Journal of Financial Economics 146 (2022) 256–276

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Executive stock options and systemic risk

Christopher Armstrong*, Allison Nicoletti, Frank S. Zhou

The Wharton School, University of Pennsylvania, 3620 Locust Walk, Philadelphia, PA, 19104, United States

A R T I C L E I N F O

Article history:
Available online 22 September 2021

JEL classification:
E32
G21
G32
J33

Keywords:
Executive compensation
Equity incentives
Systemic risk
Business cycles

A B S T R A C T

Employing a novel control function regression method that accounts for the endogenous matching of banks and executives, we find that equity portfolio vega, the sensitivity of executives' equity portfolio value to their firms' stock return volatility, leads to systemic risk that manifests during subsequent economic contractions but not expansions. We further find that vega encourages systemically risky policies, including maintaining lower common equity Tier 1 capital ratios, relying on more run-prone debt financing, and making more procyclical investments. Collectively, our evidence suggests that executives' incentive-compensation contracts promote systemic risk-taking through banks' lending, investing, and financing practices.

1. Introduction

Banks engage in a variety of risky activities that can contribute to systemic risk, or the risk that many financial institutions fail together (De Bandt and Hartmann, 2000; Freixas and Rochet, 2008, p.235). Prior research into the sources of systemic risk largely focuses on the realized outcomes of banks' risky activities (e.g., the composition of banks' capital structure and the correlation of banks' asset returns). However, these activities are ultimately the result of *bank managers' decisions*, which are shaped by their contractual incentives. We pursue this intuition by studying whether and how bank executives' compensation contracts contribute to, and are a *cause* of, their banks' overall systemic risk.

Theoretical studies suggest several ways in which bank executives' incentive-compensation contracts can lead to systemic risk.[1] First, since convex contractual payoffs encourage risk-taking in general (Lambert et al., 1991; Ross, 2004) and bank capital structure is highly levered, executives' equity holdings can encourage them to pursue activities that entail systemic risk. Second, compensation contracts that encourage risk-taking can serve as credible commitment mechanisms that allow bank managers to infer each other's risky investment and lending decisions and incorporate this information into their own decisions (e.g., Fershtman and Judd, 1987; Aggarwal and Samwick, 1999). By facilitating this inference process, compensation contracts can strengthen strategic complementarities of risk-taking among banks; that is, an increase in one bank's risk increases the likelihood that *other banks* take similar risks, thereby increasing systemic risk (e.g., Acharya and Yorulmazer, 2008; Acharya, 2009; Farhi and Tirole, 2012; Albuquerque et al., 2019).

Based on these theories, we examine whether bank executives' compensation contracts influence their banks' systemic risk by focusing on the executives' equity portfolio (i.e., stock and option) holdings. These holdings account

* Corresponding author.
E-mail address: carms@wharton.upenn.edu (C. Armstrong).

[1] We are agnostic about whether bank managers' actions and decisions are specifically chosen to increase systemic risk or, alternatively, whether greater systemic risk is a byproduct of certain activities (e.g., non-agency mortgage-backed securities). Although this is an inherently important distinction, providing evidence that speaks to which of these two occurs is beyond the scope of our paper.

https://doi.org/10.1016/j.jfineco.2021.09.010

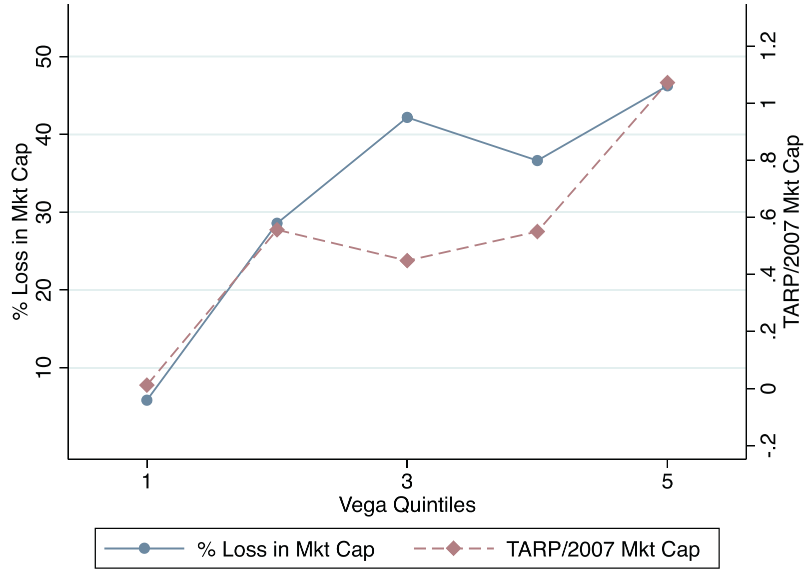


Fig. 1. Vega, TARP, and loss in market value during the 2007–2009 financial crisis. This figure presents the relations between vega and two measures of *realized* systemic risk surrounding the 2007–2009 financial crisis: (i) the amount of TARP funds received scaled by the market value of equity in 2007 (represented by the vertical axis on the right and the dashed line with diamonds), and (ii) the loss in equity market capitalization from June 2007 to December 2008, multiplied by 100 (represented by the vertical axis on the left, the solid line with circles). The horizontal axis represents the quintiles of the average pre-crisis vega (i.e., in 2005 and 2006).

for the majority of executives' monetary wealth and incentives at both financial and non-financial institutions (Core and Guay, 1999; Core et al., 2003; DeYoung et al., 2013). In particular, we focus on vega, which captures the sensitivity of executives' equity portfolio value to their firms' stock return volatility, because it provides an unambiguous incentive to increase risk in general (Lambert et al., 1991; Ross, 2004).

To motivate our focus on vega and systemic risk, Fig. 1 plots the relation between quintiles of pre-crisis vega (i.e., the 2005–2006 average) and two measures of realized systemic risk during the 2007–2009 financial crisis: the loss in equity market capitalization from June 2007 to December 2008 and the amount of TARP funds received scaled by pre-crisis market capitalization. The figure shows a striking positive relation between vega and these two measures.

Although Fig. 1 supports the existence of a relation between vega and systemic risk, identifying the causal effect of vega on systemic risk is challenging because of its potential endogenous relation with characteristics of both executives and banks that directly influence banks' risky activities but are difficult to control for. We address this identification challenge using a novel empirical technique developed by Klein and Vella (2010), which we call the "modified control function regression." A unique feature of the approach is that, unlike instrumental variables (IV) estimation, it does not require the existence of an instrument that is exogenous to both bank and executive characteristics. This feature makes the technique particularly amenable to our research setting, where such an instrument is arguably difficult to find.

A brief illustration of the intuition behind this approach is as follows.[2] In an OLS regression of systemic risk on prior year vega, the coefficient on vega is $\beta = \beta_0 + \rho\sigma_u/\sigma_x$, where β_0 is the *true* causal effect; ρ and σ_u/σ_x are, respectively, the correlation and the ratio of standard deviations between the structural error and vega; and $\rho \neq 0$ indicates an endogenous relation between vega and systemic risk. Suppose that a researcher estimates separate regressions using two different samples of banks (e.g., with operations in different markets). Further suppose that the variance of the residuals (i.e., σ_u/σ_x) is significantly different across the two regressions. To the extent that the endogeneity concern is serious (i.e., $|\rho|$ is large), the two β estimates should differ, since the variance of the residuals differs. Thus, if the β estimates do *not* differ, despite the differential variance of the residuals, this suggests that the endogeneity problem is not severe (i.e., $|\rho|$ is small). Based on this intuition, Klein and Vella (2010) show that heteroskedasticity in the residuals can be used to correct for any endogenous relation to provide an unbiased estimate of the average treatment effect.

We examine the relation between bank managers' equity incentives and their banks' *subsequent* systemic risk with two complementary sets of tests. The first set of tests uses two common, market-based measures of systemic risk: (i) marginal expected shortfall, *MES* (Acharya et al., 2017); and (ii) $\Delta CoVaR$ (Adrian and Brunnermeier, 2016). Using a sample of commercial banks during the time period 1995–2016, we first show a positive relation between the equity portfolio vega of banks' senior (i.e., five most highly paid) executives and their banks' one-, two-, and

[2] We defer technical details to Section 3.1.2.

three-year-ahead *MES* and $\Delta CoVaR$ using OLS regressions. However, we find no evidence of a relation between vega and either *MES* or $\Delta CoVaR$ using modified control function regressions. These contrasting findings suggest that the positive relation between vega and systemic risk based on OLS estimates results, at least in part, from an endogenous relation between the two. Accordingly, we rely on the modified control function approach for most of our subsequent analyses and inferences.

We next investigate whether there is a *differential* relation between vega and systemic risk during economic contractions relative to expansions. Acharya and Naqvi (2012) show that risk-taking during expansions can take the form of "excessive" lending (e.g., lending to more marginal borrowers when credit is loose), sowing the seeds of a crisis. Their model suggests that the effects of risk-taking incentives on systemic risk may only manifest during economic contractions. Consistent with this prediction, we find no evidence of a relation between vega and *subsequent MES* and $\Delta CoVaR$ during expansions but do find evidence of a significant positive relation during contractions.

Our second set of tests examines specific activities that potentially contribute to banks' exposure to and accretion of systemic risk. On the asset side of the balance sheet, we find that prior year vega encourages bank managers to extend a greater proportion of commercial and industrial (C&I) loans in their loan portfolio, to hold a greater proportion of non-agency mortgage-backed securities (MBSNA) in their available-for-sale investment portfolio, and to extend more lines of credit out of their total lending activities (but at lower rates). These lending and investment activities are highly procyclical and can generate significant losses during contractionary periods, which can lead to systemic risk (Strahan, 1999; Longstaff, 2010; Caouette et al., 2011; DeYoung et al., 2013; Bhat et al., 2019).[3] On the liability and equity side of the balance sheet, we find that vega leads to a greater reliance on short-term deposits and lower common equity Tier 1 (CET1) ratios. Banks with more short-term debt and less equity capital are more susceptible to liquidity shocks and prone to runs during economic downturns (e.g., Diamond and Rajan, 2011; Allen et al., 2012), both of which can contribute to systemic risk.

Next, we examine whether these specific lending and investing activities contribute to the risk that is subsequently *realized* during economic contractions. We find a positive relation between vega and banks' *subsequent* likelihood of suffering large losses on their C&I lending, loan portfolios, and MBSNA investments during subsequent economic contractions. These findings are consistent with vega encouraging managers to make lending and investment decisions that entail greater systemic risk that is realized during economic contractions.

Finally, we perform two sets of descriptive analyses to better understand how the relations between vega and bank activities vary with factors surrounding the 2007–2009 financial crisis. First, we examine the role of risk management, which came under significant scrutiny due to the substantial losses realized by many institutions (Stulz, 2008; Ellul and Yerramilli, 2013). We find that, prior to the financial crisis, prior year vega has a larger (smaller) effect on MBSNA (C&I lending) at banks that have stronger risk management practices, measured using the risk management index (RMI) developed by Ellul and Yerramilli (2013). In additional analyses, we find evidence consistent with "risk targeting," or shifting towards riskier assets that have regulatory capital requirements similar to those of safer alternatives (Keppo and Korte, 2018), as a potential explanation for this finding.[4] We caution that these findings are inherently descriptive in light of the potentially endogenous nature of banks' risk management practices.

Second, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 ("Dodd-Frank Act") was a direct result of the financial crisis and may have implications for how bank executives' vega influences their risk-taking decisions. For example, the Dodd-Frank Act mandated new restrictions on executive compensation and more stringent regulatory capital requirements for mortgage-related assets (U.S. Government Accountability Office, 2016). We provide descriptive evidence about whether the relation between bank executives' (prior year) vega and multiple bank activities that are thought to, or have been shown to, entail systemic risk changed following Dodd-Frank. On the asset side, we show that the effect of vega on C&I (MBSNA and lines of credit) is stronger (weaker) in the post-Dodd-Frank period. These findings are consistent with a greater attractiveness of C&I lending relative to MBSNAs and lines of credit. On the liability and equity side, we find that the relation between vega and the capital ratio or short-term deposits is stronger in the post-Dodd-Frank period. Although descriptive, these findings should inform regulators about the activities motivated by vega in the post-crisis period.

Our paper contributes to several related lines of inquiry. First, we contribute to the literature on systemic risk. Although prior research identifies certain bank characteristics that are associated with systemic risk, the contractual incentives of executives whose decisions are ultimately responsible for those characteristics have received considerably less attention as a potential cause of systemic risk.[5] We provide causal evidence that bank managers' equity portfolio vega increases systemic risk and encourages activities that likely contribute to the buildup of systemic risk.

[3] We find no evidence that vega contributes to systemic risk *through* non-interest income activities. We discuss possible explanations in Section 5.2.

