VIX. All bank-level control variables are lagged.

A.3 Foreign branches only

In this section, we focus on the subsample of foreign branches. A challenge is that this subsample is small, effectively only covering 4 banks. However, it is informative whether we find related results for this subsample. Table 9 reports the results of estimating equation (1) for this subsample.

While a larger sample yields less precisely estimated coefficients, we note that the results - except in Column (2) - is similar to te results in the main text. In Column (1), we show that - even within this small subsample - there is a negative and significant impact of bank transparency on realized risk.

Table 9: Conditional correlation, foreign branches only

	(1) Risk	(2) Risk	(3) Risk	(4) Risk
AFS securities to total assets, lagged	-7.0201**	0.0014		
	(0.8028)	(0.0020)		
Off balance sheet items to total assets, lagged			0.5797	0.0022
			(0.4639)	(0.0015)
Risk measure	Z-score	Sd(RoA)	Z-score	Sd(RoA)
N	108	108	76	76
No. of clusters	3	3	4	4
Mean of dependent variable	-2.4946	0.0025	-2.9202	0.0029
SD of dependent variable	0.7316	0.0013	0.6379	0.0015
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include the ratio of short-term funding to total assets, log(assets), loans to total assets, return on assets, equity to total assets, the growth rate of GDP and the VIX. All bank-level control variables are lagged.

A.4 Additional robustness tests

In this section, we report the results from two additional robustness tests of the results in Section 4. First, in Table 10 we re-estimate equation (1) on a subsample excluding the 8 largest banks. The results are largely unchanged, although the coefficient estimate when using off-balance sheet items is more imprecisely measured. Second, we follow Fosu et al. (2017); Köhler (2015); Mergaerts and Vander Vennet (2016) and re-estimate equation (1) adding two controls for business models, namely non-deposit funding relative to total assets, and non-interest income relative to total income. The results are largely unchanged, especially for AFS securities as opacity measure.

Table 10: Conditional correlation, small banks only

	(1) Risk	(2) Risk	(3) Risk	(4) Risk
AFS securities to total assets, lagged	-4.9435*	-0.0165**		
	(2.6718)	(0.0071)		
Off balance sheet items to total assets, lagged			0.1180	0.0003
			(0.0687)	(0.0002)
Risk measure	Z-score	Sd(RoA)	Z-score	Sd(RoA)
N	540	540	598	598
No. of clusters	18	18	22	22
Mean of dependent variable	-2.7833	0.0030	-2.7290	0.0034
SD of dependent variable	0.5658	0.0016	0.4840	0.0016
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: * $p<0.1$, ** $p<0.05$, ***$p<0.01$. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include the ratio of short-term funding to total assets, log(assets), loans to total assets, return on assets, equity to total assets, the growth rate of GDP and the VIX. All bank-level control variables are lagged. Sample contains all banks except the 8 largest banks, as measured by total assets per 2012Q4.

Table 11: Conditional correlation, with additional controls

	(1) Risk	(2) Risk	(3) Risk	(4) Risk
AFS securities to total assets, lagged	-3.4237*	-0.0115**		
	(1.9759)	(0.0050)		
Off balance sheet items to total assets, lagged			0.0372	-0.0002
			(0.0588)	(0.0003)
Risk measure	Z-score	Sd(RoA)	Z-score	Sd(RoA)
N	659	659	693	693
No. of clusters	23	23	24	24
Mean of dependent variable	-2.7491	0.0029	-2.6810	0.0034
SD of dependent variable	0.5394	0.0014	0.4410	0.0015
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: * $p<0.1$, ** $p<0.05$, ***$p<0.01$. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include the ratio of short-term funding to total assets, log(assets), loans to total assets, return on assets, equity to total assets, the growth rate of GDP, the VIX, the fraction of non-deposit funding and non-interest income relative to total income. All bank-level control variables are lagged.

