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Opacity and the comovement in the stock prices of banks

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Abstract

We examine whether the stock prices of banks co-move more than the stock prices of non-banks, and whether that comovement is driven by informational opacity. Since the risks associated with the financial intermediation process are relatively opaque to outside investors, valuing banks can be difficult and information acquisition can be costly. We introduce a measure of comovement, denoted as beta dispersion, that identifies how closely a particular stock co-moves with the average industry CAPM beta. We find that bank stock prices generally co-move more than non-bank stock prices, and that opacity is driving the higher levels of comovement.

Key words: Comovement; Banks; Opacity; Beta Dispersion

JEL classification: G0, G10, G20, G21

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1. Introduction

One of the central tenets of the asset pricing literature is the valuation of securities, where future cash flows are discounted by a rate that depends on both firm fundamentals and macroeconomic variables. Pindyck and Rotemberg (1993) indicate that the prices of different stocks can move together in response to common movements in earnings, or in response to changes in macroeconomic variables. However, the observed level of comovement among asset prices is high enough to reject these types of commonality models (Barberis *et al.*, 2005). Veldkamp (2006) argues that when information acquisition is costly, investors only buy information for a subset of assets, and then use that information to price various related assets. In the presence of

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scarce information – or information that is costly to acquire – a large number of investors might rely on the same information to price a broad range of related securities, thus leading to excess comovement.

Since the risks associated with the financial intermediation process are relatively opaque to outside investors, valuing banks can be difficult and information acquisition can be costly. For instance, Morgan (2002) finds an unusual amount of heterogeneity in analysts' valuations of bank risks, concluding that banks are more opaque than non-banks. Morgan (2002) describes banks as "black boxes" – money flows in and out, but the risks taken in the process of intermediation are difficult to observe from outside the firm. A number of other studies also provide empirical evidence that banks are relatively more opaque than non-banks (see, e.g., Flannery *et al.*, 2004, 2013; Jones *et al.*, 2012, 2013; Jiang et al., 2016; Blau et al., 2017).

In this study, we examine whether the stock prices of banks tend to co-move more than the stock prices of non-banks, and whether that comovement is driven by informational opacity. To the extent that opacity makes information acquisition costly, information revealed about one bank could be extrapolated to other banks, which would result in more comovement in their stock prices. A byproduct of this study is a newly developed measure of comovement, which we denote as beta dispersion. Specifically, we estimate a traditional Capital Asset Pricing Model (CAPM) for each stock in each industry, where the market return is the value-weighted industry return of all firms within that industry. We then measure beta dispersion as the absolute difference between a firm's estimated beta and the average industry beta. This measure inversely captures the level of comovement in a particular stock relative to the average stock in the same industry.

Admittedly, comovement is generally measured by looking at the correlation between the returns of stock pairs across time. Our measure, which has all of the important theoretical properties of the CAPM, is much less computationally intensive and captures more of what could be called "industry" comovement. Therefore, when stocks in a particular industry have low beta dispersion, we can infer that the particular industry generally has stocks with prices that move together, such that individual betas are closely clustered around the average industry beta. Conversely, when an average stock in a particular industry has high beta dispersion, the industry does not have stocks that move closely together.

Our first hypothesis predicts that stocks in the less transparent banking industry will have lower beta dispersion (higher comovement) than stocks in more transparent non-banking industries. Consistent with this hypothesis, our results show that, during our sample period, bank stocks typically have lower levels of beta dispersion than stocks in non-bank industries. This result is robust to specific controls for the recent financial crisis, different data frequencies at which beta dispersion is measured, and various econometric specifications.[1] To account for the possible endogeneity that exists between opacity and comovement, we conduct an event study by examining the subset of banks surrounding the passing of the 2002 Sarbanes-Oxley Act (SOX). This legislation aimed to increase transparency by enforcing more stringent disclosure and governance policies. If comovement is a function of transparency, as we posit, then the level of comovement among bank stock prices will decrease following the passing of SOX, which decreases opacity. The motivation for using SOX as an event is based on findings in Akhigbe and Martin (2006), who show that SOX improved the level of transparency for firms in the financial services industry. Therefore, if SOX indeed resulted in greater transparency generally, and banks are more opaque compared to non-banks, then we expect that the level of comovement among bank stock prices will decrease following the passage of SOX. Our difference-in-difference tests show that, relative to non-banks, the comovement of banks decreases during the post-SOX period. These results provide support for our first hypothesis that bank stock prices co-move more frequently than non-bank stock prices, which is driven, at least in part, by the opacity of the banking industry.

Our second hypothesis asserts that the level of comovement among bank stock prices is also driven by the opacity of the individual banks within that sector. To the extent that investors have difficulty assessing and valuing the risks of an opaque bank, we contend that comovement within the banking sector will be driven by those banks that are the most opaque. We follow Flannery *et al.* (2004) and use market microstructure measures to proxy for bank-specific informational opacity. The motivation to do so is based on the theoretical models of Demsetz (1968), Kyle (1985), Glosten and Harris (1988), and Stoll (1989), among others, which assert that measures such as the bid-ask spread, and the adverse selection component of the spread, proxy for the level of information asymmetry in financial markets. The results in our study show that banks with higher bid-ask spreads, and greater adverse selection costs, are associated with lower beta dispersion (i.e. higher comovement).[2] To the extent that these microstructure characteristics properly measure the amount of informational opacity in bank stocks, these results support our second hypothesis and indicate that banks that are more opaque experience greater comovement in their stock prices.

Since a large body of theoretical literature suggests that bank loans are informationally opaque (Campbell and Kracaw, 1980; Berlin and Loeys, 1988;

[1] Although our analysis focuses on beta dispersion at the weekly level, we also examine comovement using daily and monthly measures of beta dispersion and find results consistent with those reported in the study.

[2] The positive relation between microstructure measures of informational opacity and the comovement in bank stock prices holds for the financial crisis period and non-financial crisis period.

Diamond, 1989, 1991; Kwan and Carleton, 2010), we also proxy for bank-specific opacity using the amount of loans on the bank's balance sheet. In particular, we examine the relation between beta dispersion for bank stocks and the amount of bank assets that are made up from loans. We provide evidence that the higher levels of comovement in bank stocks is driven by banks with higher loan-to-asset ratios.[3] The results from these tests provide further support for our second hypothesis, that more opaque banks exhibit greater comovement in their stock prices.

Our study is related to Jin and Myers (2006), who develop a model that highlights some of the factors that influence the synchronicity of stock prices. The authors show that R^2 is positively related with several measures of firm opaqueness. We contribute by determining whether opaque industries, such as banking, have relatively high levels of comovement in stock prices. However, our empirical findings have important implications that extend beyond our contribution to the existing literature on comovement and bank opacity. If forward-looking stock prices provide an important leading indicator of future performance (Bodie, Kane, and Marcus, 2009), then the unusually high levels of comovement in bank stocks, relative to non-bank stocks, might make it more difficult for investors to value the risk of the banking sector. This could in turn have direct and indirect consequences on systemic risk. Shiller (1989) argues that comovement in stock prices may be, in part, responsible for market bubbles and subsequent crashes. Therefore, the identification of factors that influence comovement among asset prices can improve our understanding about the formation of bubbles and crashes and allow us to understand the characteristics that affect the overall efficiency of financial markets.[4] Understanding the effect of opacity and transparency of intermediation risk could be a critical step in avoiding future financial crises.

2. Data description

In this section, we describe the data used throughout the analysis. We obtain returns, volume, prices and market capitalisation from the Center for Research in Security Prices (CRSP). Firm-specific financial measures are obtained from Compustat, such as price-to-earnings, book-to-market and debt-to-asset ratios.