[4] Specifically, before the crisis, MBSNA and C&I lending had overlapping capital requirements. However, MBSNA investments were, on average, riskier than C&I lending, given that they experienced relatively higher returns prior to the crisis and that there was an increase in the risk weights of several mortgage-related assets after the crisis. Therefore, bank managers with stronger risk-taking incentives (e.g., those with higher equity portfolio vega), and particularly those at banks with more stringent regulatory capital oversight from strong risk management practices, had stronger incentives to shift from C&I lending to MBSNA in order to increase their banks' risk without having to hold additional capital. Section 5.3.1 provides further evidence in support of the risk targeting explanation.

[5] For example, prior research examines characteristics such as bank size, reliance on non-interest income, interbank exposures, geographic diversification, and lending concentrations (e.g., Beck and De Jonghe, 2013; Drehmann and Tarashev, 2013; Laeven et al., 2016; Brunnermeier et al., 2020; Chu et al., 2020).

Second, we adopt a novel identification technique that allows us to isolate and identify the extent to which bank executives' contractual incentives *cause* systemic risk, as opposed to simply reflecting the endogenous matching of banks and their executives. This distinction is important because regulations that target banks' compensation practices assume that managers' compensation contracts have a *causal* effect on their banks' risk, and their efficacy depends on the existence of such a link.

Finally, our findings have implications for bank regulators. Executives' compensation contracts have attracted significant attention and scrutiny from regulators, legislators, investors, governance activists, and a variety of other stakeholders. Section 956 of the Dodd-Frank Act, which is arguably one of the centerpieces of the Act, instructs bank regulators to draft regulations restricting certain executive compensation practices that are thought to encourage excessive risk-taking. Our evidence that bank executives' contractual incentives encourage systemically risky activities suggests that regulations at the microprudential level (e.g., those promulgated under Section 956 of the Dodd-Frank Act) may be one way to influence macroprudential (e.g., systemic) risk. Thus, although directly controlling systemic risk per se is not typically the stated goal of microprudential regulation (Allen and Gu, 2018), our evidence suggests that it can be an indirect effect of regulations aimed at bank executives' compensation contracts.

2. Theoretical framework

2.1. Overview of contractual risk-taking incentives

Risk-averse and undiversified managers whose financial wealth and human capital are tied to the value of their firms might forego positive net present value (NPV) projects that entail "too much" risk from their perspective. A large literature argues that because the expected payoff of stock options is increasing in the volatility of the firm's stock return, compensating managers with stock options will encourage them to pursue risky projects that they might otherwise reject (Haugen and Senbet, 1981; Smith Jr. and Watts, 1982; Smith and Stulz, 1985). However, another set of studies (e.g., Lambert et al., 1991; Carpenter, 2000; Ross, 2004; Lewellen, 2006; Armstrong and Vashishtha, 2012) argues that executives who are prevented from selling or otherwise hedging the risk associated with their options and, more generally, their equity holdings will not necessarily value them at their risk-neutral (e.g., Black-Scholes) market value, but rather at a subjective value that can entail a substantial discount.

This differential (or "wedge") between an option's risk-neutral value and its subjective value to a risk-averse, undiversified executive occurs because options increase not only the sensitivity of the executive's wealth to firm risk, or vega, but also the sensitivity of her wealth to changes in stock price, or delta. Although vega provides an unambiguous incentive to increase risk, the incentives provided by delta are theoretically ambiguous. On one hand, because a manager's expected payoff is increasing in stock price, delta will encourage managers to pursue positive NPV projects. On the other hand, delta magnifies an executive's aversion to the firm's risk because changes in stock price result in larger changes in the value of the executive's equity holdings (Ross, 2004). Consequently, the net effect of these two countervailing forces is theoretically ambiguous and is an empirical question. We therefore focus on vega, given its unambiguous relation with risk-taking incentives. We also consider delta in our analyses, but remain agnostic about the direction of its relation, if any, with risk. We note that the risk-taking incentives provided by vega and delta can be amplified in our research setting, since the highly levered nature of banks' capital structure imparts additional convexity in bank executives' equity-based payoffs.

Prior studies examining bank managers' contractual incentives primarily focus on managers' decisions that relate to systematic or idiosyncratic risk (Houston and James, 1995; Chen et al., 2006; Fahlenbrach and Stulz, 2011; DeYoung et al., 2013; Bai and Elyasiani, 2013; Larcker et al., 2017; Boyallian and Ruiz-Verdú, 2018). These studies provide mixed evidence and do not explicitly test how contractual incentives contribute to greater systemic risk through specific banking activities.

2.2. Bank risk-taking incentives and systemic risk

Theoretical models suggest that risky activities at banks can result in systemic risk through two nonexclusive channels: (i) strategic complementarities in banks' risky activities, and (ii) the contagious nature of financial distress and failure in the banking industry.

Theories that examine the first channel (i.e., strategic complementarities) posit that one bank's risky activities can encourage other banks to take similar (i.e., correlated) activities, thereby giving rise to two types of strategic complementarities in risk-taking. First, as Acharya (2009) shows, banks' incentives to avoid negative externalities that result from other banks' failures encourage bank managers to make correlated investments. Doing so increases the likelihood of collective survival and reduces the likelihood that a single bank fails while the others survive and hence the negative externality. However, correlated investments also increase the likelihood of collective failure, which banks' shareholders, including their managers, do not fully internalize (given the limited liability of their claims), which leads to greater systemic risk. Second is the anticipation of regulatory bailouts. Farhi and Tirole (2012) show that when banks increase their exposure to liquidity risk (e.g., by increasing their reliance on short-term debt as a source of financing), other banks are encouraged to follow suit, anticipating a regulatory bailout of all banks that fail in the event of a financial crisis. The expectation of a bailout reduces the ex ante cost of risk-taking, thereby encouraging all bank executives to take more risk.[6]

Theories related to the second channel (i.e., the contagious nature of distress and failure) highlight several fea-

[6] Acharya et al. (2016) develop a similar model that also shows how the anticipation of regulatory interventions can result in systemic risk-shifting across banks. However, their model does not focus on strategic complementarities in banks' risky activities.

tures of banks that make their distress and failure especially contagious. First, connections in the banking network (e.g., inter-bank lending) can propagate adverse shocks across the entire banking system (Allen and Gale, 2000). Second, banks' exposure to liquidity risk leads to a greater likelihood of fire sales of their assets during periods of distress (Diamond and Rajan, 2011). This concern is particularly acute for banks because many of their assets are complex financial instruments (e.g., mortgage-backed securities) that require expertise to value and have only a limited set of potential buyers. Third, contagion can arise from maturity mismatch. Allen et al. (2012) show that when banks' assets overlap through common portfolio holdings and the assets are financed with short-term debt, adverse shocks can result in joint bank failure, as investors infer a high joint default probability from the shock and decide to withdraw financing by not rolling over banks' debt. Alternatively, when banks' asset returns are correlated, a high bank failure rate can lead depositors to infer that surviving banks also have a higher probability of default, leading to systemic bank runs (Chen, 1999). These mechanisms illustrate the general idea that systemic bank failures can arise from coordination failures of depositors and liquidity providers (e.g., Diamond and Dybvig, 1983).

We expect that bank executives' equity portfolio vega provides them with incentives to pursue activities that entail systemic risk for two primary reasons. First, because vega provides incentives to take any type of risk in general, it could encourage activities characterized by systemic risk. In particular, it may especially encourage activities that exhibit strategic complementarities and are contagious; these activities tend to entail more risk, but also provide a greater expected return (e.g., DeYoung et al., 2013; Longstaff, 2010; Strahan, 1999). Second, we argue that managers' compensation contracts can reinforce strategic complementarities in their activities.[7] Although theoretical studies differ in the specific mechanism that gives rise to strategic complementarities in banks' risky activities, they are all premised on the notion that bank executives can draw reasonable inferences about the actions that other executives will take. In our setting, by serving as a credible and visible commitment mechanism, managers' compensation contracts allow them to infer and more accurately anticipate the risky activities that managers of other banks are encouraged to take and incorporate these expectations in their own risk-taking decisions. This can reinforce strategic complementarities in bank activities.[8]

[7] We hasten to note that there are several potential sources of strategic complementarities that we do not attempt to distinguish; nor are our tests designed to distinguish them. These sources include individual banks engaging in activities that encourage other banks to follow suit, individual banks following (or mimicking) other banks' risky activities, and banks collectively coordinating on public signals (e.g., compensation contracts) and taking similar risk.

[8] This idea follows from prior research that shows how executives' incentive-compensation contracts can serve as a commitment mechanism that facilitates coordination of their decisions in strategic settings (e.g., Fershtman and Judd, 1987; Aggarwal and Samwick, 1999; Bloomfield, 2021). For example, Fershtman and Judd (1987) show that when managers' actions (e.g., investment, production, pricing, and risk-taking) depend on other managers' expected actions, any particular manager's compensation contract not only encourages that manager to take specific actions, but also allows other managers to form expectations about these actions. The idea that features of incentive-compensation contracts can facilitate coordination in managers' behavior is also consistent with Albuquerque et al. (2019), who show that relative performance evaluation (RPE) encourages managers to make similar investments because it purges out common factors. In contrast to RPE, which has been found to be rarely used in practice (Murphy, 1999), we focus on bank managers' equity portfolio incentives (i.e., vega and delta), which arguably account for the majority of their contractual risk-taking incentives and should therefore have the strongest link with systemic risk.

3. Research design and variable measurements

3.1. Research design

3.1.1. Model specification

To examine whether vega encourages bank executives to pursue activities that contribute to (the buildup of) systemic risk, we estimate the following specification:

$$Risk_{i,t+s} = \delta_{t+s} + \beta_1 \log(vega)_{i,t-1} + \beta_2 \log(delta)_{i,t-1} + \eta_{i,t+s}. \quad (1)$$

$Risk_{i,t+s}$ represents one of several measures of either systemic risk or specific activities for bank i in year $t+s$, where s = 0, 1, or 2, as described in Section 3.2. We examine one-, two-, and three-year-ahead measures of systemic risk to allow for the possibility of a lag between when executives make risky decisions and when the resulting risk manifests in the ex post measures.[9] We measure the various bank activities one year ahead of vega, as we expect contractual incentives to have a more immediately detectable effect on the specific bank activities they are designed to encourage. The primary independent variable of interest is equity portfolio vega, measured as the natural logarithm of the change in the risk-neutral (i.e., Black-Scholes) value of the five highest-paid executives' equity portfolios (i.e., stocks and options) for a 0.01 change in the standard deviation of the underlying stock returns ($\log(vega)$).

The model controls for equity portfolio delta, $\log(delta)$, the natural logarithm of the change in the risk-neutral value of the five highest-paid executives' equity portfolios for a 1% change in the underlying stock price.[10] We also include year fixed effects to control for secular changes in

[9] Prior research primarily examines one-year-ahead risk-taking measures. Although this is sensible for typical measures of risk in non-financial firms (e.g., stock return volatility, R&D expenditures, leverage), it may not be appropriate for systemic risk, which is a "lower-frequency" variable, and negative realizations might only be empirically detectable over a sufficiently wide window. This is analogous to the "peso problem" in the asset pricing literature (e.g., Krasker, 1980).

[10] Following prior studies (e.g., Armstrong and Vashishtha, 2012; DeYoung et al., 2013), the parameters of the Black-Scholes formula are calculated as follows. Annualized volatility is calculated using continuously compounded monthly returns over the previous 60 months, with a minimum of 12 months of returns, and winsorized at the 5th and 95th percentiles. If the stock has traded for less than one year, we use the imputed average volatility of the firms in the Standard and Poor's (S&P) 1500. The risk-free rate is calculated using the interpolated interest rate on a Treasury note with the same maturity (to the closest month) as the remaining life of the option, multiplied by 0.70 to account for the prevalence of early exercise. Dividend yield is calculated as the dividends paid during the previous 12 months scaled by the stock price at the beginning of the month. This is essentially the same as the method outlined by Core and Guay (2002).

risk that are common to all banks (e.g., economic conditions across the business cycle). We do not include a more exhaustive set of controls because our use of modified control function regressions (as described in Section 3.1.2) to account for the potentially endogenous relation makes it unnecessary and arguably redundant to do so. Another reason for including fewer controls is that it reduces concerns about inadvertently including (i.e., controlling for) an outcome of managers' risk-taking decisions (i.e., conditioning on a post-treatment outcome). Including these controls introduces bad control problems and leads to biased estimates of the true causal effect (Angrist and Pischke, 2009). For example, using the natural logarithm of a bank's total assets to measure size would likely introduce a mechanical relation with many of the variables that are also based on banks' balance sheets, such as loans and investments, which inherently relate to risk-taking. As the control function regression adequately accounts for the endogenous matching, as shown in Section 5.1.1, we do not control for potential outcomes of risk-taking.