B Marginal effects

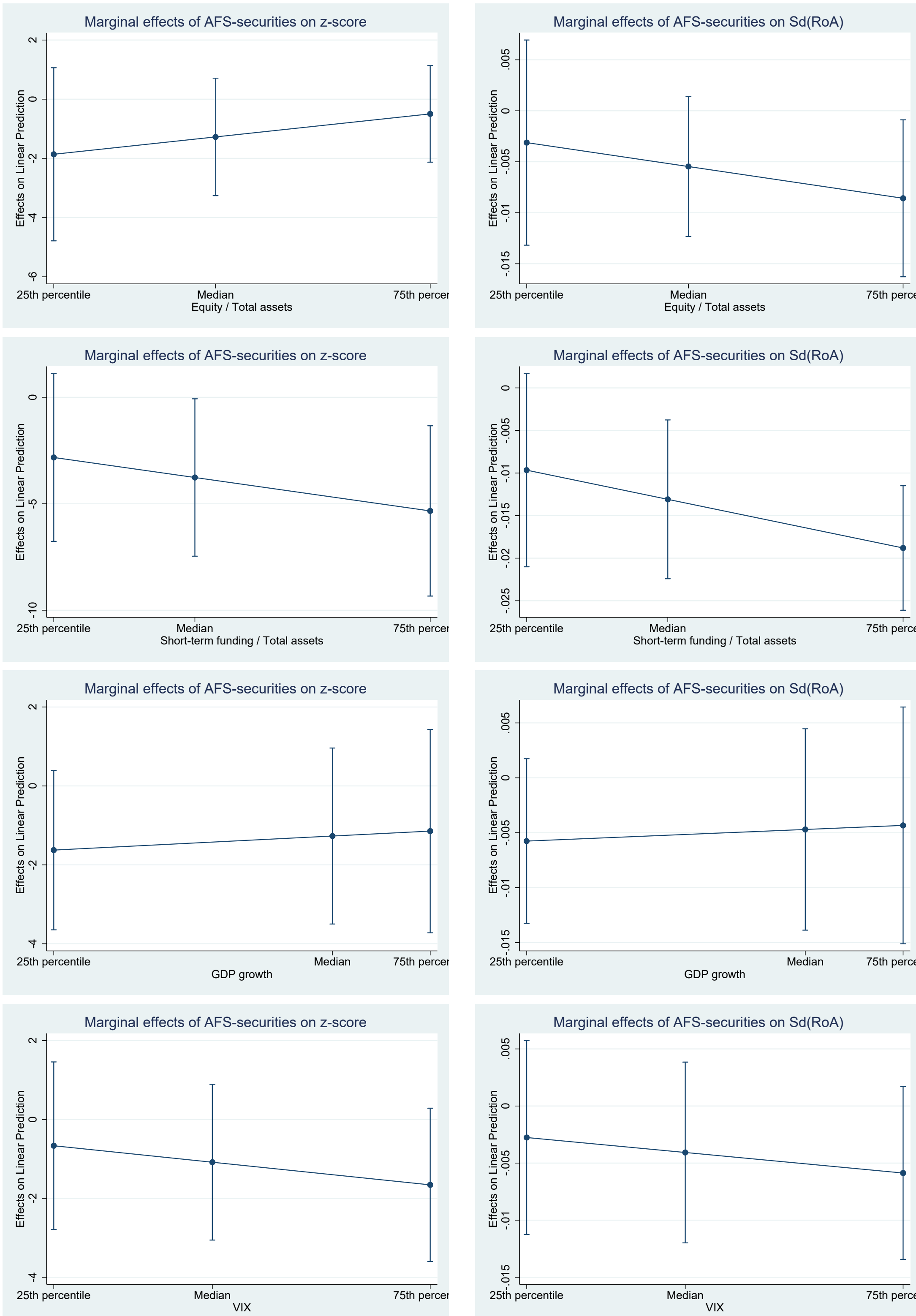

Figure 6: This figure shows the marginal effects of increasing AFS securities for the different interaction terms in Table 3. The left column focuses on z-score as the dependent variable, while the right column focuses on sd(RoA) as the dependent variable. Each interacted variable is evaluated at the 25th percentile, the median and the 75th percentile, respectively.

