Executive Stock Options and Systemic Risk*

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Abstract

We examine whether features of bank executives' compensation contracts *cause* them to take actions that contribute to systemic risk. Using multiple return-based measures of systemic risk coupled with an identification strategy that exploits heteroskedasticity to account for endogenous matching of executives and banks, we find that bank executives' equity portfolio vega leads to greater subsequent systemic risk that manifests during economic downturns, but not during expansions. We also find that vega encourages bank executives to pursue specific activities that contribute to the accretion of systemic risk, including: (i) maintaining lower Tier 1 capital ratios, (ii) investing in commercial and industrial loans, which tend to track the business cycle, and non-agency mortgage-backed securities, which are subject to greater default and liquidity risk, and (iii) greater reliance on liabilities subject to runs (i.e., short-term deposits). Collectively, our evidence suggests that bank executives' incentive-compensation contracts promote systemic risk-taking by encouraging them to adopt lending, investment, and financing policies that are highly procyclical and contagious.

Keywords: Executive compensation; Equity incentives; Systemic risk; Business cycles

JEL Classification: E32, G21, G32, J33

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1 Introduction

Banks' role in financial intermediation and the provision of other specialized financial services not only places them at the center of many important global financial markets, but also ties their health to that of other financial institutions, industrial firms, and consumers (e.g., Bernanke and Gertler, 1995; Bernanke et al., 1999). The vast reach of banks' activities was made apparent during the financial crisis of 2007-2009, which also highlighted the acute need for a better understanding of whether, how, and the extent to which banks 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' risk-taking activities (e.g., the composition of banks' financing or 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 *cause* systemic risk-taking.

Theoretical studies suggest several ways in which bank executives' incentive-compensation contracts can encourage certain risk-taking decisions that potentially contribute to systemic risk. First, since convex contractual payoffs encourage risk-taking in general (Lambert et al., 1991; Ross, 2004), executives' equity holdings can encourage them to pursue activities that entail systemic risk. Moreover, these general risk-taking incentives are likely to be amplified in banks as a result of the highly levered nature of their capital structures. Second, theories on bank systemic risk show how banks' risky activities can exhibit strategic complementarities: an increase in one bank's risk increases the likelihood that *other banks* take similar risks, which leads to an overall increase in systemic risk (e.g., Acharya and Yorulmazer, 2008; Acharya, 2009; Farhi and Tirole, 2012; Albuquerque et al., 2019). Although these studies differ in the specific mechanisms that give rise to strategic complementarities, they are all based on the notion that banks' *executives* can draw reasonable inferences about the actions that other banks' executives will take. Compensation contracts that encourage risk-taking facilitate this inferential process, as they can serve as credible commitment mechanisms that allow bank managers to infer each other's investment, lending, financing, and other decisions that entail risk and incorporate this information into their own decisions (e.g., Fershtman and Judd, 1987; Aggarwal and Samwick, 1999).[1]

Based on this intuition, we examine whether bank executives' compensation contracts influence their banks' systemic risk by focusing on bank executives' equity portfolio (i.e., stock and option) holdings, which account 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). However, identifying the effect of vega on systemic risk is challenging because of its endogenous relation with both executive and bank characteristics that may directly relate to risk-taking activities and are difficult to control for. For example, banks may offer relatively "high-powered" (e.g., more convex or option-based) compensation contracts in order to attract executives who are better able to bear this risk and therefore are more inherently inclined to take riskier actions (Cheng et al., 2015). In this scenario, bank executives' risk-tolerance (rather than any attributes of their compensation contracts, including vega) is the cause of both their choice of compensation contract and their decisions that give rise to their banks' risk.