One potential concern with model (1) is that unobserved bank and executive characteristics that influence the bank-executive match can affect both bank executives' compensation contracts and their bank's risk. This form of endogenous selection is particularly problematic because of its two-sided nature: a valid instrument for vega has to be (conditionally) exogenous with respect to *both* unobserved bank *and* executive characteristics. Therefore, an exogenous shock to bank executives' risk-taking incentives, which would otherwise be a valid instrument, might not be in our setting if executives endogenously select into (i.e., match with) banks that are either less exposed to the shock or take actions in response to it (e.g., risk averse executives leaving riskier banks). Moreover, as shown by Cheng et al. (2015), both the executive-bank match and bank risk tend to be persistent. Consequently, identification strategies that rely on time-series (i.e., within-firm and within-executive) variation are unlikely to produce powerful tests in the presence of persistent endogenous matching. We rely on the novel identification strategy developed by Klein and Vella (2010) to address concerns related to two-sided endogeneity.

3.1.2. Modified control function regression

Our identification strategy is based on the modified control function regression method developed by Klein and Vella (2010). Control function regressions explicitly "control for" the unobserved correlated omitted variable that is responsible for the endogenous relation. Klein and Vella (2010) propose a modified control function estimator, which constructs this "control variable" using information about the unobserved variables (which are captured by the residuals) that takes the form of heteroskedasticity. We refer to their specific application of the control function method as a "modified control function regression." As illustrated below, this method conceptually differs from several well-known approaches that address endogeneity concerns. First, it does not rely on the conditional independence assumption (i.e., selection on observables) invoked by OLS and traditional control function regressions (i.e., the endogenous variable is uncorrelated with the error term conditional on the observable control variables) (Heckman, 1976; Heckman and Navarro-Lozano, 2004). Second, it does not depend on a valid exclusion restriction, which is required for instrumental variables (IV) estimation. Finally, the method does not rely on normality of the error terms, which is required for identifying a Heckman two-stage model without instruments. Below, we discuss the method and the assumptions required for identification.

The modified control function regression starts with a typical two-stage regression specification:

$$\log(vega)_{i,t-1} = \alpha' X_{i,t-1} + \xi_{i,t-1} \tag{2}$$

$$Risk_{i,t+s} = \beta_1 \log(vega)_{i,t-1} + \Gamma' X_{i,t-1} + \eta_{i,t+s} \tag{3}$$

where β_1 is an estimate of the causal effect of $\log(vega)$ on bank risk, $X_{i,t-1}$ represents the same vector of observable characteristics as in (1), including intercepts, and $\xi_{i,t-1}$ and $\eta_{i,t+s}$ are unobserved factors that affect $\log(vega)_{i,t-1}$ and $Risk_{i,t+s}$, respectively.[11]

If $\eta_{i,t+s}$ is correlated with $\xi_{i,t-1}$, the coefficient estimate from an OLS regression of *Risk* on $\log(vega)$ will be biased. Denoting the correlation coefficient between $\eta_{i,t+s}$ and $\xi_{i,t-1}$ as ρ, the modified control function regression approach decomposes the error term $\eta_{i,t+s}$ as follows:

$$\eta_{i,t+s} = \rho \frac{\sigma_\eta}{\sigma_\xi} \xi_{i,t-1} + \omega_{i,t+s} \tag{4}$$

where $\rho = cov(\eta_{i,t+s}, \xi_{i,t-1})/var(\xi_{i,t-1})$. The decomposition is achieved by projecting (i.e., regressing) $\eta_{i,t+s}$ on $\xi_{i,t-1}$ and, importantly, does *not* assume that $\eta_{i,t+s}$ and $\xi_{i,t-1}$ follow a joint normal distribution. By construction, $\omega_{i,t+s}$ is uncorrelated with $\log(vega)_{i,t-1}$ conditional on $X_{i,t-1}$. Substituting (4) into (3) illustrates how the identification strategy works:

$$Risk_{i,t+s} = \beta_1 \log(vega)_{i,t-1} + \Gamma' X_{i,t-1} + \eta_{i,t+s} \tag{5}$$

$$= \beta_1 \log(vega)_{i,t-1} + \Gamma' X_{i,t-1} + \rho \frac{\sigma_\eta}{\sigma_\xi} \left(\log(vega)_{i,t-1} - \alpha' X_{i,t-1} \right) + \omega_{it+s}. \tag{6}$$

In Eq. (6), the new error term, $\omega_{i,t+s}$, is uncorrelated with $\log(vega)_{i,t-1}$ conditional on $X_{i,t-1}$ by construction. When the standard deviation ratio, σ_η/σ_ξ, is a constant, β_1 is not identified because the term $\log(vega)_{i,t-1} - \alpha X_{i,t-1}$ is collinear with the regressors $\log(vega)_{i,t-1}$ and $X_{i,t-1}$. However, when $\sigma_{\eta,i,t+s}/\sigma_{\xi,i,t-1}$ varies across observations (i.e., i, t, or both) and its interaction with $(\log(vega)_{i,t-1} - \alpha X_{i,t-1})$ is not collinear with $\log(vega)_{i,t-1}$, variation in $(\log(vega)_{i,t-1} - \alpha X_{i,t-1})\sigma_{\eta,i,t+s}/\sigma_{\xi,i,t-1}$ can identify both ρ and β_1. This implies that researchers can simply run a regression in the form of (6) and identify the causal effect.

The example below illustrates the intuition behind modified control function regressions.[12] Consider two

[11] We do not require that the coefficient estimates on $X_{i,t-1}$ (i.e., Γ) have causal interpretations. The error terms in Eqs. (2) and (3) can be interpreted as the true structural error terms that are orthogonalized with respect to X. Thus, by construction, $E(\epsilon_{i,t-1}|X) = 0$ and $E(\eta_{i,t+s}|X) = 0$. In other words, we only focus on one endogenous variable, namely $\log(vega)$, and avoid the complexity of modeling a system of endogenous relations.

[12] The idea resembles Sørensen (2007), who relies on differences across matching markets to identify the causal effect of venture capitalist experience on the likelihood of investment success.

banking markets, denoted A and B, that each consist of multiple banks. For illustrative purposes, we assume homoskedasticity of $\eta_{i,t+s}$ (i.e., the variance of $\eta_{i,t+s}$ is the same for banks in both markets) and focus on how the differences in the variances of $\xi_{i,t-1}$ *across* the two markets can be used to identify the causal effect β_1. Suppose that the variance of ξ_{it-1} in market A differs from that in market B (i.e., $\sigma_{\xi,A} \neq \sigma_{\xi,B}$). This could occur for a variety of reasons, such as differences in how executives and banks match or how banks operate. Estimating two separate OLS regressions using observations in market A and market B provides two separate coefficient estimates for $\log(vega)$, labeled $\hat{\beta}^A = \beta_1 + \rho\sigma_\eta/\sigma_{\xi,A}$ and $\hat{\beta}^B = \beta_1 + \rho\sigma_\eta/\sigma_{\xi,B}$, respectively. Any difference between the two coefficient estimates provides information about the severity of the endogeneity problem because the difference, which can be shown to be $\rho\sigma_\eta\left(1/\sigma_{\xi,A} - 1/\sigma_{\xi,B}\right)$, varies with ρ. For example, if the two coefficients are similar, despite $\sigma_{\xi,A} \neq \sigma_{\xi,B}$, then ρ is likely to be small. Alternatively, if the two coefficients differ substantially, it is symptomatic of a larger endogeneity concern. Moreover, as this simple example shows, as long as $\sigma_{\xi,A} \neq \sigma_{\xi,B}$, it is possible to solve for both β_1 and ρ as a function of the variances since there are two equations and two unknowns, ρ and β_1.

We emphasize again that the modified control function method does not assume conditional independence. In the illustration above, we explicitly allow for selection on unobservables (i.e., the error terms being correlated with the endogenous regressor conditioning on X). The method achieves identification by assuming and estimating a single correlation coefficient between the structural error terms in the two equations. Although the research designs of most prior studies that use either OLS or IV estimation also rely on these assumptions, often implicitly, a single common correlation coefficient is not innocuous and imposes structure on the nature of the endogenous relation between the treatment and the outcome of interest. If there is reason to suspect that ρ varies systematically with certain variables, it becomes necessary to specify a priori how ρ varies. The intuition is similar to that for identifying heterogeneous treatment effects in that the researcher needs to specify how β_1 varies across either individuals or groups. However, without detailed knowledge (e.g., informed by theory) about the unobserved factors that are responsible for the endogenous relation, it is difficult to develop accurate assumptions about how ρ varies in the cross-section. In other words, the modified control function approach is useful precisely when the researcher lacks detailed, a priori knowledge about the unobserved factors. For the same reason, we do not draw economic inferences regarding the sign of ρ (i.e., the specific economic forces driving a positive or negative ρ).

3.1.3. Implementation

As illustrated in the previous section, identifying the causal effect using the modified control function regression relies on variation in the standard deviation ratio, σ_η/σ_ξ. To avoid imposing assumptions on the determinants of the standard deviation ratio and to maintain a parsimonious structure, we assume that the standard deviation ratio varies across "markets" as follows:

$$\left\{\frac{\sigma_{\eta,m}}{\sigma_{\xi,m}} \mid m \in \{1, \ldots, M\}\right\},$$

where m denotes a market.[13] Equipped with the standard deviation ratios of each market, we then run a regression in the form of (6). The standard errors need to be adjusted to reflect that the first-stage errors are estimated. To do so, we jointly estimate the first- and second-stage regressions to ensure consistent standard errors.

The definition of "markets" should be justified on a priori theoretical grounds. Although we are agnostic about the specific factors that affect the standard deviation ratio, we argue that differences in local labor market supply and demand, regional economic conditions, and regulatory incentives are all likely to result in variation in the standard deviation ratio. Since most of these factors stem from differences in geographic and regulatory exposure, we assign banks to four geographic regions that align with the Office of the Comptroller of the Currency (OCC) supervision structure. We then consider each region-year combination to be a distinct market. For purposes of our analysis, this simply means that σ_η/σ_ξ varies both across geographic markets and over time. It is also important to note that the modified control function regression does not require the determinants of the standard deviation ratio to be exogenous. Instead, this approach only requires the standard deviation ratio to *differ* in the cross-section, regardless of whether this occurs for reasons that are endogenous or exogenous with respect to the model.

Estimating the variances of ξ and η in each market presents a practical issue. A broader definition of markets (e.g., region level rather than region-year level) increases the number of observations in a market, allowing for more precise variance estimates. However, it leaves fewer markets to identify ρ, which can lead to large standard errors for ρ and low-powered statistical tests. Accordingly, in Section 5.1.1 we assess the extent to which our inferences may be susceptible to a lack of power in our tests. We estimate bootstrapped standard errors to address the concern that statistical significance may be an artifact of influential observations. We also use an iterative approach to overcome the inherent circularity that arises because the coefficient estimates from the second-stage model depend on estimates of the residual η, which, in turn, depends on the coefficient estimates. Specifically, for each iteration, we first obtain the estimated residuals based on the coefficient estimates from the previous iteration, and then update the coefficient estimates using the new residuals. We repeat this procedure until convergence is achieved.[14]

3.2. Dependent variable measurements

3.2.1. Systemic risk measures

Our first set of tests relies on two common measures of systemic risk: (i) marginal expected shortfall, and

[13] Klein and Vella (2010) use a more flexible semi-parametric approach that assumes that σ_η/σ_ξ depends on the vector of control variables.

[14] The estimation starts by assuming that ρ is zero, which corresponds to the limiting case of no endogenous relation.

(ii) $\Delta CoVaR$. Marginal expected shortfall (*MES*) captures a bank's expected equity loss when the market experiences losses in the extreme left-tail of the distribution (Acharya et al., 2017). *MES* is calculated as the bank's average return (in percentage points) during the S&P500's 5% worst days during year *t*, multiplied by negative one so that larger values of *MES* correspond to greater systemic risk.

$\Delta CoVaR$ captures the extent to which relatively extreme (or "tail") losses of a particular bank are associated with those of the banking system as a whole. As discussed by Adrian and Brunnermeier (2016), $\Delta CoVaR$ is based on the conditional value at risk (*CoVaR*) and involves the contribution of each bank *i* to tail risk of the financial system (*sys*) (i.e., examining tail risk of the financial system conditional on bank *i* being in a certain state). Specifically, we first estimate the following bank-level quantile regressions using bank *i*'s complete time series of weekly returns during the sample period, requiring at least 260 observations:

$$Ret_{i,t} = \alpha_i^q + \gamma_i^q M_{t-1} + \epsilon_{i,t}^q, \tag{7}$$

$$Ret_{sys,t} = \alpha_{sys|i}^q + \gamma_{sys|i}^q M_{t-1} + \beta_{sys|i}^q Ret_{i,t} + \epsilon_{sys|i,t}^q, \tag{8}$$

where the superscript *q* denotes the chosen quantile, $Ret_{i,t}$ represents bank *i*'s weekly return, $Ret_{sys,t}$ represents the value-weighted weekly return of the commercial banking sector (three-digit SIC codes 602 and 603), and M_t is a vector of macroeconomic variables (measured weekly unless otherwise specified) that includes (i) the change in the three-month Treasury bill rate, (ii) the change in the slope of the yield curve, measured as the difference between the composite long-term bond yield and the three-month Treasury bill rate, (iii) the short-term TED spread, measured as the difference between the three-month LIBOR rate and the three-month secondary market Treasury bill rate, (iv) the change in the aggregate credit spread, measured as the difference between Moody's *Baa*-rated bond yield and the 10-year Treasury rate, (v) the standard deviation of the value-weighted market return during the previous 22 trading days, (vi) the value-weighted market return, and (vii) the value-weighted return of the real estate sector (two-digit SIC codes 65 and 66).