[3] The negative association between beta dispersion and loans is neither stronger nor weaker during the recent financial crisis.

[4] Previous literature has identified various factors influencing comovement among asset prices. For instance, Barberis *et al.* (2005) find that sentiment, instead of fundamentals, directly affects the level of comovement. Pirinsky and Wang (2006) show that stocks in the same geographical area are more likely to have prices that move together, while Pirinsky and Wang (2004) and Kumar and Lee (2006) report that correlated trading drives the observed level of comovement. Green and Hwang (2009) show that comovement can be explained by low-priced stocks.

We also use Bank Compustat to identify banks, and gather bank-specific data, such as loan portfolio compositions. The final sample, which extends from 1980 to 2012, includes more than 25,000 unique stocks and 258,716 stock-year observations. We note that the subsample of banks consists of 2,039 bank stocks and 30,774 stock-year observations.

Table 1 reports statistics that describe our sample. In the table, we report a number of different variables that are used throughout the analysis. *Beta* is a standard CAPM beta that is estimated using weekly returns and obtained for each stock in each year. In this CAPM-style estimate, the market return is the value-weighted industry average return, where industries are defined according to the 48 Fama-French classifications.[5] To calculate beta dispersion, we estimate the absolute value of the difference between a firm's beta and the average industry beta:

$$\beta\_DISP_{i,k} = \left|\beta_{i,k} - \bar{\beta}_k\right| \tag{1}$$

Since beta measures the correlation of assets to a market portfolio, a high concentration of betas implies more comovement between the respective securities. It is also worth noting that while the value-weighted average beta of a market portfolio will be, by definition, equal to one, the arithmetic average beta does not face this same constraint. Since we are interested in the distributional properties of beta, we use and report the arithmetic average. Although we limit our tabulated results to those associated with a weekly measure of beta dispersion, we also analyse daily and monthly measures of beta dispersion, and find similar results.[6]

Size is the market capitalisation in billions of dollars. *Price* is the closing annual share price. *B/M* is the book-to-market ratio. *D/A* is the debt-to-assets ratio. *Assets* is the total assets in billions of dollars. *P/E* is the price-earnings ratio according to closing annual share prices and earnings per share in the calendar year. *Turn* is the average daily share turnover, or the ratio of trade volume to shares outstanding. *Volt* is the standard deviation of daily returns during each year for each stock. *Spread* is the average daily bid-ask spread for a particular stock during a particular year, where spreads are calculated as the difference between the daily closing ask price and the daily closing bid price

[5] We note that the specification of Fama-French industries is obtained from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

[6] In particular, we estimate CAPM-style regressions using both daily and monthly returns. We also examine percentage differences from mean industry betas instead of raw differences. We find that correlation between beta dispersion described in Equation (1) and beta dispersion using percentage differences are extremely high (0.90 or above depending on the frequency of returns: daily, weekly or monthly). Additionally, we use equal-weighted instead of value-weighted industry returns and, after replicating much of our analysis below, the results are qualitatively similar to those reported in the paper.

Table 1
Summary statistics

	Entire sample			Sample of banks		
	Mean [1]	SD [2]	Median [3]	Mean [4]	SD [5]	Median [6]
Beta	0.6430	0.6084	0.6098	0.4638	0.4955	0.3705
β_DISP	0.4477	0.3716	0.3610	0.3714	0.2990	0.3065
Size	1.4989	9.1415	0.1112	1.5319	9.3930	0.0942
Price	26.3176	787.1363	13.2600	21.0535	18.2825	17.2500
B/M	0.3328	12.5179	0.1509	0.1448	0.1505	0.1294
D/A	0.5793	0.6680	0.5710	0.8879	0.1088	0.9127
Assets	7.0674	67.3580	0.2478	26.3425	159.0672	1.0391
P/E	13.4890	107.1016	10.8601	15.7661	52.7943	13.1429
Turnover	0.0061	0.0451	0.0027	0.0034	0.0137	0.0016
Volt	0.0341	0.0249	0.0275	0.0271	0.0183	0.0223
Spread	0.0318	0.0475	0.0172	0.0325	0.0386	0.0217
P_Impact	1.7012	21.0924	0.1554	3.8071	13.1119	0.7369

This table reports statistics that describe the sample. *Beta* is the weekly estimate of the industry betas. *β_DISP* is the weekly measure of beta dispersion, which is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta. *Size* is the market capitalisation in $ billions. *Price* is the closing annual share price. *B/M* is the book-to-market ratio. *D/A* is the debt-to-assets ratio. *Assets* is the total assets in $ billions. *P/E* is the price-earnings ratio according to closing annual share prices and earnings per share in the calendar year. *Turn* is the average daily share turnover, or the ratio of trade volume to shares outstanding. *Volt* is the standard deviation of daily returns during each year for each stock. *Spread* is the average daily bid-ask spread, or the difference between the daily closing ask price and the daily closing bid price scaled by the spread midpoint. *P_Impact* is the average daily measure of Amihud's (2002) illiquidity, or the ratio of the absolute value of daily returns scaled by daily volume. Columns [1]–[3] show the results for the entire time period while columns [4]–[6] show the results for the financial crisis period (2008–2009). The sample includes more than 25,000 individual stocks and 258,716 stock-year observations.

scaled by the spread midpoint (see Roll and Subrahmanyam, 2010; Chung and Zhang, 2014).[7] *P_Impact* is the average daily measure of Amihud's (2002) illiquidity, or the ratio (in 100,000s) of the absolute value of daily returns scaled by daily volume.

[7] Chung and Zhang (2014) show that the use of CRSP closing bid-ask spreads is a very close approximation to using high frequency data when calculating relative effective bid-ask spreads. Roll and Subrahmanyam (2010) also find that closing bid-ask spreads in CRSP properly approximate intraday effective bid-ask spreads. We note that CRSP does not begin reporting closing bid and ask prices until 1982. Therefore, when including bid-ask spreads in our analysis, the time period ranges from 1982 to 2012.

Columns [1]–[3] of Table 1 show the results for the entire sample. We find that the average stock in the sample has a beta of 0.6430. We note that the reason the mean beta in column [1] is not equal to one is because we report the standard arithmetic average, which gives equal weight to each observation.[8] We also find that the average stock has a beta dispersion of 0.4477. The average stock also has an average market capitalisation of $1.4989 billion, a share price of $26.32, a book-to-market ratio of 0.3328, a debt-to-assets ratio of 0.5793, assets of more than $7 billion, a price-to-earnings ratio of 13.49, share turnover of 0.0061, return volatility of 0.0341, an average daily bid-ask spread of 0.0318, and an average daily price impact of 1.7012.

Columns [4]–[6] of Table 1 show the summary statistics for the subsample of banks. The average bank has a beta of 0.4638 and a beta dispersion of 0.3714. These averages seem to indicate that banks have lower beta dispersion than non-banks; however, we will test whether the difference is statistically significant in the following section. The average bank in our sample has a market capitalisation of $1.5319 billion and a share price of $21.05. We also show that the average bank has a book-to-market ratio of 0.1448, a debt-to-assets ratio of 0.8879, assets of more than $26 billion, a price-to-earnings ratio of 15.77, share turnover of 0.0034, return volatility of 0.0271, an average daily bid-ask spread of 0.0325, and an average daily price impact of 3.8071.

3. Empirical results

In this section, we begin by examining whether the beta dispersion among banks is different than a sample of non-banks. We then examine whether beta dispersion for banks is affected by legislation that enhanced the transparency across the entire financial services industry. Next, we analyse whether the beta dispersion in banks is driven by market microstructure characteristics that proxy for bank-specific informational opacity. Last, we examine whether beta dispersion for banks is explained by the amount of loans on a particular bank's balance sheet.