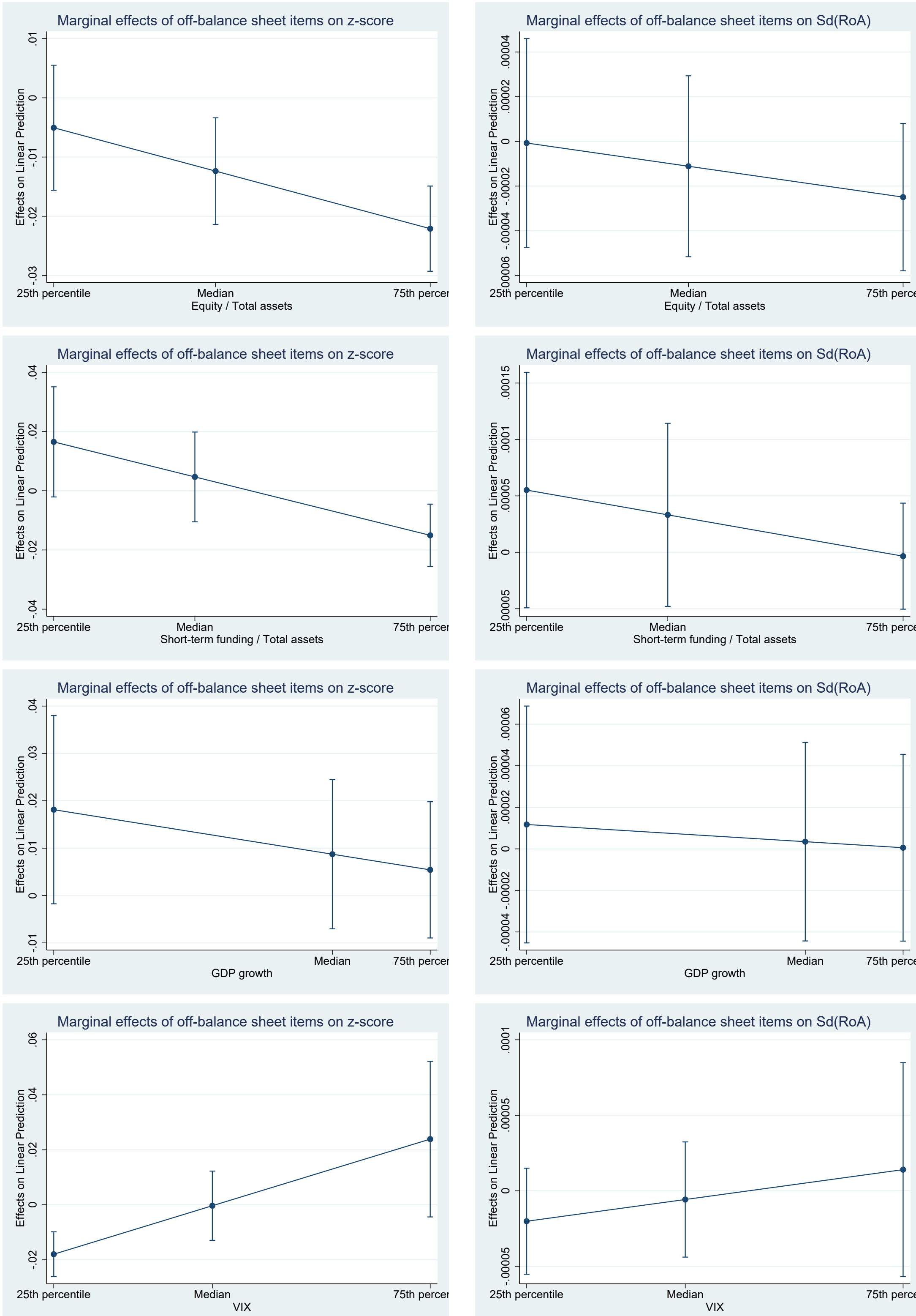

Figure 7: This figure shows the marginal effects of increasing off-balance sheet items for the different interaction terms in Table 4. The left column focuses on z-score as the dependent variable, while the right column focuses on sd(RoA) as the dependent variable. Each interacted variable is evaluated at the 25th percentile, the median and the 75th percentile, respectively.