Using the predicted values from Eqs. (7) and (8), we construct both *VaR* and *CoVaR* as follows:

$$VaR_{i,t}^q = \hat{\alpha}_i^q + \hat{\gamma}_i^q M_{t-1} \tag{9}$$

$$\begin{aligned} CoVaR_{i,t}^q &= \left(VaR_{sys,t}^q \middle| Ret_{i,t} = VaR_{i,t}^q \right) \\ &= \hat{\alpha}_{sys|i}^q + \hat{\gamma}_{sys|i}^q M_{t-1} + \hat{\beta}_{sys|i}^q VaR_{i,t}^q \end{aligned} \tag{10}$$

The final step is to calculate the difference between *CoVaR* when bank *i* is in a distressed state (the 1% worst weeks, $Ret_{i,t} = VaR_{i,t}^{q=1\%}$) and a typical state (median, $Ret_{i,t} = VaR_{i,t}^{q=50\%}$):

$$\Delta CoVaR_{i,t}^{1\%} = \hat{\beta}_{sys|i}^{1\%} (VaR_{i,t}^{1\%} - VaR_{i,t}^{50\%}) \tag{11}$$

Since $\Delta CoVaR_{i,t}^{1\%}$ is calculated at a weekly frequency, we sum the weekly values to construct an annual measure, which corresponds to the frequency of our tests, and multiply by negative one so that larger values correspond to greater systemic risk.[15]

3.2.2. Bank activity measures

Our second set of analyses complements our previous tests by examining specific activities that may contribute to the build-up of systemic risk during economic expansions. Studying specific activities allows us to more directly isolate managers' ex ante risk-taking decisions. It also allows us to develop alternative and arguably more precise measures to ensure that our inferences are not dependent solely on empirical measures based on realized negative outcomes (i.e., returns), which may occur too infrequently or with too long of a lag to detect any effect of vega. We develop several measures that capture banks' risk-taking activities on both the asset and liability/equity sides of the balance sheet.

First, we examine commercial and industrial (C&I) lending, defined as the proportion of a bank's loans that are commercial and industrial (*CommLoans*). Prior research shows that banks collectively increase their commercial and industrial (C&I) lending during economic expansions (Berger and Udell, 2004; Becker and Ivashina, 2014) and that the performance of these loans tends to be procyclical (Ryan, 2007; Caouette et al., 2011; Bhat et al., 2019). Moreover, C&I loans exhibit higher realized loss rates, on average, compared to other types of loans (e.g., mortgages) (DeYoung et al., 2013).

Second, we examine the contribution of line of credit issuance to total bank lending activity, which we define as the amount of unused lines of credit scaled by total credit (i.e., total loans plus unused lines of credit) (*LOC*). We use the all-in spread for revolving loans available in Dealscan to capture the price of lines of credit (*LOCRate*). Strahan (1999) discusses how extending lines of credit exposes banks to not only greater liquidity and credit risk but also complementarities between the two. Specifically, borrowers are more likely to draw down lines of credit when their alternative financing options are limited (e.g., in economic contractions), which is precisely when borrowers also have a greater likelihood of default. Consequently, extending lines of credit is a procyclical activity that potentially exposes banks to systemic risk through correlated losses.

Third, we examine the proportion of non-agency mortgage-backed securities in a bank's available-for-sale investment portfolio (*MBSNA*). The available-for-sale portfolio comprises the majority of investment in securities for the average bank. Non-agency mortgage-backed securities are not guaranteed by a government agency or government sponsored enterprise (i.e., Ginnie Mae, Fannie Mae, and Freddie Mac) and are thought to have contributed to the 2007–2009 financial crisis. For example,

[15] By construction, both *MES* and $\Delta CoVaR$ are not meant to distinguish among the underlying sources of systemic risk (e.g., interconnectedness of the financial sector due to spillover effects arising from fire sales or correlated investments such as similar lending exposures). However, regardless of the source(s) of systemic risk, understanding the cause(s) of banks' exposure to systemic risk is important for understanding the overall health and riskiness of the financial system as well as that of individual banks.

Longstaff (2010) shows that subprime mortgage-related securities contributed to contagion during the crisis by decreasing market liquidity and increasing risk premiums across markets.

Fourth, we examine the proportion of revenue generated from non-interest income activities (*NII*), which includes "income from trading and securitization, investment banking and advisory fees, brokerage commissions, venture capital, fiduciary services, and gains on nonhedging derivatives" (Brunnermeier et al., 2020). Prior studies argue that non-interest income activities increase overall volatility (Stiroh, 2006) and expose banks to systemic risk through greater interconnectedness risk and greater exposure to tail risk (Brunnermeier et al., 2020).

Finally, banks are also exposed to contagion on the liability and equity side of their balance sheets. Prior research shows that reliance on short-term debt increases exposure to liquidity shocks in poor economic conditions (e.g., Diamond and Rajan, 2011; Allen et al., 2012). In other words, an increase in the bank failure rate due to greater risk-taking can result in the propagation of bank failures throughout the system due to simultaneous depositor withdrawals. Time deposits are held for a specific amount of time and are generally longer-term than are other types of deposits (i.e., demand deposits). As such, more reliance on shorter-term deposits (i.e., non-time deposits) increases bank exposure to liquidity risk. We define $STdep$ as the proportion of non-time deposits out of total deposits. We also examine leverage (or lower capital ratios), measured as either $Capital$, the ratio of total equity to total assets, or $CET1$, a proxy for the Common Equity Tier 1 capital ratio, defined as the sum of common equity and retained earnings scaled by risk-weighted assets.[16]

4. Sample selection and descriptive statistics

4.1. Sample selection and data sources

Our sample comprises observations with required data at the intersection of Bank Compustat, Center for Research in Security Prices (CRSP), Execucomp, and FR Y-9C regulatory reports during the period 1995–2016. We use the Federal Reserve Bank of New York's PERMCO-RSSD dataset to link the CRSP identifier to the FR Y-9C identifier.

We use Execucomp data to calculate the contractual incentive measures, namely $\log(vega)$ and $\log(delta)$ (described in Section 3.1.1). To calculate *MES* and $\Delta CoVaR$, we obtain daily return data from CRSP and macroeconomic variables from the Federal Reserve Economic Data (FRED) database, the U.S. Treasury Department, and CRSP.[17] We use data from the FR Y-9C regulatory reports to calculate our bank activity measures, namely C&I loans, lines of credit, MBSNA investments, non-interest income, capital ratio, and deposit variables. We also use the regulatory reports to calculate measures of *realized* losses from bank activities, namely net charge-offs on C&I loans, net charge-offs on the total loan portfolio, and changes in MBSNA value (i.e., the difference between amortized cost and fair value). We collect rates for lines of credit (i.e., revolvers) from Dealscan, which primarily covers syndicated loans. Given that we use one-, two-, and three-year ahead measures of systemic risk, the final sample period in our analyses is 1995–2013 and includes 1279 bank-year observations, after requiring non-missing variables.

4.2. Descriptive statistics

We present descriptive statistics for the pooled sample in Table 1. The first panel of the table presents the distribution of the systemic risk. The table shows that the average loss of market value on the worst 5% days for the S&P 500 during the year is 2.98% (*MES*), while the mean of $\Delta CoVaR^{1\%}$ is 3.92%.

The second panel reports measures of banks' operations that are reflected on the asset and liability/equity sides of their balance sheets. Approximately 21.33% of banks' loan portfolios are C&I loans. The proportion of unused lines of credit out of total credit (i.e., total loans plus unused lines of credit) is 30.09%, and the average spread on lines of credit is 5.02%. Approximately 5.45% of banks' investment portfolios are *MBSNA*, on average, while close to 25.52% of bank income is derived from non-interest activities (*NII*). The equity to asset ratio ($Capital$) for an average bank equals 9.38%, and the average CET1 ratio (CET) is 14.17%. Finally, the ratio of short-term deposits to total deposits is 68.51%.

The third panel presents the measures of *realized* losses from bank activities. C&I loan charge-offs are on average 0.79% of total C&I loans, whereas total loan charge-offs are on average 0.69% of total loans. The average difference between the fair value and amortized cost of MBSNA investments in the available-for-sale portfolio is around 0.11% of the total AFS investments.

The fourth panel provides descriptive statistics for the compensation variables, which, for purposes of interpretation, we report both before and after taking the natural logarithm. The descriptive statistics for *vega* indicate that a 0.01 increase in stock return volatility results in an approximately $292,310 increase in the average risk-neutral value of bank executives' equity portfolio. Similarly, the descriptive statistics for $delta$ indicates that a 1% increase in stock price increases the equity portfolio value by $969,301, on average.[18] The last panel provides the distribution of the risk management index (*RMI*) for the observations with available data.

[16] We use a proxy for the CET1 ratio, because it is not available until 2014. For banks with available data during our sample period (i.e., 2014 - 2016), we find a 90% correlation between our proxy and the actual CET1 ratio.

[17] Market volatility, the market return, and the real estate sector return are constructed using CRSP data. The three-month Treasury bill rates, three-month LIBOR rate, 10-year Treasury rate, and Moody's *Baa*-rated bond yield are taken from the FRED database. The long-term composite bond yield is taken from the FRED database prior to 2000 and the U.S. Treasury Department thereafter.

[18] The values of *vega* and *delta* are larger than those reported in many of the prior related studies (e.g., DeYoung et al., 2013) because they represent the collective risk-taking incentives of the five highest-paid executives rather than only those of the CEO.

Table 1

Descriptive statistics. This table presents descriptive statistics. The sample period is 1995–2013. *MES* is marginal expected shortfall, the average bank return on the worst 5% days for the market during the year, following Acharya et al. (2017), multiplied by 100. $\Delta CoVaR^{1\%}$ is the conditional value-at-risk of the banking system conditional on bank i being in a distressed state, following Adrian and Brunnermeier (2016), multiplied by 100. Both *MES* and $\Delta CoVaR^{1\%}$ are multiplied by -1 so that larger values correspond to greater systemic risk. *MES* and $\Delta CoVaR$ are defined in more detail in Section 3.2. *CommLoans* is commercial and industrial loans scaled by total loans, multiplied by 100. *LOC* is the amount of unused lines of credit scaled by total credit (i.e., total loans plus unused lines of credit), multiplied by 100. *LOCRate* is the all-in loan spread for revolving loans from Dealscan. *MBSNA* is non-agency mortgage-backed securities scaled by total available-for-sale investments, multiplied by 100. *NII* is the proportion of non-interest income out of total income (i.e., revenue), multiplied by 100. *Capital* is the ratio of equity to total assets, multiplied by 100. *CET* is the CET1 risk-adjusted capital ratio, multiplied by 100. *STdep* is short-term deposits (total deposits less time deposits) scaled by total deposits, multiplied by 100. *CICO* is net C&I charge-offs scaled by C&I loans, multiplied by 100. *CO* is net charge-offs on the total loan portfolio scaled by total loans, multiplied by 100. $\Delta MBSNA$ is the difference between the fair value and amortized cost of MBSNA securities scaled by total AFS investments, multiplied by -100 so that larger values indicate greater losses. $\log(vega)$ and $\log(delta)$ are the log of equity portfolio vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. *RMI* is risk management index according to Ellul and Yerramilli (2013), discussed in Section 5.3.1. Continuous variables are winsorized at the 1st and 99th percentiles.