3.1. Beta dispersion banks vs. non-banks

We begin by examining whether beta dispersion for banks is different than that for non-banks. To do so, we create a sample of banks and a sample of non-banks (or firms in all other industries). We then estimate mean levels of beta dispersion and examine the difference in means. Table 2 reports these mean estimates of beta dispersion for banks and non-banks and the difference in means with corresponding *p*-values. Columns [1] and [2] show the results for the entire time period, while columns [3] and [4] show the results for the financial

[8] If we take the value-weighted average of each firm beta in column [1] of Table 1, we obtain a mean beta very close to one.

Table 2
Difference in beta dispersion banks vs. non-banks – univariate

	Entire time period		Crisis time period	
	Beta [1]	*β_DISP* [2]	*Beta* [3]	*β_DISP* [4]
Banks	0.4638	0.3713	0.5279	0.3382
Non-Banks	0.6690	0.4588	0.9175	0.4246
Difference	−0.2052***	−0.0875***	−0.3896***	−0.0864***
	(0.000)	(0.000)	(0.000)	(0.000)

This table reports beta and beta dispersion for banks and non-banks. *Beta* is the weekly estimate of the industry betas. *β_DISP* is our measures of beta dispersion defined in Equation (1), which is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta. The table reports the mean beta and the mean beta dispersion for banks and non-banks and the difference in means with corresponding *p*-values. Columns [1] and [2] show the results for the entire time period while columns [3] and [4] show the results for the financial crisis period (2008–2009). ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

crisis time period (2008–2009). We find that the average bank has a weekly beta dispersion of 0.3713, while the average non-bank has a weekly beta dispersion of 0.4588. This difference (0.0875) is statistically significant at the 0.01 level and economically meaningful, as it represents nearly 25 percent of the mean beta dispersion for banks. As shown in Table 1, beta dispersion decreases for the average firm during the crisis period. Our objective here is to determine whether it is banks or non-banks that drives this reduction in beta dispersion. The reduction in beta dispersion is virtually identical for both banks and non-banks, and the differences remain negative and significant.

Overall, the results in Table 2 indicate that, relative to non-banks, the stock prices of banks co-move more than the stock prices of non-banks. This is true in both general time periods and during the financial crisis. To the extent that banks are more opaque than other non-banks (Morgan, 2002; Flannery *et al.*, 2004; and others), our results support the idea that more informationally opaque industries have greater comovement among their stock prices.

We recognise the need to control for other stock characteristics when comparing the beta dispersion of banks to non-banks. To do so, we estimate the following equation using pooled stock-year data:

$$\begin{aligned}\beta\_DISP_{i,t} = \alpha + \delta_t + \beta_1 BANK_i + \beta_2 Size_{i,t} + \beta_3 price_{i,t} + \beta_4 B/M_{i,t} \\ + \beta_5 Assets_{i,t} + \beta_6 D/A_{i,t} + \beta_7 P/E_{i,t} + \beta_8 Turn_{i,t} + \beta_9 Volt_{i,t} \\ + \varepsilon_{i,t},\end{aligned} \tag{2}$$

where the dependent variable is our measure of beta dispersion with betas calculated using weekly returns. The variable of interest is the indicator variable *BANK*, which is equal to 1 if stock *i* is a bank, 0 otherwise. The control variables are as defined previously. We recognise the need to make appropriate adjustments to our econometric specifications. First, in response to a Hausman test, we find observed differences across years, so we include controls for year fixed effects.[9] Second, given the nature of our pooled stock-year data, we acknowledge the need to account for two-dimensional clustering in the standard errors. We therefore report OLS estimates with corresponding *p*-values obtained from robust standard errors. Third, OLS estimates may be biased and asymptotically inconsistent given that the dependent variable is left truncated at zero by construction. Therefore, we account for this truncation by estimating a one-tailed Tobit model while still controlling for year fixed effects.

Table 3 reports the regression results from Equation (2). Columns [1] and [2] show the results from the OLS regressions while columns [3] and [4] present the results from the truncated Tobit regressions. In column [1], we find that the indicator variable, *BANK*, produces a negative estimate that is statistically different from zero. The magnitude of this coefficient is similar in size to the difference in means reported in column [2] of Table 2. In column [2] of Table 3, we include various stock characteristics as additional control variables. A few results on the control variates are noteworthy. We find that larger stocks with higher share prices, stocks with more assets, and stocks with higher turnover and volatility have higher beta dispersion. Importantly, we continue to find that the coefficient on *BANK* in column [2] remains both negative and significant. However, we note that the magnitude of the coefficient decreases markedly relative to the corresponding coefficient in column [1]. In economic terms, the coefficient on *BANK* in column [2] decreases by more than 50 percent, relative to the corresponding coefficient in column [1] of the same table. Columns [3] and [4] show the truncated regression results. The findings in these latter two columns are similar to those in columns [1] and [2]. Thus, according to our measure of beta dispersion, banks typically have stock prices that co-move more than non-banks even after controlling for various stock characteristics and time series trends.

The results in Table 3 provide some initial evidence that beta dispersion is lower for firms in the banking industry than for firms in other industries. Given that our sample focuses on the banking sector and the time period encompasses a financial crisis, it is important to make sure that our results are not driven by that crisis. The unusual and unprecedented nature of the financial crisis surely impacted the banking sector in many ways. As it is unclear how a financial crisis will impact the relation between many of our variables, our main focus is to make sure that our results are not driven by the financial crisis and its

[9] We do not control for stock fixed effects as we include the indicator variable *BANK*. Doing so would violate the full rank condition required for consistent estimates.

Table 3
Difference in beta dispersion banks vs. non-banks – multivariate

	OLS regressions		Truncated regressions	
	[1]	[2]	[3]	[4]
Intercept	0.4442***	0.2704***	−0.5016***	−0.7049***
	(0.000)	(0.000)	(0.000)	(0.000)
$BANK_i$	−0.0850***	−0.0377***	−0.3930***	−0.1982***
	(0.000)	(0.000)	(0.000)	(0.000)
$Size_{i,t}$		0.0005***		0.0013***
		(0.000)		(0.000)
$Price_{i,t}$		−0.0106		−0.1895***
		(0.186)		(0.005)
$B/M_{i,t}$		0.0001		0.0002
		(0.105)		(0.210)
$Assets_{i,t}$		0.1937***		0.5294***
		(0.000)		(0.000)
$D/A_{i,t}$		0.0027		0.0022
		(0.103)		(0.464)
$P/E_{i,t}$		0.0039		0.0024
		(0.622)		(0.931)
$Turn_{i,t}$		1.0078***		1.8697***
		(0.000)		(0.000)
$Volt_{i,t}$		0.0421***		0.1076***
		(0.000)		(0.000)
Adj. R^2	0.0178	0.0850		
Sigma			0.7440***	0.6531***
Year FE	Yes	Yes	Yes	Yes
N	258,716	175,879	258,716	175,879

This table reports the results from estimating the following equation using pooled stock-year data:

$$\beta\_DISP_{i,t} = \alpha + \delta_t + \beta_1 BANK_i + \beta_2 Size_{i,t} + \beta_3 Price_{i,t} + \beta_4 B/M_{i,t} + \beta_5 Assets_{i,t} + \beta_6 D/A_{i,t} + \beta_7 P/E_{i,t} + \beta_8 Turn_{i,t} + \beta_9 Volt_{i,t} + \varepsilon_{i,t}.$$