We address this identification challenge using the modified control function regression developed by Klein and Vella (2010). This approach exploits heteroskedasticity in the unobserved determinants of executives' compensation contracts and banks' systemic risk and constructs a variable that "controls for" the endogenous relationship between the two. Consequently, this approach differs from instrumental variables (IV) estimation, which is arguably

[1] Fershtman and Judd (1987, p.987) observe that, in general, "... whenever the profit accruing to a principal-agent pair depends on decisions that other rational agents make, the potential interactions must be considered." Since banks' profits (and bank managers' contractual payoffs) depend on other bank managers' systemic risk-taking decisions, strategic considerations are inherently important in our setting.

the most common way to address this particular type of endogeneity concern. Although modified control functions and instrumental variables are both techniques to address correlated omitted variables, they do so in fundamentally different ways: modified control functions explicitly "control for" the endogenous relation, while IV uses a valid instrument that produces exogenous variation in the endogenous variable of interest. However, there are no obvious or even plausible candidates for such a variable in our research setting, because the instrument should be exogenous to both bank and executive characteristics.

A brief illustration of the intuition behind this approach is as follows.[2] In an OLS regression of systemic risk on vega, the coefficient on vega is $\beta = \beta_0 + \rho\frac{\sigma_u}{\sigma_x}$, where β_0 is the true causal effect, ρ and $\frac{\sigma_u}{\sigma_x}$ are, respectively, the correlation and the ratio of standard deviations between the structural error and vega, and $\rho \neq 0$ is symptomatic of 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., $\frac{\sigma_u}{\sigma_x}$) is significantly different across the two regressions. To the extent that the endogeneity concern is serious (i.e., $|\rho|$ is large), then the two β coefficients should differ since the variance of the residuals differs. Thus, if the β coefficient 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' systemic risk with two complementary sets of tests. The first set of tests relies on two common, market-based measures of *realized* systemic risk: (i) marginal expected shortfall, MES (Acharya et al., 2017); and (ii) $\Delta CoVaR$ (Adrian and Brunnermeier, 2016), both measured annually for up to three years following the measurement of vega. Using a sample of commercial banks during the time period 1995 – 2016, we first document a positive

[2] We defer technical details to Section 3.2.

association between the equity portfolio vega of banks' senior (i.e., five most highly-paid) executives and their banks' one-, two-, and three-year-ahead MES and $\Delta CoVaR$ using OLS regressions. However, we find no evidence of a significant relation between vega and either MES or $\Delta CoVaR$ using modified control function regressions. Moreover, the magnitude of the coefficient estimates on vega are significantly smaller (from 52% to 91% smaller) than their OLS counterparts. These contrasting findings suggest that the positive relation between vega and systemic risk based on OLS estimates, at least in part, reflects a statistical artefact of an endogenous relation between the two. Accordingly, we rely on the modified control function approach for our subsequent analyses and inferences.

We next investigate whether there is a *differential* relation between vega and systemic risk during economic downturns relative to expansions. The intuition for this test follows from Acharya and Naqvi (2012), who show that risk-taking during expansions can take the form of excessive lending (e.g., lending to more marginal borrowers when credit is loose), which sows the seeds of a crisis. Their result suggests that the effects of risk-taking incentives on systemic risk may only manifest during economic downturns. We find that banks whose executives have one standard deviation larger vega have a 0.10, 0.13, and 0.08 percentage point higher MES one-, two-, and three-years ahead, respectively, if the economy is in expansion during those years, respectively, and a 0.33, 0.52, and 0.56 percentage point higher MES during the subsequent one, two, and three years if there is an economic downturn during those years. We find similar results using $\Delta CoVaR$. Collectively, our evidence based on these two widely used market-based measures of systemic risk suggests that bank executives' equity incentives encourage them to take actions during economic expansions that contribute to systemic risk that is only realized during economic downturns.[3]

Our second set of tests examines specific activities that potentially contribute to banks' exposure to and accretion of systemic risk. We focus on banks' capital structure as well

[3] As we explain in more detail in Section 2, 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. Although this is an inherently important distinction, providing evidence that speaks to which of these two occurs is beyond the scope of our paper.

as activities on both sides of the balance sheet using multiple proxies that are arguably better equipped to capture the *ex ante* build-up of systemic risk during economic expansions than are the common measures based on realized market returns. In addition, examining bank managers' specific decisions more directly captures their risk-taking intentions (i.e., the nature of the risk that they intended to take). This approach is less susceptible to the influence of other factors, such as disclosure, information trade, and other features of their firm's information environment, that are also captured by traditional measures of risk based on realized market returns (Roll, 1988; Ross, 1989).