	N	Mean	SD	25%	50%	75%
Systemic risk measures						
MES	1279	2.978	2.187	1.526	2.239	3.663
$\Delta CoVaR^{1\%}$	1279	3.915	1.750	2.719	3.662	4.860
Bank activities						
CommLoans	1279	21.332	11.776	13.766	19.554	26.862
LOC	1279	30.091	15.469	19.637	26.790	37.287
LOCRate	43626	5.015	0.777	4.605	5.165	5.541
MBSNA	1279	5.452	10.324	0.000	0.612	5.903
NII	1279	25.517	13.969	15.533	23.224	32.110
Capital	1279	9.381	2.333	7.791	9.235	10.840
CET	1279	14.170	4.975	10.949	13.337	16.318
STdep	1279	68.510	15.031	58.757	69.512	79.302
Realized losses from business activities						
CICO	1279	0.793	1.029	0.174	0.445	0.946
CO	1279	0.693	0.905	0.179	0.377	0.795
$\Delta MBSNA$	1279	0.108	0.527	0.000	0.000	0.029
Compensation variables						
$\log(vega)$	1279	4.399	1.804	3.462	4.410	5.681
$\log(delta)$	1279	6.003	1.430	4.961	6.091	7.028
vega	1279	292.310	533.677	30.726	81.278	292.582
delta	1279	969.301	1379.025	141.387	440.896	1130.653
Cross-sectional variables						
RMI	1032	0.649	0.313	0.379	0.596	0.876

5. Results

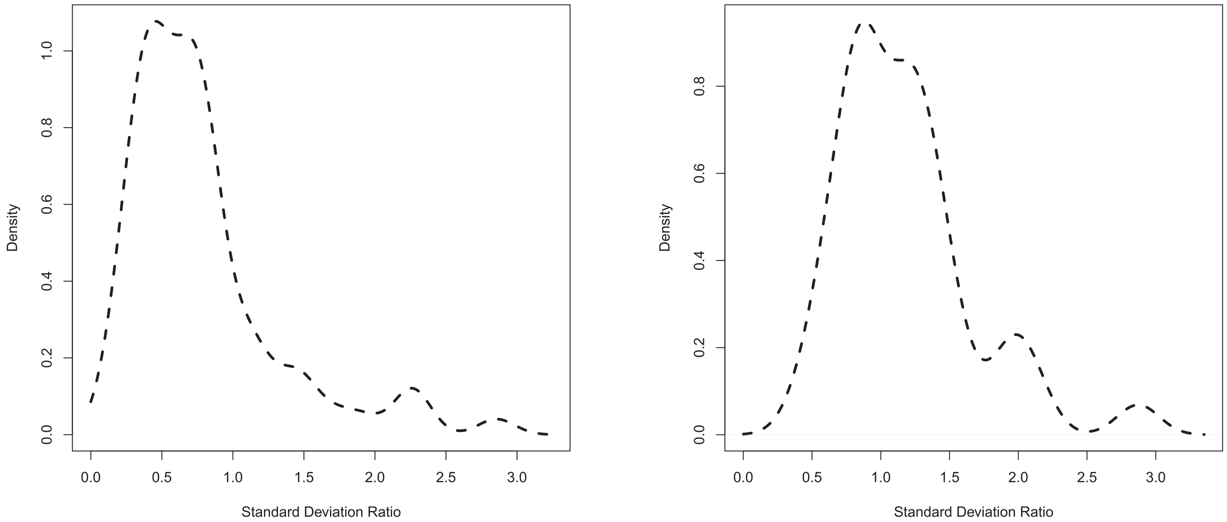
5.1. Vega and systemic risk

5.1.1. OLS and modified control function estimation

Table 2 Panel A (B) presents OLS (modified control function regression) estimates of the relation between vega and systemic risk controlling for $\log(delta)$ and year fixed effects. Columns (1)–(3) use one-, two-, and three-year-ahead *MES* as the dependent variable, respectively, while columns (4)–(6) use $\Delta CoVaR^{1\%}$ as the dependent variable over the same windows. We present 90% confidence intervals below the coefficient estimates based on 200 bootstrapped samples. We use bootstrapping to maintain consistency with our modified control function regression approach.

Table 2, Panel A indicates a positive and significant coefficient on vega across all six columns. In contrast, using modified control function regressions in Panel B, we find no evidence that the coefficient on vega is statistically distinguishable from zero at the 10% level across all six columns. Moreover, the economic magnitude of the coefficient on vega is much smaller than its OLS counterpart. For the one-year-ahead measures, a one standard deviation increase in vega (1.804) is associated with an increase in systemic risk of 0.004% for *MES* and 0.002% for $\Delta CoVaR^{1\%}$. These estimates correspond to approximately 0.2% and 0.1% of the respective standard deviations of *MES* and $\Delta CoVaR^{1\%}$.

As discussed in Section 3.1.2, the modified control function regression includes the ratio of the standard deviations of the first- and second-stage residuals interacted



(a) MES (b) CoVaR

Fig. 2. Density of standard deviation ratios. This figure presents the kernel density of the ratios of the standard deviations of the first- and second-stage residuals based on Eqs. (2) and (3), repeated below:

$$\log(vega)_{it-1} = \alpha' X_{it-1} + \xi_{it-1};\ Risk_{it+s} = \beta_1 \log(vega)_{it-1} + \Gamma' X_{it-1} + \eta_{it+s}.$$

The left panel presents the density of the standard deviation ratios for the case where the dependent variable is *MES* (i.e., column (1) of Table 2, Panel B), and the right panel for the case where the dependent variable is $\Delta CoVaR^{1\%}$ (i.e., column (4) of Table 2, Panel B).

with the first-stage residuals as an additional regressor. The coefficient on this interaction, ρ, equals the correlation coefficient between the two residuals. We find a statistically significant ρ for all systemic risk measures except for three-year-ahead *MES* (where $\rho = 0.096$), which indicates the existence of endogenous factors driving the relation between vega and systemic risk shown in the OLS regressions. In further untabulated analyses, we include bank size and book-to-market ratio as additional control variables. These controls have little effect on the coefficient estimates on $\log(vega)$, which indicates that the modified control function approach effectively accounts for endogeneity concerns.

One potential concern with the modified control function approach in our research setting is the potential lack of power since we have a relatively small number of markets with which to identify the correlation coefficient, ρ. We address this potential concern in two ways. First, we present the kernel density of the standard deviation ratios across markets (i.e., OCC region-years) in Fig. 2. The left panel shows the ratios based on one-year-ahead *MES* (i.e., column (1) of Table 2, Panel B), and the right panel shows those based on $\Delta CoVaR^{1\%}$ (i.e., column (4) of Table 2, Panel B). Both plots show evidence of large variation in the ratios across markets.[19] Next, in untabulated analyses, we confirm that the coefficient estimates on $\log(vega)$ from the OLS regressions are significantly larger than their counterparts from the modified control function regressions at the 1% level.[20] These two pieces of evidence suggest that the difference in results between the OLS and modified control function regressions is unlikely to be due solely to insufficient statistical power of the latter.

Collectively, the results in the section indicate that the positive relation between vega and systemic risk in the OLS specification is at least partially due to a spurious endogenous relation and, consequently, likely overstates the economic magnitude of its true causal effect. Therefore, we use the modified control function approach for the majority of our remaining analyses.

5.1.2. Expansions vs. contractions

Our next set of tests focus on whether the relation between vega and systemic risk varies over the business cycle. Theory posits that latent systemic risk builds up during economic expansions, and subsequently manifests during economic contractions. For example, Acharya and Naqvi (2012) illustrate how excess liquidity leads to lax lending standards during economic expansions, which results in riskier lending portfolios and sows the seeds for financial crises.[21] Their model implies that negative out-

[19] We do not interpret the magnitude of the ratio as it is not economically meaningful. For the sake of brevity, we do not present plots of standard deviation ratios based on two- and three-year-ahead systemic risk measures, but note that they also exhibit significant variation across markets.

[20] We compute the difference in the coefficient estimates between the OLS and modified control function regressions for each of the 200 bootstrapped samples and then test whether they differ from zero on average.

[21] Similarly, Dell'Ariccia and Marquez (2006) show how information asymmetry between borrowers and banks can lead to looser credit standards and lending booms during which banks take additional risk in their lending portfolios, which increases the likelihood of a banking crisis. Ruckes (2004) shows that competition can influence lending standards, leading to more risk-taking during economic expansions when credit standards are lower.

Table 2

Vega and systemic risk. This table presents OLS (Panel A) and modified control function (Panel B) regression results of regressing the systemic risk measures on log(*vega*) and log(*delta*). In both panels, columns (1)-(3) present results using *MES* as the systemic risk measure, and columns (4)-(6) $\Delta CoVaR^{1\%}$. *MES* is marginal expected shortfall, the average bank return on the worst 5% days for the market during the year, following Acharya et al. (2017), multiplied by 100. $\Delta CoVaR$ is the conditional value-at-risk of the banking system conditional on bank *i* being in a distressed state, following Adrian and Brunnermeier (2016), multiplied by 100. Both *MES* and $\Delta CoVaR^{1\%}$ are multiplied by −1 so that larger values correspond to greater systemic risk. *MES* and $\Delta CoVaR$ are defined in more detail in Section 3.2. The columns present systemic risk at multiple intervals ($t+s$), including one year ahead (t), two years ahead ($t+1$), and three years ahead ($t+2$) of the measurement of vega. log(*vega*) and log(*delta*) are the log of equity portfolio vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. Continuous variables are winsorized at the 1st and 99th percentiles. All columns include year fixed effects. 90% confidence intervals are reported in parentheses below the coefficient estimates, based on 200 bootstrapped samples.

Panel A: OLS regressions

	(1) MES_t	(2) MES_{t+1}	(3) MES_{t+2}	(4) $\Delta CoVaR^{1\%}_t$	(5) $\Delta CoVaR^{1\%}_{t+1}$	(6) $\Delta CoVaR^{1\%}_{t+2}$
$\log(vega)_{t-1}$	0.117	0.108	0.076	0.152	0.148	0.133
	[0.08, 0.165]	[0.063, 0.143]	[0.044, 0.107]	[0.096, 0.203]	[0.089, 0.201]	[0.08, 0.185]
$\log(delta)_{t-1}$	−0.067	−0.008	0.039	0.375	0.379	0.372
	[−0.134, −0.002]	[−0.073, 0.057]	[−0.018, 0.099]	[0.3, 0.462]	[0.303, 0.464]	[0.287, 0.46]
R^2	0.799	0.797	0.803	0.469	0.47	0.494
Obs	1279	1279	1279	1279	1279	1279
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Modified control function regressions

	(1) MES_t	(2) MES_{t+1}	(3) MES_{t+2}	(4) $\Delta CoVaR^{1\%}_t$	(5) $\Delta CoVaR^{1\%}_{t+1}$	(6) $\Delta CoVaR^{1\%}_{t+2}$
$\log(vega)_{t-1}$	0.002	0.013	0.018	0.001	−0.070	−0.046
	[−0.086, 0.086]	[−0.058, 0.078]	[−0.057, 0.090]	[−0.141, 0.142]	[−0.199, 0.079]	[−0.180, 0.081]
$\log(delta)_{t-1}$	0.039	0.081	0.093	0.516	0.583	0.542
	[−0.042, 0.133]	[0.003, 0.165]	[0.002, 0.191]	[0.372, 0.664]	[0.423, 0.722]	[0.414, 0.688]
ρ	0.178	0.149	0.096	0.163	0.232	0.200
	[0.017, 0.346]	[0.009, 0.28]	[−0.048, 0.228]	[0.015, 0.326]	[0.054, 0.366]	[0.042, 0.358]
R^2	0.802	0.799	0.804	0.472	0.477	0.499
Obs	1279	1279	1279	1279	1279	1279
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

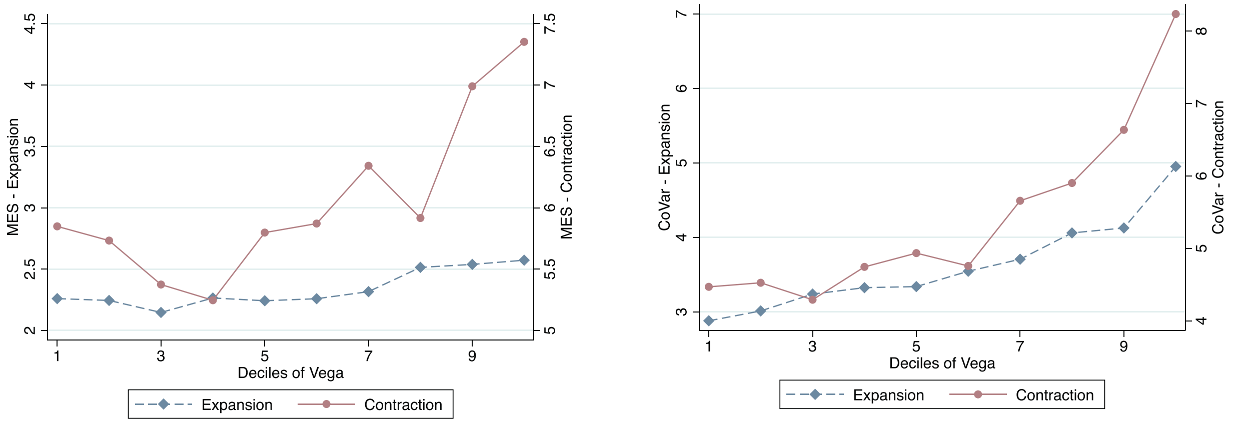
comes from risk-taking, which include financial distress, are more likely to manifest during economic contractions. Based on the intuition from these theories, we estimate a more flexible empirical specification that allows the relation between vega and systemic risk to differ during economic expansions and contractions. We expect vega to exhibit a stronger relation with systemic risk if systemic risk primarily manifests during economic contractions.