The dependent variable is beta dispersion, which is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta. The independent variables include the following: *Size* is the market capitalisation in \$ billions. *Price* is the closing annual share price. *B/M* is the book-to-market ratio. *D/A* is the debt-to-assets ratio. *Assets* is the total assets in \$ billions. *P/E* is the price-earnings ratio according to closing annual share prices and earnings per share in the calendar year. *Turn* is the average daily share turnover, or the ratio of trade volume to shares outstanding. *Volt* is the standard deviation of daily returns during each year for each stock. The variable of interest is the indicator variable *BANK*, which is equal to 1 if stock *i* is a bank, 0 otherwise. Columns [1] and [2] show the results from the OLS regressions. Given that our beta dispersion measure is truncated at zero, we control for this using one-tailed Tobit regressions in columns [3] and [4]. We control for year fixed effects and report *p*-values in parentheses obtained from robust standard errors. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

unexpected consequences. We examine this by estimating the following regression equation using pooled stock-year data for our entire sample:

$$\begin{aligned}\beta\_DISP_{i,t} = \alpha + \beta_1 BANK_i + \beta_2 CRISIS_t + \beta_3 BANK_i \times CRISIS_t + \beta_4 Size_{i,t} \\ + \beta_5 Price_{i,t} + \beta_6 B/M_{i,t} + \beta_7 Assets_{i,t} + \beta_8 D/A_{i,t} + \beta_9 P/E_{i,t} \\ + \beta_{10} Turn_{i,t} + \beta_{11} Volt_{i,t} + \varepsilon_{i,t}.\end{aligned} \tag{3}$$

As before, the dependent variable is our measure of beta dispersion. The independent variables are the same as before except we include an indicator variable that captures the most recent financial crisis. Specifically, *CRISIS* is an indicator variable equal to 1 during 2008 and 2009, 0 otherwise. We then interact the two indicator variables *BANK* and *CRISIS* in order to determine whether the lower levels of beta dispersion for banks is driven by the crisis period. We do not control for year fixed effects since doing so would violate the full rank condition required for consistent estimates. We do, however, obtain *p*-values from robust standard errors.

We report the estimated coefficients from Equation (3) in Table 4. While column [1] reports the results from the OLS regression, column [2] reports the results from the truncated Tobit regression. The coefficients on the control variables are similar in sign and magnitude to those in the previous table. Therefore, we focus our attention on the indicator variables and the interaction term. In column [1], we find that the indicator variable *CRISIS* produces a negative and significant estimate. Furthermore, we find that the interaction estimate is also negative and significant. There are two distinct interpretations for these findings. First, the negative coefficient on *CRISIS* suggests that, during the financial crisis, beta dispersion was markedly lower for all stocks than during other time periods. This result is consistent with the idea that crises are associated with greater levels of comovement. Second, the negative interaction estimate suggests that beta dispersion decreases substantially for banks, relative to non-banks, during the financial crisis period. However, the negative coefficient on *BANK* suggests that during the non-crisis period, banks still have lower beta dispersion than non-banks. A closer examination of the coefficients in column [1] suggests that the total effect for banks during the crisis period, which is the sum of β_1 and β_3, is -0.0895 (*p*-value = 0.000). Thus, the lower levels of beta dispersion in banks, relative to non-banks, was impacted by the financial crisis, but the crisis does not entirely drive the results. The truncated regression results are qualitatively similar to the OLS regression results.

Table 4
Difference in beta dispersion banks vs. non-banks – financial crisis

	OLS regressions [1]	Truncated regressions [2]
Intercept	0.3127***	−0.6829***
	(0.000)	(0.000)
$BANK_i$	−0.0444***	−0.2233***
	(0.000)	(0.000)
$CRISIS_t$	−0.0721***	−0.2391***
	(0.000)	(0.000)
$BANK_i \times CRISIS_t$	−0.0451***	−0.1633***
	(0.000)	(0.000)
$Size_{i,t}$	0.0003***	0.0007*
	(0.002)	(0.033)
$Price_{i,t}$	−0.0125	−0.3175***
	(0.211)	(0.000)
$B/M_{i,t}$	0.0001	0.0002
	(0.131)	(0.221)
$Assets_{i,t}$	0.2001***	0.5856***
	(0.000)	(0.000)
$D/A_{i,t}$	0.0028*	0.0031
	(0.087)	(0.330)
$P/E_{i,t}$	0.0059	0.0114
	(0.461)	(0.694)
$Turn_{i,t}$	0.8990***	1.7215***
	(0.000)	(0.000)
$Volt_{i,t}$	0.0372***	0.1014***
	(0.000)	(0.000)
Adj. R^2	0.0622	
Sigma		0.6821***
Year FE	No	No
N	175,879	175,879

This table reports the results from estimating the following equation using pooled stock-year data:

$$\beta\_DISP_{i,t} = \alpha + \beta_1 BANK_i + \beta_2 CRISIS_t + \beta_3 BANK_i \times CRISIS_t + \beta_4 Size_{i,t} + \beta_5 Price_{i,t} + \beta_6 B/M_{i,t} + \beta_7 Assets_{i,t} + \beta_8 D/A_{i,t} + \beta_9 P/E_{i,t} + \beta_{10} Turn_{i,t} + \beta_{11} Volt_{i,t} + \varepsilon_{i,t}.$$

The dependent variable is beta dispersion, which is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta. The independent variables include the following: *Size* is the market capitalisation in $ billions. *Price* is the closing annual share price. *B/M* is the book-to-market ratio. *D/A* is the debt-to-assets ratio. *Assets* is the total assets in $ billions. *P/E* is the price-earnings ratio according to closing annual share prices and earnings per share in the calendar year. *Turn* is the average daily share turnover, or the ratio of trade volume to shares outstanding. *Volt* is the standard deviation of daily returns during each year for each stock. The variable of interest includes the following: *BANK* is an indicator variable, which is equal to 1 if stock *i* is a bank, 0 otherwise. *CRISIS* is an indicator variable equal to 1 during 2008 and 2009, 0 otherwise. Columns [1] and [2] report the results from the OLS regressions. We do not control for year fixed effects as doing so would violate the full rank condition required for consistent estimates. We report p-values in parentheses obtained from robust standard errors. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

3.2. Beta dispersion across industries

To test whether the lower levels of beta dispersion (higher comovement) among banks, relative to non-banks, is driven by regulation, we analyse the beta dispersion across the Fama-French industry classifications. Figure 1 shows the industry rankings of beta dispersion during the entire sample time period. We find that banks have the sixth lowest weekly beta dispersion (0.37). Interestingly, we find that four of the other top five industries with the lowest beta dispersion seem to be more heavily regulated (smoking/tobacco, coal, automobiles, and utilities). Perhaps these rankings are observed because regulation reduces heterogeneity in the time series of stock returns. Or, perhaps industry-wide regulation is justified by the opacity of firms within that industry as argued in Morgan (2002).

In unreported tests, we re-estimate Equation (2) substituting in for banks, an indicator variable equal to 1 if a firm is in the utilities industry, 0 otherwise. We do not find that comovement in utilities is significantly different than non-utilities once we control for other firm characteristics. To further investigate the possibility of regulation fully explaining our results, we re-estimate Equation (2) using only petroleum and natural gas companies as the treatment sample. Again, we do not find more comovement in oil companies vis-à-vis non-oil companies. Combined, the results in this subsection seem to suggest that regulation is not fully explaining the differences in comovement between banks and non-banks. These tests do not rule out the possibility that regulation affects stock price comovement, and we believe that this might be a fruitful area for future research.