We first examine whether managers' vega leads to an increase in bank leverage. Although we find no evidence of a relation between managers' vega and their banks' equity-to-asset ratios, we document a negative relation between vega and banks' Tier 1 risk-adjusted capital ratios. These findings suggest that, although vega does not lead managers to alter their banks' overall capital structure, it does encourage activities that increase the riskiness of their bank's assets. These activities increase the risk of financial difficulty during economic downturns when borrowers tend to have higher default rates and the resulting unexpected loan losses have an adverse effect on banks' capital ratios. Collectively, these findings are consistent with vega leading to actions that can potentially increase systemic risk. They also illustrate the importance of identifying the specific activities encouraged by bank managers' compensation contracts and vega in particular. In other words, since changes in systemic risk may not be discernible from leverage alone, examining whether vega causes managers to shift towards activities that entail greater systemic risk provides a more complete and comprehensive picture.

Although bank managers can increase *bank-level* risk through different activities, we are interested in whether they engage in activities that have the potential to contribute to *systemic* risk. Therefore, we next examine specific investments on the asset side of the balance sheet that can amplify both the magnitude of and correlation among banks' losses during economic downturns, namely commercial and industrial lending (C&I) and non-agency mortgage-backed securities (MBSNA). Prior studies argue and find evidence that banks collectively increase their C&I lending during economic expansions (Berger and Udell, 2004; Becker and Ivashina, 2014), that C&I losses are more sensitive to the business cycle (Caouette et al., 2011; Bhat et al., 2019), and that C&I loans experience higher loss rates (DeYoung et al., 2013). MBSNA are not guaranteed by a government agency or government sponsored enterprise (e.g., Ginnie Mae and Freddie Mac) and therefore have greater default risk. Longstaff (2010) shows that these types of assets contribute to contagion during economic downturns due to liquidity and risk-premium concerns. Consistent with our expectations, we find that vega leads bank managers to hold a greater proportion of C&I loans and MBSNA in their loan and investment portfolios, respectively.

Finally, we turn to the liability side of the balance sheet and examine financing activities that can increase the risk of contagious bank defaults due to information and illiquidity spillovers. Greater risk-taking can increase the rate of bank failure and lead depositors to withdraw their funds from other banks (e.g., Chen, 1999; Acharya and Yorulmazer, 2008; Diamond and Rajan, 2011; Allen et al., 2012). The effects of this withdrawal of funding can be further exacerbated if banks hold short-term debt, which is more susceptible to liquidity shocks and prone to "runs" during economic downturns (e.g., Diamond and Rajan, 2011; Allen et al., 2012), and ultimately lead to greater systemic risk. Consistent with these arguments, we find that vega leads to a greater reliance on short-term deposits. Collectively, our findings provide evidence that vega encourages managers to make lending, investment, and financing decisions that likely entail greater systemic risk as evidenced by their greater degree of procyclicality and susceptibility to spreading contagion during economic downturns.

Our paper makes several contributions that span multiple literatures. First, we contribute to the literature on systemic risk by providing new evidence about whether and how bank managers' incentive-compensation contracts contribute to systemic risk. Although prior research identifies certain bank characteristics that are associated with systemic risk, the contractual incentives of the agents whose decisions are ultimately responsible for those characteristics have received considerably less attention as a potential cause of systemic risk.[4] We document *causal* evidence that bank managers' equity portfolio vega leads to an increase in systemic risk that primarily manifests during economic downturns. We also find that vega encourages managers to make specific lending, investment, and financing decisions that are more procyclical and contagious and therefore likely entail greater systemic risk. These findings collectively corroborate not only traditional theories of systemic risk that relate to the structure of banks' liabilities (e.g. Rochet and Tirole, 1996; Kiyotaki and Moore, 1997; Freixas and Parigi, 1998; Allen and Gale, 2000), but also more recent theory (Acharya, 2009) that shows how systemic risk can also arise on the asset side of banks' balance sheets. Our findings are also consistent with theories that show how managers' compensation contracts can serve an additional role in strategic settings by signaling the actions that they are designed to encourage and that managers are likely to take. Thus, managers' compensation contracts can facilitate coordination of their individual decisions, which is particularly relevant for understanding *systemic* risk since it is an inherently collective phenomenon.