C Additional results

C.1 Reporting coefficient estimates on the full set of controls

Table 12: Conditional correlation and heterogeneity, using AFS as opacity measure. All coefficients

	(1) Risk	(2) Risk	(3) Risk	(4) Risk	(5) Risk	(6) Risk	(7) Risk	(8) Risk
AFS securities to total assets, lagged	-11.5039*	3.6258	-2.4143	-1.8622	-0.0193	0.0074	-0.0090	-0.0097*
	(6.2109)	(5.0706)	(2.8590)	(1.5994)	(0.0143)	(0.0153)	(0.0081)	(0.0055)
AFS securities to total assets, lagged×Equity to total assets	190.6706*				0.1684			
	(107.5491)				(0.2403)			
AFS securities to total assets, lagged×Short-term funding to total assets		-11.2697				-0.0315		
		(7.1918)				(0.0193)		
AFS securities to total assets, lagged×GDP growth			-0.3109				-0.0011	
			(0.5028)				(0.0017)	
AFS securities to total assets, lagged×VIX				-0.0732				-0.0001
				(0.0757)				(0.0002)
Short-term funding to total assets	-0.3332	-0.0150	-0.1709	-0.1993	-0.0026***	-0.0020**	-0.0024***	-0.0025***
	(0.3069)	(0.3260)	(0.3195)	(0.3203)	(0.0008)	(0.0009)	(0.0008)	(0.0008)
Log(assets)	-0.2005**	-0.2420**	-0.1996*	-0.1732*	-0.0005**	-0.0007**	-0.0006**	-0.0005*
	(0.0955)	(0.1044)	(0.1021)	(0.0974)	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Loans to total assets	0.0229	0.0206	0.0636	0.0231	-0.0002	-0.0003	-0.0001	-0.0002
	(0.9340)	(0.9210)	(0.9563)	(0.9546)	(0.0022)	(0.0021)	(0.0022)	(0.0023)
RoA	17.5747*	17.0445*	17.7368*	17.2998*	0.0399	0.0384	0.0405	0.0394
	(9.8042)	(9.7560)	(10.0001)	(9.9370)	(0.0291)	(0.0288)	(0.0285)	(0.0287)
Equity to total assets	-13.6705	-11.4664	-10.8101	-9.8578	0.0202	0.0196	0.0210	0.0238
	(8.0273)	(6.9392)	(7.1180)	(7.4077)	(0.0164)	(0.0148)	(0.0160)	(0.0144)
GDP growth	-0.0039	-0.0050	0.0035	-0.0062	-0.0000	-0.0000	0.0000	-0.0000
	(0.0127)	(0.0154)	(0.0137)	(0.0145)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
VIX	-0.0065**	-0.0059*	-0.0058*	-0.0038	-0.0000**	-0.0000**	-0.0000**	-0.0000*
	(0.0031)	(0.0032)	(0.0032)	(0.0035)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Risk measure	Z-score	Z-score	Z-score	Z-score	Sd(RoA)	Sd(RoA)	Sd(RoA)	Sd(RoA)
N	701	701	701	701	701	701	701	701
No. of clusters	25	25	25	25	25	25	25	25
Mean of dependent variable	-2.7641	-2.7641	-2.7641	-2.7641	0.0029	0.0029	0.0029	0.0029
SD of dependent variable	0.5450	0.5450	0.5450	0.5450	0.0015	0.0015	0.0015	0.0015
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p<0.1, ** p<0.05, ***p<0.01. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include log(assets), loans to total assets, short-term funding to total assets, return on assets, equity to total assets, the growth rate of GDP and the VIX. All control variables are lagged.