3.3. Beta dispersion and bank opacity – 2002 Sarbanes-Oxley Act

In this subsection, we analyse the comovement of bank stock prices surrounding the 2002 Sarbanes-Oxley Act. In general, this legislation was intended to increase the transparency of firms and improve the integrity of financial reporting through more stringent disclosure requirements. Up until now, our findings only document a correlation between opacity and comovement. However, our hypothesis predicts that opacity is driving the comovement and observing correlations is not tantamount to documenting a causal relationship between the variables in question. To draw stronger causal inferences and to provide a more appropriate test of our first hypothesis, we use the passage of SOX as an (arguably) exogenous shock to the transparency. Akhigbe and Martin (2006) show that SOX improved the level of transparency in general and, particularly, in the financial services industry. Motivated by the

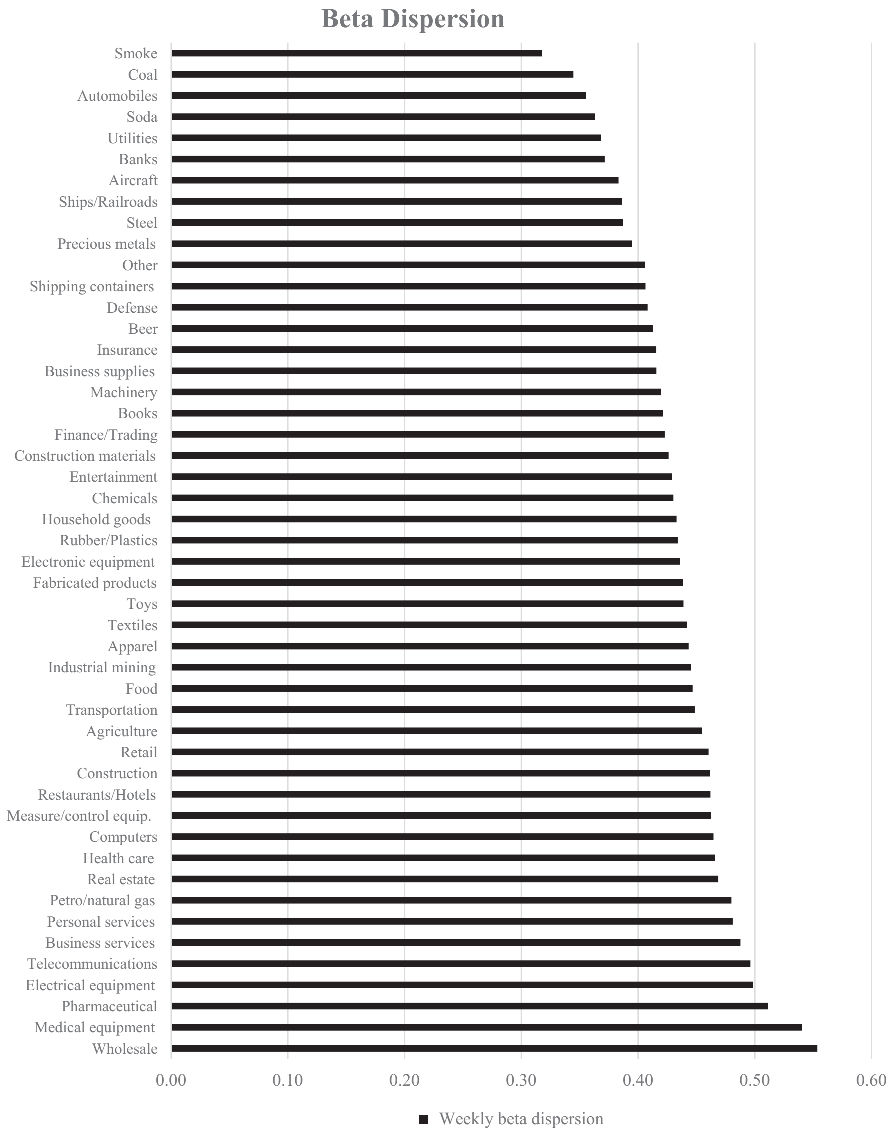

Figure 1 Weekly beta dispersion by industry for the entire time period (1980–2012).

findings in Akhigbe and Martin (2006), we hypothesise that, relative to less opaque stocks, the comovement of bank stock will decrease during the post-SOX period. To test this conjecture, we estimate specifications of the following difference-in-difference regression equation using pooled stock-year observations on the subsample of banks over the four-year period 2000–2003:

$$\beta\_DISP_{i,t} = \alpha + \beta_1 BANK_i + \beta_2 SOX_t + \beta_3 BANK_i \times SOX_t + \beta_4 Size_{i,t} + \beta_5 Price_{i,t} + \beta_6 B/M_{i,t} + \beta_7 Assets_{i,t} + \beta_8 D/A_{i,t} + \beta_9 P/E_{i,t} + \beta_{10} Turn_{i,t} + \beta_{11} Volt_{i,t} + \varepsilon_{i,t}, \quad (4)$$

where the dependent and control variables have been defined in previous equations. The independent variables of interest are the indicator variables *BANK*, *SOX* and the interaction between the two. SOX takes on the value of 1 in years 2002 and 2003 and 0 for years 2000 and 2001. To avoid violating the full column rank assumption for consistent estimation, we do not include year fixed effects. According to our hypothesis, we expect the interaction coefficient, β_3, to be positive and significant (i.e. more beta dispersion, less comovement).[10]

Tables 5 presents the results from this difference-in-difference analysis. While columns [1] and [3] present the results from estimating Equation (4) using OLS, columns [2] and [4] report the results from estimating Equation (4) using censored Tobit. The results are similar with or without including the control variables. So, for brevity, we only discuss our findings generally. The coefficient on the interaction variable is positive and significant in each column. Specifically, the interaction coefficient in column [1] indicates that, relative to non-banks, the beta dispersion of banks is 0.0405 lower during the post-SOX period, relative to the pre-SOX period. This reflects about 10.90 percent of the mean bank beta dispersion reported in the summary statistics. We note that the beta coefficient on the interaction term is only significant at the 0.10 level in the full OLS model specification. However, in the full truncated model specification, we find that the coefficient on the interaction term is 0.1134 and significant at the 0.05 level.

These results support our first hypothesis, and seem to indicate that increasing the transparency in the banking industry decreases the comovement between the stock prices within that industry. To the extent that the passage of SOX is exogenous to comovement, causation seem to flow from opacity to bank stock price comovement instead of the other way around.

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[10] We note an important institutional detail in these tests. As discussed in Iliev (2010), SOX allowed a loophole for smaller firms to delay compliance with Section 404, which required greater disclosure. To account for the possibility that the inclusion of smaller banks in our treatment sample is confounding our results, we ensure that we control for firm size in our multivariate tests. Second, we conduct a series of robustness tests where we cut our sample based on size. In particular, we eliminate the bottom 5 percent of firms (based on size) and replicate Table 5. The results reported in Table 5 hold in these unreported tests. Additionally, we perform two additional cuts where we eliminate the bottom 10 percent and the bottom 25 percent of firms (based on size). In this replication of Table 5, our results show interaction estimates that remain positive and statistically significant. Therefore, our findings in this section do not appear to be affected by including smaller firms in our sample.