Figure 3 displays the relation between vega and the systemic risk measures (*MES* on the left and $\Delta CoVaR^{1\%}$ the right) separately during economic contractions and expansions to investigate whether risk-taking incentives exacerbate systemic risk during economic downturns. We identify economic contractions as occurring during the years 2001, 2008, or 2009 and construct an indicator, *Contraction*, that equals one if systemic risk is measured during any of these years and zero otherwise.[22] The dashed line presents the relation between vega and one-year ahead systemic risk measured during economic expansions, while the solid line presents the same relation when systemic risk is measured during economic downturns. Figure 3 shows that although there is a positive relation between vega and one-year-ahead systemic risk during *both* expansions and contractions, the magnitude of the relation is much larger during contractions.

Next, Table 3 presents results from estimating the modified control function regressions using one-, two-, and three-year-ahead *MES* in columns (1)-(3) and $\Delta CoVaR^{1\%}$ in columns (4)-(6) as the dependent variables. All of the specifications allow the coefficients on vega to vary with *Contraction*.[23] We again present 90% confidence intervals beneath coefficient estimates based on 200 bootstrapped samples. Table 3 provides consistent evidence of a positive and significant coefficient on the interaction $\log(vega) * Contraction$ across all six specifications. In contrast, the baseline coefficients on log(*vega*) are not statistically significant at the 10% level, suggesting that vega has little effect on *MES* or $\Delta CoVaR^{1\%}$ during economic expansions. In terms of economic magnitude, a one standard deviation

[22] We define contraction years based on the NBER classification.

[23] As long as the endogenous relation can be characterized as $\eta_{it+s} = \rho\xi_{it-1}\sigma_\eta/\sigma_\xi + \omega_{it+s}$, no further adjustments to the regression model are needed. In theory, we can also allow ρ to vary with *Contraction*. Although this would arguably result in a more flexible specification, as discussed in Section 3.1.2, it is *a priori* unclear whether and why ρ varies over time absent detailed knowledge about the unobserved factors. As a practical matter, doing so comes with a significant cost, as our sample only includes 12 markets for the contraction periods (i.e., four regions times three years), preventing us from estimating a separate ρ for economic contraction. Thus, we do not interact ρ with *Contraction*.



(a) MES **(b)** ΔCoVaR

Fig. 3. Vega and systemic risk in expansions vs. contractions. This figure presents the relations between vega and systemic risk measures conditional on the business cycle. The systemic risk measure is *MES* on the left panel and $\Delta CoVaR^{1\%}$ on the right. *MES* is marginal expected shortfall, the average bank return on the worst 5% days for the market during the year, following Acharya, Pedersen, Philippon and Richardson (2017), multiplied by 100. $\Delta CoVaR$ is the conditional value-at-risk of the banking system conditional on bank *i* being in a distressed state, following Adrian and Brunnermeier (2016), multiplied by 100. Both *MES* and $\Delta CoVaR^{1\%}$ are multiplied by −1 so that larger values correspond to greater systemic risk. *MES* and $\Delta CoVaR$ are defined in more detail in Section 3.2. *MES* is presented in panel (a), and $\Delta CoVaR^{1\%}$ is presented in panel (b). In each panel, the vertical axis on the left presents the systemic risk measure during expansions (the dashed line with diamonds) and on the right presents the systemic risk measure during contractions (the solid line with circles). The horizontal axis represents the deciles of vega. Contraction years are classified as the years 2001, 2008, and 2009. The measurement of systemic risk leads the measurement of vega by one year.

Table 3
Vega and systemic risk: expansions vs. contractions. This table presents modified control function regression results of regressing the systemic risk measures on $\log(vega)$, the interaction between $\log(vega)$ and *Contraction*, and $\log(delta)$. *Contraction* is equal to one if systemic risk is measured during 2001, 2008, or 2009, and zero otherwise. Columns (1)-(3) present results using *MES* as the systemic risk measure, and columns (4)-(6) present results using $\Delta CoVaR^{1\%}$. *MES* is marginal expected shortfall, the average bank return on the worst 5% days for the market during the year, following Acharya et al. (2017), multiplied by 100. $\Delta CoVaR$ is the conditional value-at-risk of the banking system conditional on bank *i* being in a distressed state, following Adrian and Brunnermeier (2016), multiplied by 100. Both *MES* and $\Delta CoVaR^{1\%}$ are multiplied by −1 so that larger values correspond to greater systemic risk. *MES* and $\Delta CoVaR$ are defined in more detail in Section 3.2. The columns present systemic risk at multiple intervals $(t+s)$, including one year ahead (t), two years ahead $(t+1)$, and three years ahead $(t+2)$ of the measurement of vega. $\log(vega)$ and $\log(delta)$ are the log of equity portfolio vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. Continuous variables are winsorized at the 1st and 99th percentiles. All columns include year fixed effects. 90% confidence intervals are reported in parentheses below the coefficient estimates, based on 200 bootstrapped samples.

	(1)	(2)	(3)	(4)	(5)	(6)
	MES_t	MES_{t+1}	MES_{t+2}	$\Delta CoVaR^{1\%}_t$	$\Delta CoVaR^{1\%}_{t+1}$	$\Delta CoVaR^{1\%}_{t+2}$
$\log(vega)_{t-1}$	0.016	0.058	0.045	0.024	−0.033	−0.030
	[−0.073, 0.100]	[−0.023, 0.144]	[−0.045, 0.123]	[−0.131, 0.172]	[−0.177, 0.118]	[−0.165, 0.089]
$\log(vega)_{t-1} * Contraction_t$	0.152			0.244		
	[0.017, 0.307]			[0.069, 0.473]		
$\log(vega)_{t-1} * Contraction_{t+1}$		0.300			0.282	
		[0.118, 0.486]			[0.093, 0.466]	
$\log(vega)_{t-1} * Contraction_{t+2}$			0.318			0.345
			[0.153, 0.543]			[0.175, 0.505]
$\log(delta)_{t-1}$	0.004	−0.008	0.029	0.457	0.504	0.484
	[−0.089, 0.104]	[−0.098, 0.080]	[−0.065, 0.139]	[0.303, 0.614]	[0.354, 0.668]	[0.350, 0.609]
ρ	0.118	0.013	−0.025	0.096	0.155	0.128
	[−0.074, 0.283]	[−0.168, 0.176]	[−0.182, 0.137]	[−0.082, 0.268]	[−0.023, 0.292]	[−0.038, 0.291]
R^2	0.804	0.805	0.813	0.480	0.487	0.514
Obs	1279	1279	1279	1279	1279	1279
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

increase in vega (1.804) corresponds to an *additional* 0.27, 0.54, or 0.57 percentage point (0.44, 0.51, and 0.62 percentage points) increase in *MES* ($\Delta CoVaR^{1\%}$) if the economy is in contraction one, two, or three years ahead. Overall, the evidence from Table 3 is consistent with the theoretical prediction that systemic risk accumulates during economic expansions and subsequently manifests during economic contractions (Acharya and Naqvi, 2012).

Table 4

Vega and bank activities. This table presents modified control function regression results of regressing the business activity measures on log(*vega*) and log(*delta*). Panel A examines activities on the asset side. *CommLoans* is commercial and industrial loans scaled by total loans, multiplied by 100. *LOC* is the amount of unused lines of credit scaled by total credit (i.e., total loans plus unused lines of credit), multiplied by 100. *LOCRate* is the all-in loan spread for revolving loans from Dealscan. *MBSNA* is non-agency mortgage-backed securities scaled by total available-for-sale investments, multiplied by 100. *NII* is the proportion of non-interest income out of total income (i.e., revenue), multiplied by 100. Panel B examines activities on the liabilities and equity side. *Capital* is the ratio of equity to total assets, multiplied by 100. *CET* is the CET1 risk-adjusted capital ratio, multiplied by 100. *STdep* is short-term deposits (total deposits less time deposits) scaled by total deposits, multiplied by 100. log(*vega*) and log(*delta*) are the log of equity portfolio vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. Continuous variables are winsorized at the 1st and 99th percentiles. All columns include year fixed effects. 90% confidence intervals are reported in parentheses below the coefficient estimates, based on 200 bootstrapped samples.

Panel A: Bank Assets

	(1)	(2)	(3)	(4)	(5)
	$CommLoans_t$	LOC_t	$LOCRate_t$	$MBSNA_t$	NII_t
$\log(vega)_{t-1}$	1.826	2.100	−0.047	0.992	−0.431
	[0.629, 2.987]	[1.031, 3.402]	[−0.082, −0.004]	[0.393, 1.671]	[−1.751, 0.88]
$\log(delta)_{t-1}$	−0.657	3.535	−0.068	0.876	4.999
	[−1.802, 0.511]	[2.356, 4.752]	[−0.106, −0.034]	[0.168, 1.540]	[3.578, 6.239]
ρ	−0.130	0.120	0.050	−0.132	0.332
	[−0.254, 0.008]	[−0.036, 0.246]	[0.029, 0.071]	[−0.275, −0.009]	[0.208, 0.44]
R^2	0.063	0.370	0.157	0.127	0.299
Obs	1279	1279	43,626	1279	1279
Year FE	Yes	Yes	Yes	Yes	Yes

Panel B: Bank Liabilities and Equity

	(1)	(2)	(3)
	Capital	*CET1*	*STdep*
$\log(vega)_{t-1}$	−0.050	−0.780	1.910
	[−0.273, 0.172]	[−1.304, −0.277]	[0.324, 3.395]
$\log(delta)_{t-1}$	−0.012	0.883	0.930
	[−0.246, 0.229]	[0.336, 1.422]	[−0.658, 2.330]
ρ	0.000	0.190	−0.163
	[−0.154, 0.135]	[0.030, 0.338]	[−0.310, −0.020]
R^2	0.218	0.185	0.276
Obs	1279	1279	1279
Year FE	Yes	Yes	Yes

5.2. Vega and bank activities

This section examines whether vega encourages bank executives to engage in certain types of activities that arguably have the greatest potential to contribute and expose their banks to systemic risk and whether these activities contribute to *realized* risk during economic contractions.

5.2.1. Vega and bank activities on the asset side

We first examine the relation between vega and banks' lending activities. Column (1) of Table 4, Panel A examines C&I lending (*CommLoans*) and shows that bank executives' vega has a significant positive relation with the proportion of their bank's C&I lending. Our estimates imply that a one standard deviation increase in vega leads to a 3.29 percentage-point increase in *CommLoans*. Column (2) reports results from unused lines of credit. The coefficient on vega is positive and significant and implies that a one standard deviation increase in vega leads to an increase in the unused lines of credit of 3.79 percentage points. Column (3) uses loan facility-level data from Dealscan to measure spreads for lines of credit and reveals a negative effect of vega on the spread for lines of credit. A decrease in borrowing costs combined with an increase in the borrowing amount indicates an increase in credit supply.

We next examine the relation between vega and *MBSNA* investments. The results are presented in column (4) of Table 4, Panel A. The coefficient on vega is positive and significant, consistent with bank executives' vega encouraging them to invest more heavily in MBSNA as a proportion of their bank's available-for-sale investment portfolio. Our estimates imply that a one standard deviation increase in vega leads to a 1.79 percentage-point increase in the proportion of non-agency mortgage-backed securities in their bank's available-for-sale investment portfolio.

Finally, we investigate banks' reliance on non-interest income generating activities in column (5). We find no evidence of a relation between vega and the proportion of income derived from non-interest income activities. This finding suggests that although these activities may be associated with systemic risk (Brunnermeier et al., 2020), they do not appear to be a channel through which vega increases systemic risk. One potential explanation is that non-interest income activities typically require the bank to have a costly infrastructure, such as an investment banking function. However, not all banks have this infrastructure, and their managers may find it difficult to quickly exploit these potential opportunities, despite their contractual incentives to do so. In contrast, lending and investing in available-for-sale securities are core activities of virtually every bank and are arguably easier (i.e., less costly) for bank managers to adjust in response to their contractual incentives.[24]

5.2.2. Vega and bank activities on the liability and equity side

We examine whether bank executives' vega encourages them to choose greater leverage (or lower capital ratios), measured as either $Capital$ or $CET1$. The results are presented in Table 4, Panel B. Column (1) provides no evidence of a negative relation between bank executives' vega and their banks' total equity-to-asset ratios. Column (2) shows that vega exhibits a statistically significant negative relation with the CET1 risk-based capital ratio, consistent with bank executives' equity risk-taking incentives encouraging them to choose higher leverage at their banks (lower capital ratios) after accounting for the riskiness of their bank's assets.[25] Our estimates imply that a one standard deviation increase in bank executives' vega leads to a 1.4 percentage point decline in their bank's CET1 capital ratio.

Next, we examine whether vega encourages bank executives to rely more on short-term debt. The result is presented in column (3) of Table 4, Panel B. We show that bank executives' vega has a positive relation with $STdep$, indicating that vega encourages a greater reliance on short-term debt financing. Our estimates imply that a one standard deviation increase in vega leads to a 3.4 percentage point increase in $STdep$ as a source of financing. This finding suggests that vega encourages managers to utilize more short-term debt, which has the potential to contribute to systemic risk.