Table 13: Conditional correlation and heterogeneity, using off-balance sheet items as opacity measure. All coefficients

	(1) Risk	(2) Risk	(3) Risk	(4) Risk	(5) Risk	(6) Risk	(7) Risk	(8) Risk
Off balance sheet items to total assets, lagged	0.0371***	0.1057***	0.0426***	-0.0877***	0.0001	0.0002	0.0001**	-0.0001
	(0.0131)	(0.0275)	(0.0077)	(0.0136)	(0.0001)	(0.0002)	(0.0000)	(0.0001)
Off balance sheet items to total assets, lagged×Equity to total assets	-0.7817***				-0.0013**			
	(0.1192)				(0.0005)			
Off balance sheet items to total assets, lagged×Short-term funding to total assets		-0.1522***				-0.0003*		
		(0.0297)				(0.0002)		
Off balance sheet items to total assets, lagged×GDP growth			-0.0068***				-0.0000***	
			(0.0005)				(0.0000)	
Off balance sheet items to total assets, lagged×VIX				0.0057***				0.0000***
				(0.0006)				(0.0000)
Short-term funding to total assets	0.2947	0.3950	0.2652	0.2829	0.0013	0.0015	0.0012	0.0013
	(0.3810)	(0.3821)	(0.3836)	(0.3877)	(0.0014)	(0.0013)	(0.0014)	(0.0014)
Log(assets)	0.1293	0.1364	0.1286	0.1314	0.0003	0.0003	0.0003	0.0003
	(0.1068)	(0.1080)	(0.1085)	(0.1096)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Loans to total assets	-0.2237	-0.1985	-0.2119	-0.2320	-0.0012	-0.0011	-0.0012	-0.0012
	(0.4292)	(0.4301)	(0.4356)	(0.4354)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
RoA	3.7937	3.4605	3.7572	3.9554	0.0161	0.0153	0.0162	0.0165
	(7.9136)	(7.8732)	(7.9275)	(7.9074)	(0.0322)	(0.0321)	(0.0323)	(0.0323)
Equity to total assets	-6.2754**	-6.6415**	-6.8249**	-6.8379**	0.0110	0.0106	0.0099	0.0098
	(3.0429)	(3.0620)	(3.0173)	(3.0251)	(0.0150)	(0.0150)	(0.0148)	(0.0147)
GDP growth	-0.0261**	-0.0268***	-0.0190*	-0.0214**	-0.0001**	-0.0001***	-0.0001**	-0.0001**
	(0.0097)	(0.0094)	(0.0099)	(0.0098)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
VIX	-0.0127***	-0.0126***	-0.0131***	-0.0151***	-0.0000**	-0.0000**	-0.0000**	-0.0000**
	(0.0040)	(0.0040)	(0.0041)	(0.0040)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Risk measure	Z-score	Z-score	Z-score	Z-score	Sd(RoA)	Sd(RoA)	Sd(RoA)	Sd(RoA)
N	878	878	878	878	878	878.0000	878	878
No. of clusters	29	29	29	29	29	29.0000	29	29
Mean of dependent variable	-2.6978	-2.6978	-2.6978	-2.6978	0.0034	0.0034	0.0034	0.0034
SD of dependent variable	0.4728	0.4728	0.4728	0.4728	0.0015	0.0015	0.0015	0.0015
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p<0.1, ** p<0.05, ***p<0.01. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include log(assets), loans to total assets, short-term funding to total assets, return on assets, equity to total assets, the growth rate of GDP and the VIX. All bank-level control variables are lagged.