Table 5
Beta dispersion and bank opacity – 2002 Sarbanes-Oxley Act

	OLS regressions [1]	Truncated regressions [2]	OLS regressions [3]	Truncated regressions [4]
Intercept	0.4410***	−0.4814***	0.2641***	−0.6115***
	(0.000)	(0.000)	(0.000)	(0.000)
$BANK_i$	−0.0111**	−0.0462**	−0.0806***	−0.4181***
	(0.016)	(0.010)	(0.000)	(0.000)
SOX_t	−0.1507***	−0.8486***	0.0295***	0.0794***
	(0.000)	(0.000)	(0.000)	(0.000)
$BANK_i \times SOX_t$	0.0405***	0.2612***	0.0180*	0.1134**
	(0.000)	(0.000)	(0.081)	(0.033)
$Size_{i,t}$			0.0002	0.0007
			(0.200)	(0.205)
$Price_{i,t}$			0.174	−0.0434
			(0.702)	(0.817)
$B/M_{i,t}$			0.0002	0.0006
			(0.489)	(0.321)
$Assets_{i,t}$			0.6914***	1.6775***
			(0.000)	(0.000)
$D/A_{i,t}$			0.0068**	0.0058
			(0.033)	(0.451)
$P/E_{i,t}$			0.0065	0.0114
			(0.746)	(0.848)
$Turn_{i,t}$			0.3312***	0.6964***
			(0.007)	(0.000)
$Volt_{i,t}$			0.0319***	0.0846***
			(0.000)	(0.000)
Adj. R^2	0.0209		0.0801	
Sigma		0.7337***		0.6040***
Year FE	No	No	No	No
N	34,259	34,259	24,301	24,301

This table reports the results from estimating the following equation using pooled stock-year data for our sample of banks and non-banks surrounding the 2002 Sarbanes-Oxley Act, which increased the level of transparency among firms:

$$\beta\_DISP_{i,t} = \alpha + \beta_1 BANK_i + \beta_2 SOX_t + \beta_3 BANK_i \times SOX_t + \beta_4 Size_{i,t} + \beta_5 Price_{i,t} + \beta_6 B/M_{i,t} + \beta_7 Assets_{i,t} + \beta_8 D/A_{i,t} + \beta_9 P/E_{i,t} + \beta_{10} Turn_{i,t} + \beta_{11} Volt_{i,t} + \varepsilon_{i,t}.$$

The dependent variable is beta dispersion, which is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta. The independent control variables include the following: *Size* is the market capitalisation in \$ billions. *Price* is the closing annual share price. *B/M* is the book-to-market ratio. *D/A* is the debt-to-assets ratio. *Assets* is the total assets in \$ billions. *P/E* is the price-earnings ratio according to closing annual share prices and earnings per share in the calendar year. *Turn* is the average daily share turnover, or the ratio of trade volume to shares outstanding. *Volt* is the standard deviation of daily returns during each year for each stock. The variables of interest include the following. *BANK* is an indicator variable, which is equal to 1 if stock *i* is a bank, 0 otherwise. *SOX* is an indicator variable capturing the time period after the Act was debated in Congress and passed. We also include the interaction between the two indicator variables. To isolate the Act on the level of beta dispersion, we only include four years 2000 and 2003. The variable SOX is equal to unity in years 2002 and 2003 given that discussions about the Act started in early 2002. Columns [1] and [2] report the results from the OLS regressions, while columns [3] and [4] show the results for the one-tailed Tobit regressions. We do not control for year fixed effects since doing so would violate the full rank condition required for consistent estimates. We report *p*-values in parentheses obtained from robust standard errors. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

3.4. Beta dispersion and bank opacity – bank illiquidity

In our next set of tests, we continue to explore whether opacity can explain the difference in beta dispersion, or comovement, between banks and non-banks. If the opacity of banks indeed adversely affects the level of beta dispersion, then we expect to find that, within our sample of banks, beta dispersion is lowest among the more opaque banks. We follow a broad stream of market microstructure theory that suggests that trading characteristics can proxy for informational uncertainty (Benston and Hagerman, 1974; Kyle, 1985; Glosten and Harris, 1988; Stoll, 1989; George *et al*., 1991; Huang and Stoll, 1994; Lin *et al*., 1995). Empirical studies find that microstructure characteristics, such as the bid-ask spreads and price impacts, are related to factors that might cause informational opacity (Brennan and Subrahmanyam, 1995; Krinsky and Lee, 1996).

Accordingly, we examine the relation between bank beta dispersion and microstructure characteristics that proxy firm-specific opacity. Following Flannery *et al*. (2004, 2013), we approximate bank opacity with the average daily bid-ask spread as well as Amihud’s (2002) measure of price impact. The idea behind these potential measures of opacity is based on the notion that market makers will increase the bid-ask spread when uncertainty about the true value of a stock increases. In fact, Kyle (1985) explicitly argues that opaque assets will likely have higher bid-ask spreads. We, therefore, estimate the following regression equation for our subsample of banks using stock-year observations:

$$\begin{aligned}\beta\_DISP_{i,t} = \alpha + \delta_t + \beta_1 Illiquidity_{i,t} + \beta_2 Size_{i,t} + \beta_3 Price_{i,t} + \beta_4 B/M_{i,t} \\ + \beta_5 Assets_{i,t} + \beta_6 D/A_{i,t} + \beta_7 P/E_{i,t} + \beta_8 Turn_{i,t} + \beta_9 Volt_{i,t} \\ + \varepsilon_{i,t}.\end{aligned} \tag{5}$$

The dependent variable and the control variables are as defined previously. The independent variable of interest *Illiquidity* is defined two different ways. First, we include the natural log of the average daily bid-ask spread (*Ln*

(Spread)). Second, we include the natural log of the average daily Amihud (2002) measure of price impact (*Ln(P_Impact)*). We control for year fixed effects and report *p*-values obtained from robust standard errors.

The results of estimating Equation (5) are found in Table 6. Columns [1] and [2] report the results from OLS regressions, while columns [3] and [4] show the results from truncated Tobit regressions. We note that the coefficients on the control variables are similar in sign to those in previous tables. Interestingly, we find that in each column, the coefficients on the illiquidity variables are negative and significant. In economic terms, column [1] suggests that a 1 percent increase in bid-ask spreads results in a reduction in beta dispersion by 0.0120, which represents slightly more than 5 percent of the mean beta dispersion for banks. Column [2] shows that, if anything, the economic magnitude of the coefficient on the log of price impact is greater. Columns [3] and [4] show the results from the truncated regressions. As before, we find that the variables of interest produce negative coefficients that are both statistically and economically significant. In fact, the magnitude of the coefficients is markedly stronger than the corresponding coefficients in columns [1] and [2], suggesting that when controlling for truncation in the beta dispersion measures, the conclusions that we are able to draw are stronger. The findings in this table suggest that the more opaque banks (in terms of firm illiquidity) experience greater comovement in their stock prices.

3.5. Beta dispersion and bank opacity – bank loans

In the previous subsection, we identified a negative relation between microstructure measures of bank-specific opacity and beta dispersion. In our final set of tests, we examine the robustness of this finding using an alternative proxy of firm opacity. Again, we focus exclusively on the subsample of banks. Flannery *et al*. (2004) argue that what makes banks informationally opaque is the intermediation channel. In particular, bank loans drive the opacity of banks because of the information asymmetry between insiders and outsiders about the true loan default risk. Several theoretical studies justify this assertion (Campbell and Kracaw, 1980; Berlin and Loeys, 1988; Diamond, 1989, 1991; Kwan and Carleton, 2010). Therefore, we explore the relation between beta dispersion and the amount of loans on a bank's balance sheet.