5.2.3. Vega and realized risk from bank activities

To capture realized risk from lending and investing activities, we examine large losses in banks' loan portfolios and valuation declines from their MBSNA investments.[26] We focus on large losses because the realization of systemic risk is a relatively extreme event that is characterized as a tail risk phenomenon. Although losses specific to the C&I loan portfolio and changes in MBSNA values are separately reported, regulatory reports do not include separate information on losses from lines of credit. Thus, we use losses on the total loan portfolio as an additional measure to capture the risk of the loan portfolio with the intuition that this metric will include losses on lines of credit that were ultimately extended. Specifically, we examine instances of (i) large C&I net charge-offs, (ii) large net charge-offs on the total loan portfolio, and (iii) large declines in the MBSNA value. We consider these amounts to be "large" if they are in the top decile of the respective variable's full sample distribution. We then repeat our test that examines the relation between vega and systemic risk during economic expansions and contractions in Section 5.1.2, using indicators for large losses in banks' loan portfolios and from their MBSNA investments as dependent variables. We present 90% confidence intervals beneath coefficient estimates based on 200 bootstrapped samples.

Table 5 provides consistent evidence of a positive and statistically significant coefficient on the interaction $\log(vega) * Contraction$ in all three specifications. In terms of the economic magnitude, a one standard deviation increase in vega (1.804) corresponds to an *additional* 6.9, 7.6, and 10.8 percentage-point increase in the likelihood of large losses from C&I loans, total loans, and MBSNA investments, respectively, if the economy is in contraction one-year ahead. In contrast, there is no evidence, in terms of both statistical significance and economic magnitude, that greater vega leads to large losses in banks' loan portfolios and from their MBSNA investments during economic expansions. Collectively, our results from this section provide consistent evidence that bank executives' equity risk-taking incentives encourage them to adopt lending and investment policies that contribute to greater realized risk during economic contractions.[27]

5.3. Additional analyses

In this section, we conduct two sets of analyses to shed light on factors associated with the relations between vega and bank activities surrounding the 2007–2009 financial crisis. First, bank risk management practices came under scrutiny surrounding the 2007–2009 financial crisis, given the substantial losses suffered by many institutions (Stulz, 2008; Ellul and Yerramilli, 2013). Thus, we examine whether risk management oversight is associated with the effect of vega on bank investments in the lead-up to the financial crisis. Second, the Dodd-Frank Act, a major legislative change resulting from the 2007–2009 financial crisis, includes several requirements, discussed further below, that may affect the relations between vega and bank activities. We thus also examine whether the relations between

[24] Most banks have available-for-sale (AFS) investment portfolios, which generate *interest* income. In contrast, the investments in their trading portfolios generate *non-interest* income (e.g., capital gains and losses, both realized and unrealized). While banks can technically hold MBSNA in either portfolio, most hold these securities in their AFS portfolio due to the illiquid nature of these securities. These features, coupled with the fact that non-interest income arises from several additional activities, are a potential explanation for the difference between our estimates of the effect of vega on MBSNA vs. non-interest income.

[25] Although most banks are typically well above the threshold to be considered "well-capitalized," it is also typical to have internal capital ratio targets that exceed, and are therefore more stringent than, the regulatory thresholds (Berger et al., 2008).

[26] We focus on realized risk from activities on the asset side of the balance sheet, given that we can construct measures based on losses from those specific activities. We do not examine non-interest activities in this test, as there is no evidence of a relation between vega and non-interest income. In addition, non-interest income is already an income-statement measure that reflects the realized amount from these activities.

[27] In untabulated analyses, we find that the effect of vega on systemic risk is greater when banks lend to more distant borrowers. The evidence is consistent with Granja et al. (2021), who show that distant lending is procyclical and potentially exacerbates systemic risk.

Table 5
Vega and realized risk from bank activities. This table presents modified control function regression results of regressing indicators for large losses on bank lending and MBSNA on vega, the interaction between $\log(vega)$ and *Contraction*, and $\log(delta)$. *Contraction* is equal to one if systemic risk is measured during 2001, 2008, or 2009, and zero otherwise. Columns (1)-(3) examine instances of large net C&I charge-offs (*CICO*), large net charge-offs on the total loan portfolio (*CO*), and large declines in the MBSNA value ($\Delta MBSNA$), respectively. *CICO* is net C&I charge-offs scaled by C&I loans, multiplied by 100. *CO* is net charge-offs on the total loan portfolio scaled by total loans, multiplied by 100. $\Delta MBSNA$ is the difference between the fair value and amortized cost of MBSNA securities scaled by total AFS investments, multiplied by −100 so that larger values indicate greater losses. *CICO*, *CO*, and $\Delta MBSNA$ are considered to be "large," if they are in the top decile of the respective variable's full sample distribution. $\log(vega)$ and $\log(delta)$ are the log of equity portfolio vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. Continuous variables are winsorized at the 1st and 99th percentiles. All columns include year fixed effects. 90% confidence intervals are reported in parentheses below the coefficient estimates, based on 200 bootstrapped samples.

	(1)	(2)	(3)
	$LargeCICO_t$	$LargeCO_t$	$Large\Delta MBSNA_t$
$\log(vega)_{t-1}$	0.003	0.006	0.000
	[−0.010, 0.015]	[−0.004, 0.017]	[−0.009, 0.009]
$\log(vega)_{t-1} * Contraction_t$	0.038	0.042	0.060
	[0.002, 0.070]	[0.006, 0.075]	[0.027, 0.099]
$\log(delta)_{t-1}$	−0.042	−0.029	0.012
	[−0.061, −0.024]	[−0.049, −0.013]	[−0.004, 0.029]
ρ	0.000	−0.054	−0.029
	[−0.089, 0.091]	[−0.145, 0.045]	[−0.136, 0.079]
R^2	0.203	0.266	0.191
Obs	1279	1279	1279
Year FE	Yes	Yes	Yes

vega and bank activities change following the Dodd-Frank Act.

5.3.1. The role of risk management oversight before the 2007–2009 financial crisis

The scrutiny on risk management oversight following the 2007–2009 financial crisis is unsurprising due to the importance of banks' internal risk management practices as a governance mechanism. Specifically, risk management can help managers identify, quantify, and limit exposure to excessive systemic risk and other sources of value-destroying risk. Moreover, risk management plays an important governance role, given that many bank activities (e.g., lending and investments) are inherently opaque (Morgan, 2002) and therefore, challenging for outsiders to discipline. Finally, the risk management function considers compliance with regulatory requirements, including regulatory capital ratios, as part of its monitoring duties.

We examine whether banks' risk management practices moderate the positive relation between vega and banks' MBSNA and C&I lending during the period leading up to the 2007–2009 financial crisis. We focus on activities on the asset side of the balance sheet, because risk management primarily focuses on quantifying risk-return tradeoffs of bank investments. For example, as Stulz (2008) explains, "The job of risk management is to ensure that top management knows and understands the probabilities associated with possible outcomes of the firm's strategy before they make decisions to commit the firm's capital." In addition, we focus on MBSNA and C&I lending given their significant roles in contributing to bank losses during the financial crisis.

We expand the specification in model (1) by interacting $\log(vega)$ with a measure of bank risk management practices.

$$\begin{aligned} Risk_{i,t} &= \delta_t + \beta_1 \log(vega)_{i,t-1} * HighRMI_{i,t-1} \\ &\quad + \beta_2 HighRMI_{i,t-1} + \beta_3 \log(delta)_{i,t-1} + \epsilon_{i,t}. \end{aligned} \tag{12}$$

In Eq. (12), the dependent variable is either C&I lending (*CommLoans*) or MBSNA investments (*MBSNA*). We measure the strength of banks' risk management using the risk management index (RMI) developed by Ellul and Yerramilli (2013).[28] RMI captures the "importance attached to the risk management function within each BHC [bank holding company], and the quality of risk oversight provided by the BHC's board of directors." One concern is that banks tend to implement stronger risk management practices when they provide their executives with higher-powered incentives, because they expect these incentives to encourage riskier activities and decisions. In this case, sorting on RMI could essentially be the same as sorting on vega. To address this concern, we construct a modified version of our RMI measure by orthogonalizing RMI against $\log(vega)$. We use the residuals to create an indicator, *HighRMI*, that equals one if the residual is in the top quartile, and zero otherwise. Making this adjustment helps to ensure that this modified measure better captures variation in the strength of banks' risk management practices

[28] We are extremely grateful for the RMI data shared with us by Prof. Andrew Ellul.

Table 6
Vega and bank activities: the role of risk management. This table examines the role of risk management. Panel A presents modified control function regression results of regressing C&I lending (*CommLoans*) and MBSNA investments (*MBSNA*) on log(*vega*), the interaction between log(*vega*) and *HighRMI*, *HighRMI*, and log(*delta*), using observations prior to 2007. *CommLoans* is commercial and industrial loans scaled by total loans, multiplied by 100. *MBSNA* is non-agency mortgage-backed securities scaled by total available-for-sale investments, multiplied by 100. *HighRMI* is an indicator variable that equals one if a bank's risk management index (RMI) from Ellul and Yerramilli (2013), residualized against log(*vega*), falls in the top quartile of the variable's distribution and zero otherwise. log(*vega*) and log(*delta*) are the log of equity portfolio vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. Panel B presents OLS regression results of regressing MBSNA investments (*MBSNA*) on C&I lending (*CommLoans*), using observations prior to 2007. Continuous variables are winsorized at the 1st and 99th percentiles. All columns include year fixed effects. 90% confidence intervals are reported in parentheses below the coefficient estimates, based on 200 bootstrapped samples.

Panel A: Vega, RMI, and Bank Activities

	(1) $CommLoans_t$	(2) $MBSNA_t$
$\log(vega)_{t-1}$	1.460	0.559
	[0.015, 2.584]	[−0.565, 1.574]
$\log(vega)_{t-1} * HighRMI_{t-1}$	−0.534	1.336
	[−1.549, 0.538]	[0.141, 2.780]
$\log(delta)_{t-1}$	−0.557	1.485
	[−1.955, 0.989]	[0.473, 2.887]
$HighRMI_{t-1}$	5.011	−2.829
	[−1.706, 11.272]	[−8.761, 1.765]
ρ	−0.084	−0.129
	[−0.235, 0.076]	[−0.299, 0.033]
R^2	0.055	0.113
Obs	605	605
Year FE	Yes	Yes

Panel B: Risk Targeting

	(1) $MBSNA_t$
CommLoans	−0.041
	[−0.118, 0.028]
CommLoans ∗ *HighRMI*	−0.204
	[−0.412, −0.006]
HighRMI	10.076
	[4.667, 15.805]
R^2	0.077
Obs	605
Year FE	Yes

that is unrelated to their executives' equity risk-taking incentives (i.e., vega).

The results of this analysis are presented in Table 6, Panel A. Column (1) presents results with *Commloans* as the dependent variable and shows that the coefficient on $\log(vega) * HighRMI$ is negative but statistically insignificant at the 10% level. However, the magnitude of the coefficient (−0.534) is large relative to the baseline coefficient on $\log(vega)$ (1.460). Therefore, there is weak evidence that high RMI weakens the positive effect of vega on *Commloans*. Column (2) examines *MBSNA* and shows that the coefficient on $\log(vega) * HighRMI$ is positive and statistically significant at the 10% level. The results suggest that stronger risk management practices amplify the positive relation between managers' risk-taking incentives and MBSNA investments. Collectively, these results suggest that strong risk management is associated with a relatively smaller (larger) effect of vega on C&I lending (MBSNA) in the pre-crisis period. We next examine whether regulatory capital treatment of investments, and, more specifically, "risk targeting" incentives may at least partially explain this finding.

Risk targeting entails a shift towards riskier assets that have regulatory capital requirements similar to those of safer alternatives (Keppo and Korte, 2018). Before the 2007–2009 crisis, MBSNA and C&I loans had overlapping capital requirements.[29] However, MBSNA was likely viewed as riskier relative to C&I lending, which is evident from its relatively higher returns prior to the crisis and an increase in the risk weights of several mortgage-related assets after the crisis (U.S. Government Accountability Office, 2016). Therefore, prior to the crisis, shifting from C&I lending to MBSNA allowed risk-seeking managers (i.e., those with high vega) to increase their banks' risk without having to alter their regulatory capital. If stronger risk management practices (i.e., high RMI banks) entail more stringent monitoring of capital requirements, vega should motivate managers at high RMI banks to decrease C&I lending and increase MBSNA investments more, relative to their counterparts at low RMI banks.[30]

The risk targeting explanation for our finding in Table 6, Panel A presumes that strong risk management is associated with stronger risk targeting incentives. To provide evidence on this presumption, we examine the extent of risk targeting at high RMI vs. low RMI banks in the pre-crisis period. Other things equal, risk targeting implies that an increase in MBSNA investment should coincide with a reduction in C&I lending, as managers shift towards relatively riskier assets with similar regulatory capital risk weight. Therefore, if bank managers at high RMI banks are more likely to engage in risk targeting prior to the crisis due to the monitoring by strong risk management, there should be more substitution (i.e., a larger negative relation) between MBSNA and C&I lending at high RMI banks than

[29] Prior to the crisis, the risk-weights for MBSNA generally ranged from 20% to 100% depending on the credit rating of the security, while the risk-weights for C&I loans generally ranged from 0% to 100% depending on whether the loan was guaranteed by a governmental-agency.