C.2 Market discipline proxied by interbank position

Table 14: Conditional correlation and heterogeneity, using AFS as opacity measure. Interbank funding as a proxy for market discipline

	(1) Risk	(2) Risk	(3) Risk	(4) Risk	(5) Risk	(6) Risk	(7) Risk	(8) Risk
AFS securities to total assets, lagged	-10.6082	-1.5265	-2.3750	-1.9420	-0.0162	-0.0065	-0.0077	-0.0064
	(6.3494)	(1.8497)	(3.0436)	(1.7432)	(0.0156)	(0.0063)	(0.0085)	(0.0060)
AFS securities to total assets, lagged×Equity to total assets	172.2250				0.1172			
	(105.9138)				(0.2517)			
AFS securities to total assets, lagged×Interbank funding to total assets		-25.2967***				-0.0686***		
		(7.5661)				(0.0214)		
AFS securities to total assets, lagged×GDP growth			-0.3057				-0.0012	
			(0.5209)				(0.0018)	
AFS securities to total assets, lagged×VIX				-0.0662				-0.0002
				(0.0774)				(0.0002)
Risk measure	Z-score	Z-score	Z-score	Z-score	Sd(RoA)	Sd(RoA)	Sd(RoA)	Sd(RoA)
N	703.0000	703.0000	703.0000	703.0000	703.0000	703.0000	703.0000	703.0000
No. of clusters	25.0000	25.0000	25.0000	25.0000	25.0000	25.0000	25.0000	25.0000
Mean of dependent variable	-2.7635	-2.7635	-2.7635	-2.7635	0.0029	0.0029	0.0029	0.0029
SD of dependent variable	0.5445	0.5445	0.5445	0.5445	0.0015	0.0015	0.0015	0.0015
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p<0.1, ** p<0.05, ***p<0.01. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include log(assets), loans to total assets, interbank funding to total assets, return on assets, equity to total assets, the growth rate of GDP and the VIX. All bank-level control variables are lagged.

Table 15: Conditional correlation and heterogeneity, using off-balance shee titems as opacity measure. Interbank funding as a proxy for market discipline

	(1) Risk	(2) Risk	(3) Risk	(4) Risk	(5) Risk	(6) Risk	(7) Risk	(8) Risk
Off balance sheet items to total assets, lagged	0.0316***	0.0694***	0.0373***	-0.0927***	0.0001	0.0003**	0.0001*	-0.0001*
	(0.0103)	(0.0102)	(0.0059)	(0.0145)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Off balance sheet items to total assets, lagged×Equity to total assets	-0.7844***				-0.0013**			
	(0.1080)				(0.0005)			
Off balance sheet items to total assets, lagged×Interbank funding to total assets		-0.1287***				-0.0004***		
		(0.0147)				(0.0001)		
Off balance sheet items to total assets, lagged×GDP growth			-0.0068***				-0.0000***	
			(0.0006)				(0.0000)	
Off balance sheet items to total assets, lagged×VIX				0.0056***				0.0000**
				(0.0008)				(0.0000)
Risk measure	Z-score	Z-score	Z-score	Z-score	Sd(RoA)	Sd(RoA)	Sd(RoA)	Sd(RoA)
N	984.0000	984.0000	984.0000	984.0000	984.0000	984.0000	984.0000	984.0000
No. of clusters	39.0000	39.0000	39.0000	39.0000	39.0000	39.0000	39.0000	39.0000
Mean of dependent variable	-2.7037	-2.7037	-2.7037	-2.7037	0.0034	0.0034	0.0034	0.0034
SD of dependent variable	0.4677	0.4677	0.4677	0.4677	0.0016	0.0016	0.0016	0.0016
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p<0.1, ** p<0.05, ***p<0.01. Mean and standard deviations are taken over the full sample period (1993Q1-2015Q4). Standard errors clustered at the bank level. Controls include log(assets), loans to total assets, interbank funding to total assets, Return on assets, equity to total assets, the growth rate of GDP and the VIX. All bank-level control variables are lagged.