After obtaining the balance sheet information from Bank Compustat, we replicate earlier regressions but include the amount of loans as the independent variable of interest. Specifically, we estimate the following equation for our pooled stock-year observations for the subsample of banks:

Table 6
Beta dispersion and bank opacity – bank liquidity

	OLS regressions		Truncated regressions	
	[1]	[2]	[3]	[4]
Intercept	−0.0035	−0.0079	−0.7351***	−0.7947***
	(0.954)	(0.890)	(0.001)	(0.002)
$Ln(Spread_{i,t})$	−0.0120***		−0.0393***	
	(0.007)		(0.000)	
$Ln(P\_Impact_{i,t})$		−0.0189***		−0.0513***
		(0.000)		(0.000)
$Size_{i,t}$	0.0029***	0.0019***	0.0045***	0.0025***
	(0.000)	(0.000)	(0.000)	(0.000)
$Price_{i,t}$	0.3368**	−0.0128	0.9097**	−0.1265
	(0.036)	(0.930)	(0.016)	(0.741)
$B/M_{i,t}$	0.0516*	0.0352	0.1136***	0.0787**
	(0.072)	(0.138)	(0.001)	(0.016)
$Assets_{i,t}$	0.0120	−0.0059	0.0418	−0.0089
	(0.622)	(0.800)	(0.279)	(0.816)
$D/A_{i,t}$	−0.0034	0.0139	−0.0200	0.0216
	(0.897)	(0.556)	(0.672)	(0.606)
$P/E_{i,t}$	−0.0202	0.0095	−0.0617	0.0219
	(0.773)	(0.882)	(0.624)	(0.842)
$Turn_{i,t}$	3.3462**	1.9465**	4.4655***	2.0871***
	(0.015)	(0.046)	(0.000)	(0.000)
$Volt_{i,t}$	0.0508***	0.0551***	0.1134***	0.1153***
	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.1560	0.1758		
Sigma			0.4398***	0.4390***
Year FE	Yes	Yes	Yes	Yes
N	13,281	13,281	13,281	13,281

This table reports the results from estimating the following equation using pooled stock-year data for our sample of banks:

$$\beta\_DISP_{i,t} = \alpha + \delta_t + \beta_1 Illiquidity_{i,t} + \beta_2 Size_{i,t} + \beta_3 Price_{i,t} + \beta_4 B/M_{i,t} + \beta_5 Assets_{i,t} + \beta_6 D/A_{i,t} + \beta_7 P/E_{i,t} + \beta_8 Turn_{i,t} + \beta_9 Volt_{i,t} + \varepsilon_{i,t}.$$

The dependent variable is beta dispersion, which is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta. The independent variables include the following: *Size* is the market capitalisation in \$ billions. *Price* is the closing annual share price. *B/M* is the book-to-market ratio. *D/A* is the debt-to-assets ratio. *Assets* is the total assets in \$ billions. *P/E* is the price-earnings ratio according to closing annual share prices and earnings per share in the calendar year. *Turn* is the average daily share turnover, or the ratio of trade volume to shares outstanding. *Volt* is the standard deviation of daily returns during each year for each stock. The variable of interest is *Illiquidity*, which is measured two different ways. First, we include the natural log of the average daily bid-ask spread (*Ln(Spread)*). Second, we include the natural log of the average daily Amihud's (2002) measure of price impact (*Ln(P_Impact)*). Columns [1] and [2] report the results from the OLS regressions, while columns [3] and [4] show the results for the one-tailed Tobit regressions. We control for year fixed effects and report p-values in parentheses obtained from robust standard errors. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

$$\beta\_DISP_{i,t} = \alpha + \delta_t + \beta_1 Loan_{i,t} + \beta_2 Size_{i,t} + \beta_3 Price_{i,t} + \beta_4 B/M_{i,t} + \beta_5 Assets_{i,t} + \beta_6 D/A_{i,t} + \beta_7 P/E_{i,t} + \beta_8 Turn_{i,t} + \beta_9 Volt_{i,t} + \varepsilon_{i,t}. \tag{6}$$

The dependent and independent variables are similar to those in previous tables. However, here we include *Loan* as the variable of interest, which is the amount of total loans (in $ millions) on the bank's balance sheet.[11] We include year fixed effects and report p-values obtained from robust standard errors.

The results of estimating Equation (6) are reported in Table 7. While column [1] reports the results from the OLS regressions, column [2] shows the robustness results from the truncated Tobit regressions. In general, the results are similar whether we estimate Equation (6) using OLS or a one-tailed Tobit model. The coefficients on the control variables are similar to those in previous tables. In column [1], we find that the variable *Loan* produces an estimate that is negative and significant. In economic terms, a one standard deviation increase in the amount of loans reduces daily beta dispersion by more than 41 basis points, which represents about 1 percent of the mean beta dispersion for banks. To the extent that bank loans indeed drive the opacity in the banking industry, these results suggest that more opaque banks have less beta dispersion. We are able to draw similar conclusions in column [2], which controls for the truncation of the dependent variable.[12]

It is possible that other time-varying macroeconomic factors are influencing our results. For instance, underlying economic factors could be generating the industry comovement that we observe in bank stocks. To test for this possibility, we obtain annual GDP growth estimates from the Federal Research Economic Data and include these estimates as an additional control variable. We note that when doing so, we do not include year fixed effects. After replicating much of our analysis, we find that including macroeconomic conditions does not meaningfully affect the results. We are left to conclude that,

[11] In a number of unreported tests, we include the amount of assets made up from real estate loans only as the independent variable of interest and the results are similar.

[12] We note that when we replicate the analysis in Table 7 using the different measures of beta dispersion (measures that account for percentage differences and equal-weighting), we find only weak support for our first hypothesis. Specifically, in each case, we find that the coefficient on *Loan* is negative, but not always reliably different from zero.

Table 7
Beta dispersion and bank opacity – bank loans

	OLS regressions [1]	Truncated regressions [2]
Intercept	0.0301	−0.6826***
	(0.567)	(0.008)
$Loan_{i,t}$	−0.1884*	−0.6343*
	(0.070)	(0.060)
$Size_{i,t}$	0.0030***	0.0049***
	(0.000)	(0.000)
$Price_{i,t}$	0.5557***	1.5603***
	(0.001)	(0.000)
$B/M_{i,t}$	0.0603**	0.1395***
	(0.039)	(0.000)
$Assets_{i,t}$	0.0369	0.1071**
	(0.202)	(0.010)
$D/A_{i,t}$	−0.0140	−0.0483
	(0.559)	(0.271)
$P/E_{i,t}$	0.0105	0.0183
	(0.875)	(0.876)
$Turn_{i,t}$	3.5584***	5.1723***
	(0.006)	(0.000)
$Volt_{i,t}$	0.0504***	0.1065***
	(0.000)	(0.000)
Adj. R^2	0.1556	
Sigma		0.4526***
Year FE	Yes	Yes
N	14,347	14,347

This table reports the results from estimating the following equation using pooled stock-year data for our sample of banks:

$$\beta\_DISP_{i,t} = \alpha + \delta_t + \beta_1 Loan_{i,t} + \beta_2 Size_{i,t} + \beta_3 Price_{i,t} + \beta_4 B/M_{i,t} + \beta_5 Assets_{i,t} + \beta_6 D/A_{i,t} + \beta_7 P/E_{i,t} + \beta_8 Turn_{i,t} + \beta_9 Volt_{i,t} + \varepsilon_{i,t}.$$

The dependent variable is beta dispersion, which is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta. The independent variables include the following: *Size* is the market capitalisation in $ billions. *Price* is the closing annual share price. *B/M* is the book-to-market ratio. *D/A* is the debt-to-assets ratio. *Assets* is the total assets in $ billions. *P/E* is the price-earnings ratio according to closing annual share prices and earnings per share in the calendar year. *Turn* is the average daily share turnover, or the ratio of trade volume to shares outstanding. *Volt* is the standard deviation of daily returns during each year for each stock. The variable of interest is *Loan*, which is the amount (in $ millions) of loans on a bank's balance sheet. Columns [1] and [2] report the results from the OLS regressions, while columns [3] and [4] show the results for the one-tailed Tobit regressions. We control for year fixed effects and report *p*-values in parentheses obtained from robust standard errors. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

to the extent that the amount of loans on a bank's balance sheet is a good proxy for bank opacity, less transparency is associated with greater comovement.