[30] Risk targeting presumes that managers are aware that MBSNA investments are, on average, riskier than C&I loans. We believe that this is a reasonable assumption for several reasons; perhaps the most notable is that MBSNAs offered higher expected returns than did C&I loans during the pre-crisis period. It is also important to note that risk targeting (at least in the context of our research question and research setting) is agnostic about regulators' knowledge about the riskiness of MBSNA investments relative to C&I loans. Given that regulatory risk weights are based on discrete and somewhat "coarse" categories (e.g., 50%, 100%) rather than a more continuous measure, regulators were presumably aware that any given set of assets with the same risk-weights contained assets with different degrees of risk (within a tolerable range). And, specifically in our setting, although MBSNAs were riskier on average than C&I loans, this difference was not perceived by the regulators as being large enough to warrant moving either MBSNAs to the next highest risk-weight category or C&I loans to the next lowest. In other words, the coarse and discrete nature of regulators' risk-weight categories allowed (and presumably still allows) for risk targeting by banks and their executives.

that at low RMI banks. To examine this, we estimate the following OLS specification.[31]

$$MBSNA_{i,t} = \delta_t + \beta_1 CommLoans_{i,t} * HighRMI_{i,t-1} + \beta_2 CommLoans_{i,t} + \beta_3 HighRMI_{i,t-1} + \epsilon_{i,t}. \quad (13)$$

In Table 6, Panel B, we present the relation between *MBSNA* and *CommLoans* in the pre-crisis period. We also allow the relation to vary for high RMI banks relative to low RMI banks. The table reveals a negative and significant coefficient on the interaction term, suggesting that prior to the 2007–2009 crisis, MBSNA and C&I lending exhibited a stronger negative relation at high RMI banks relative to low RMI banks. The result is consistent with stronger risk targeting incentives for high RMI banks prior to the crisis.

Overall, the evidence in Table 6 supports our interpretation that strong risk management, by magnifying risk targeting incentives, explains the effects of vega on C&I lending and MBSNA investments leading up to the 2007–2009 crisis. However, we hasten to add that the results in the section are subject to alternative interpretations, given that the strength of risk management may still be endogenous to other bank characteristics, such as the underlying bank business model or hedging incentives (Ellul and Yerramilli, 2013). In an effort to address this concern, we find that our results are qualitatively similar using an instrumental variable (IV) approach (untabulated) following Ellul and Yerramilli (2013).[32] Nonetheless, our empirical findings should be viewed as providing descriptive evidence on how the effects of vega on bank risk-taking activities vary with the strength of risk management, as opposed to on the causal effect of risk management on bank risk-taking.

5.3.2. Vega and bank activities before and after Dodd-Frank

The Dodd-Frank Act of 2010 significantly changed the regulatory landscape of financial institutions. For exam-

[31] We use an OLS regression rather than the control function regression, because we are interested in examining the endogenous relation between C&I lending and MBSNA, rather than the causal effect of C&I lending.

[32] Specifically, Ellul and Yerramilli (2013) find a significant increase in RMI during the 1998 to 2000 period, which may be in part attributed to "the experience of BHCs during the 1998 Russian crisis, and in part to the passage of the Gramm Leach Bliley Act in 1999." They use the average change in RMI of each bank's peer banks (i.e., those in the same size decile) during the 1998–2000 period (excluding the focal bank) as an instrument for the focal bank's RMI during the post-2000 period. They argue that the assumed exclusion restriction is likely valid because "the proximate causes of the 1998 crisis were very different from those of the financial crisis in 2007 to 2008; the former was triggered by events in Russia, whereas the latter was triggered by problems in the housing sector in the United States." We follow their approach and replicate our analysis reported in Table 6, Panel A with the following two research design changes: (i) we limit the pre-crisis sample to the period from 2001 to 2006 (after the construction of the instrument but before the 2007 financial crisis); and (ii) we use the average change in RMI of peer banks during the 1998–2000 period (excluding the focal bank) within the same size quartile as an instrument. We use quartiles rather than deciles because of our smaller sample size. Due to the requirement that banks have non-missing RMI in the 1998–2000 period and using data from only post 2000, the resulting sample consists of only 231 observations, compared to the 605 in our full pre-crisis sample. We find (untabulated) similar coefficient magnitudes to those in Table 6, Panel A, although the coefficient estimates are not statistically significant at conventional (i.e., 10%) levels.

Table 7

Vega and Bank Activities: Pre vs. Post Dodd-Frank. This table presents modified control function regression results of regressing the business activity measures on log(*vega*), the interaction between log(*vega*) and *Post_DF*, and log(*delta*). The sample excludes bank-year observations during economic contractions (i.e., 2001, 2008, and 2009). *Post_DF* is an indicator that equals one if vega is measured in or after 2010. *CommLoans* is commercial and industrial loans scaled by total loans, multiplied by 100. *LOC* is the amount of unused lines of credit scaled by total credit (i.e., total loans plus unused lines of credit), multiplied by 100. *LOCRate* is the all-in loan spread for revolving loans from Dealscan. *MBSNA* is non-agency mortgage-backed securities scaled by total available-for-sale investments, multiplied by 100. *NII* is the proportion of non-interest income out of total income (i.e., revenue), multiplied by 100. *Capital* is the ratio of equity to total assets, multiplied by 100. *CET* is the CET1 risk-adjusted capital ratio, multiplied by 100. *STdep* is short-term deposits (total deposits less time deposits) scaled by total deposits, multiplied by 100. log(*vega*) and log(*delta*) are the log of equity portfolio vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. Continuous variables are winsorized at the 1st and 99th percentiles. All columns include year fixed effects. 90% confidence intervals are reported in parentheses below the coefficient estimates, based on 200 bootstrapped samples.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$CommLoans_t$	LOC_t	$LOCRate_t$	$MBSNA_t$	NII_t	$Capital_t$	$CET1_t$	$STdep_t$
$\log(vega)_{t-1}$	1.236	2.611	−0.020	1.383	−0.168	0.031	−0.671	1.023
	[0.124, 2.471]	[1.396, 3.891]	[−0.056, 0.020]	[0.440, 2.257]	[−1.448, 1.222]	[−0.172, 0.252]	[−1.247, −0.143]	[−0.576, 2.934]
$\log(vega)_{t-1} * Post\_DF_{t-1}$	0.909	−1.133	0.155	−0.612	−0.092	−0.179	0.112	1.204
	[0.195, 1.619]	[−1.955, −0.289]	[0.137, 0.169]	[−1.250, −0.014]	[−0.887, 0.606]	[−0.334, −0.063]	[−0.224, 0.424]	[0.345, 1.946]
$\log(delta)$	−0.478	3.420	−0.195	0.728	4.858	−0.037	0.704	1.235
	[−1.727, 0.716]	[2.304, 4.544]	[−0.233, −0.157]	[−0.022, 1.564]	[3.304, 6.397]	[−0.252, 0.161]	[0.155, 1.34]	[−0.620, 2.788]
ρ	−0.094	0.120	0.011	−0.183	−6.518	0.01	0.152	−0.110
	[−0.239, 0.035]	[−0.016, 0.233]	[−0.013, 0.034]	[−0.339, −0.008]	[−11.699, −2.296]	[−0.145, 0.150]	[−0.004, 0.326]	[−0.270, 0.043]
R^2	0.072	0.372	0.152	0.140	0.309	0.253	0.202	0.297
Obs	1057	1057	39,001	1057	1057	1057	1057	1057
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

ple, it tightened restrictions on executive compensation (e.g., clawbacks), called for greater bank capitalization and periodic stress testing, and increased regulatory capital requirements for certain risky assets, including several mortgage-related assets (U.S. Government Accountability Office, 2016). These changes may have altered the relations between vega and bank activities. To investigate whether this is the case, we interact vega with an indicator for the post-Dodd-Frank period (*Post_DF*) that is equal to one for the years 2010 and after, and zero otherwise. We remove observations during economic contractions to ensure relatively similar economic conditions in the pre- and post-periods, resulting in a smaller sample size relative to our main sample.

Table 7 shows interesting changes in the relation between vega and bank activities from before to after Dodd-Frank. On the asset side, the effect of vega on MBSNA investments and lines of credit is weaker in the post-Dodd-Frank period than before, while the effect of vega on C&I lending is larger in the post-Dodd-Frank period than before. These findings are consistent with the attractiveness of C&I lending increasing relative to MBSNA or lines of credit. We find no evidence of a change in the relation between vega and non-interest income before and after Dodd-Frank. On the liability and equity side, we find that the effect of vega on the capital ratio and short-term deposits is stronger in the post-Dodd-Frank period, but there is no evidence of a change for the CET1 ratio. Although these tests do not allow us to attribute these differences to the Dodd-Frank Act specifically, given all of the other contemporaneous changes during this period, our findings suggest that changes in the institutional environment following the crisis may have led to changes in the types of lending, investing, and financing activities that vega encourages bank managers to pursue. Nonetheless, this descriptive evidence may provide useful information to regulators regarding the types of activities motivated by vega in the post-Dodd-Frank environment.

6. Conclusion

Our paper provides evidence about whether bank executives' contractual incentives *cause* systemic risk using a novel control function regression method developed by Klein and Vella (2010). We find that bank executives' portfolio vega causes systemic risk that manifests only during economic contractions. We also show that vega motivates bank managers to take actions that contribute to the build-up of systemic risk. On the asset side, this involves greater investment in commercial and industrial (C&I) lending and non-agency mortgage-backed securities, and line of credit issuance. On the liability and equity side, this involves lower common equity Tier 1 capital ratios and greater reliance on short-term deposits. Collectively, our results suggest that vega causes managers to alter their lending, investing, and financing activities during economic expansions, resulting in greater systemic risk during economic contractions.

We contribute to the literature by showing that features of managerial compensation contracts influence systemic risk. Prior research identifies certain bank characteristics that are associated with systemic risk, but the role of managerial incentives has been relatively unexplored. Importantly, we provide causal evidence using the modified control function regression developed by Klein and Vella (2010) that accounts for endogenous matching between executives and banks. This technique allows us to distinguish between the causal effect of vega on systemic risk and the effect of endogenous matching between banks and managers.

The control function regression technique can be particularly useful for settings that entail two-sided endogeneity concerns, which usually make it extremely difficult to find sufficiently powerful (i.e., not "weak") instruments that satisfy the exclusion restrictions on both sides. Therefore, this method has the potential to be applied in numerous settings in financial economics. Examples of potential settings include contracts offered to employees that depend on employees' personal backgrounds as well as the economic characteristics of their employers. Banks' lending decisions are jointly affected by their liquidity sources (e.g., depositors) and the composition of assets (e.g., borrowers). Firms' choice of financiers (e.g., venture capitalists) is a function of both the nature of their operations and the level of interests from potential financiers. The essential requirement for applying the modified control function technique is that the standard deviation ratio (i.e., the standard deviation of the first-stage residuals divided by the standard deviation of the second-stage residuals) differs across the markets or groups. Examples of markets or groups in financial economics settings include geographic segmentation, as in our study, or some other form of segmentation that results from legislation, regulation, industry structure, transactions costs, demographics, or frictions.

Our findings also have implications for regulators. Following the most recent financial crisis, the structure of bank executives' compensation contracts has received increased attention and scrutiny as a potential source of their incentives to take risk. Symptomatic of these concerns, in Section 956 of the Dodd-Frank Act, bank regulators have been charged with writing rules to restrict compensation contracts that encourage "inappropriate risk-taking." Our evidence suggests that, despite the fact that microprudential regulations are not typically thought to help control systemic risk, regulation of incentive-compensation contracts can at least partially influence systemic risk.

Acknowledgements

Bill Schwert was the editor of this article. We thank an anonymous referee, Wayne Guay, Michael Iselin, Chongho Kim, Shawn Kim, James Li, Bradford Lynch, and seminar participants at Carnegie Mellon University, Lancaster University, and the Wharton School for helpful comments and suggestions, Dengsheng Chen for excellent research assistance, and Lynn Selhat for editorial assistance. We are grateful to Andrew Ellul and Vijay Yerramilli for sharing their data on the risk management index. We gratefully acknowledge financial support from the Wharton School and the Jacobs Levy Equity Management Center for Quantitative Financial Research. Armstrong and Nicoletti gratefully acknowledge financial support from EY and the Alfred H. Williams Faculty Scholar Award, respectively.

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