Combined, our findings in Tables 57 provide strong support for the notion that the comovement among bank stock prices is driven, at least in part, by opacity both at the industry level and the bank level. Specifically, more informational opacity is associated with greater comovement among bank stock prices.

4. Concluding remarks

In this study, we examine whether the stock prices of banks co-move more than the stock prices of non-banks, and whether that comovement is influenced by opacity. To the extent that banks are more informationally opaque than non-banks, and this opacity adversely affects the ability of outsiders to properly assess the risks associated with the intermediation process, we might expect to find more comovement among bank stock prices, relative to non-bank stock prices. Consistent with this notion, our empirical results show that bank stock prices exhibit greater comovement than non-bank stock prices. These results are robust to controls for the recent financial crisis and various econometric specifications.

Next, we analyse whether changes in disclosure requirements surrounding the 2002 Sarbanes-Oxley Act influence the comovement among bank stock prices. To the extent that the passing of this Act provides a shock to the transparency in the banking industry, we expect to find a decrease in the comovement of bank stock prices. Our difference-in-difference analysis reveals that, relative to non-banks, the comovement of bank stock prices decreases post-SOX. These results are robust to both OLS and Tobit specifications and the inclusion of a number of different control variables.

Last, we examine whether banks that are more opaque have higher levels of comovement among their stock prices than banks that are less opaque. We show that microstructure characteristics that capture informational opacity (Demsetz, 1968; Kyle, 1985; Glosten and Harris, 1988; Stoll, 1989; among others) directly influence the level of comovement among bank stock prices. We note that this relation has persisted across time. In additional tests, we find that the amount of loans on a bank's balance sheet, which may provide a more direct proxy for informational opacity (Campbell and Kracaw, 1980; Berlin and Loeys, 1988; Diamond, 1989, 1991; Kwan and Carleton, 2010), is also positively related with the level of comovement among bank stock prices.

The implications from our analysis are broad. First, we contribute to the literature on the informational opacity of banks (Campbell and Kracaw, 1980; Berlin and Loeys, 1988; Diamond, 1989, 1991; Morgan, 2002; Flannery *et al.*, 2004, 2013; Kwan and Carleton, 2010; Jones *et al.*, 2012). Second, our analysis sheds light on the effects of bank opacity on price formation. Our findings seem to suggest that the inability of outsiders to properly assess the risks associated with the intermediation process influences asset prices, by the way of greater comovement. Finally, an important byproduct of our analysis is a newly developed measure of "industry comovement", which we denote as beta dispersion. This measure has all of the same theoretical properties as the CAPM, but it is easier to compute relative to other measures of comovement that examine the return correlations of various stock pairs. As research on comovement continues to become more popular in the financial economics literature, perhaps future research can incorporate beta dispersion as a measure of industry-wide comovement.

References

Akhigbe, A., and A. D. Martin, 2006, Valuation impact of Sarbanes–Oxley: evidence from disclosure and governance within the financial services industry, *Journal of Banking and Finance* 30(3), 989–1006.

Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5(1), 31–56.

Barberis, N., A. Shleifer, and J. Wurgler, 2005, Comovement, *Journal of Financial Economics* 75(2), 283–317.

Benston, G. J., and R. L. Hagerman, 1974, Determinants of bid-asked spreads in the over-the-counter market, *Journal of Financial Economics* 1(4), 353–364.

Berlin, M., and J. Loeys, 1988, Bond covenants and delegated monitoring, *The Journal of Finance* 43(2), 397–412.

Bodie, Z., Kane, A. and Marcus, A. 2009, *Investments*, 8th edn (McGraw-Hill, New York).

Brennan, M. J., and A. Subrahmanyam, 1995, Investment analysis and price formation in securities markets, *Journal of Financial Economics* 38(3), 361–381.

Campbell, T. S., and W. A. Kracaw, 1980, Information, production, market signaling, and the theory of financial intermediation, *The Journal of Finance* 35(4), 863–882.

Chung, K. H., and H. Zhang, 2014, A simple approximation of intraday spreads using daily data, *Journal of Financial Markets* 17, 94–120.

Demsetz, H., 1968, The cost of transacting, *Quarterly Journal of Economics* 82(1), 33–53.

Diamond, D. W., 1989, Reputation acquisition in debt markets, *Journal of Political Economy* 97(4), 828–862.

Diamond, D. W., 1991, Debt maturity structure and liquidity risk, *Quarterly Journal of Economics* 106(3), 709–739.

Flannery, M. J., S. H. Kwan, and M. Nimalendran, 2004, Market evidence on the opaqueness of banking firms' assets, *Journal of Financial Economics* 71(3), 419–460.

Flannery, M. J., S. H. Kwan, and M. Nimalendran, 2013, The 2007–2009 financial crisis and bank opaqueness, *Journal of Financial Intermediation* 22(1), 55–84.

George, T. J., G. Kaul, and M. Nimalendran, 1991, Estimation of the bid-ask spread and its components: a new approach, *The Review of Financial Studies* 4(4), 623–656.

Glosten, L. R., and L. E. Harris, 1988, Estimating the components of the bid/ask spread, *Journal of Financial Economics* 21(1), 123–142.

Green, T. C., and B.-H. Hwang, 2009, Price-based return comovement, *Journal of Financial Economics* 93(1), 37–50.

Huang, R. D., and H. R. Stoll, 1994, Market microstructure and stock return predictions, *The Review of Financial Studies* 7(1), 179–213.

Iliev, P. 2010, The effect of SOX Section 404: Costs, earnings quality, and stock prices, *The Journal of Finance* 65, 1163–1196.

Jin, L., and S. Myers, 2006, R2 around the world: new theory and new tests, *Journal of Financial Economics* 79, 257–292.

Jones, J. S., W. Y. Lee, and T. J. Yeager, 2012, Opaque banks, price discovery, and financial instability, *Journal of Financial Intermediation* 21(3), 383–408.

Krinsky, I., and J. Lee, 1996, Earnings announcements and the components of the bid-ask spread, *The Journal of Finance* 51(4), 1523–1535.

Kumar, A., and C. M. C. Lee, 2006, Retail investor sentiment and return comovements, *The Journal of Finance* 61(5), 2451–2486.

Kwan, S., and W. Carleton, 2010, Financial contracting and the choice between private placement and publicly offered bonds, *Journal of Money, Credit and Banking* 42(5), 907–929.

Kyle, A. S., 1985, Continuous auctions and insider trading, *Econometrica* 53(6), 1315–1336.

Lin, J.-C., G. C. Sanger, and G. G. Booth, 1995, Trade size and components of the bid-ask spread, *The Review of Financial Studies* 8(4), 1153–1183.

Morgan, D. P., 2002, Rating banks: risk and uncertainty in an opaque industry, *American Economic Review* 92(4), 874–888.

Pindyck, R. S., and J. J. Rotemberg, 1993, The comovement of stock prices, *The Quarterly Journal of Economics* 108(4), 1073–1104.

Pirinsky, C., and Q. Wang, 2004, Institutional investors and the comovement of equity prices, available at SSRN: https://ssrn.com/abstract = 585884

Pirinsky, C., and Q. Wang, 2006, Does corporate headquarters location matter for stock returns?, *The Journal of Finance* 61(4), 1991–2015.

Roll, R., and A. Subrahmanyam, 2010, Liquidity skewness, *Journal of Banking and Finance* 34(10), 2562–2571.

Shiller, R. J., 1989, Comovements in stock prices and comovements in dividends, *The Journal of Finance* 44(3), 719–730.

Stoll, H. R., 1989, Inferring the components of the bid-ask spread: theory and empirical tests, *Journal of Financial Economics* 44(1), 115–134.