Second, our paper extends the literature that examines the effect of bank managers' incentives on their risk-taking activities. Prior studies on the role of 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, 2017). These studies document mixed evidence and do not explicitly test for a link between managers' contractual incentives and either systemic risk in general or specific banking activities that potentially entail greater systemic risk. We advance this literature by offering consistent evidence that bank managers' equity portfolio vega encourages them to pursue various activities that have the potential to contribute to the build up of systemic risk. Moreover,

[4] For example, prior research examines characteristics such as bank size, reliance on non-interest income, interbank exposures, and lending concentrations (e.g., Beck and De Jonghe, 2013; Drehmann and Tarashev, 2013; Laeven et al., 2016; Brunnermeier et al., 2019). Iqbal and Vähämaa (2019) document a *negative* association between vega and systemic risk during the 2005–2010 period. However, their results are perhaps a reflection of the endogenous matching of banks and executives.

our inferences are based on evidence from a novel identification approach that allows us to isolate the extent to which bank executives' contractual incentives *cause* them to take risk as opposed to simply reflecting the endogenous matching of banks and their executives, which may at least partially explain the mixed findings in the literature. This is an important distinction, because regulations that target banks' compensation practices assume that managers' compensation contracts have a *causal* effect on their banks' risk.

Finally, our results have implications for bank regulators. Executives' compensation contracts, which are widely thought to be a first-order determinant of their risk-taking decisions and, in turn, their bank's risk, have received tremendous attention–as well as scrutiny–from regulators, legislators, and other stakeholders. For example, one of the centerpieces of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Section 956) requires bank regulators to draft regulations that restrict executive compensation practices that encourage excessive risk-taking. Our evidence that contractual incentives can induce systemic risk suggests that regulation at the microprudential level can, at least partially, influence macroprudential (i.e., systemic) risk. Thus, although controlling systemic risk is not the goal of microprudential regulation *per se* (Allen and Gu, 2018), we show that it can be a side effect of regulating 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 firm 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 precluded 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 not only increase the sensitivity of the executive's wealth to firm risk, or vega, but also increase the sensitivity of her wealth to changes in stock price, or delta. And 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. However, we also consider delta in our analyses, but remain agnostic about the direction of its relation, if any, with risk. We also 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.

2.2 Empirical predictions

Theoretical models suggest that risky activities at banks can result in systemic risk through two non-exclusive 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 posit that one bank's risky activities can encourage other banks to take similar (i.e., correlated) activities, thereby giving rise to several types of strategic complementarities in risk-taking. First, as Acharya (2009) shows, banks' incentives to avoid negative externalities that result from other banks' failure 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.[5] However, correlated investments also increase the likelihood of collective failure, which banks' shareholders – including their managers– do not fully internalize given 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 short-term debt as a source of financing), other banks are encouraged to follow suit, anticipating a regulatory bail out of all banks that fail in the event of a financial crisis. The expectation of a bailout reduces the *ex ante* cost of risk-raking, thereby encouraging all banks' executives to take more risk.[6]

Theories related to the second systemic risk channel highlight several features that can make bank distress and failure especially contagious. First, connections in the banking network (e.g., transaction processing and inter-bank lending) can transmit adverse shocks across the 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. Moreover, banks' inherent opacity can exacerbate valuation difficulties. Third, contagion can arise from maturity mismatch. For example, Allen et al. (2012) show that when banks' assets overlap through common portfolio

[5] In the Acharya (2009) model, correlated investments increase the joint likelihood of survival, due to the distributional assumptions on bank cash flows.

[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.

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 several reasons. First, vega provides incentives to take any type of risk in general, and could conceivably encourage managers to pursue systemically risky activities, namely activities that exhibit strategic complementarity and are contagious, because these activities typically have higher risks and produce higher expected returns for banks.

Second, although the aforementioned studies differ in the specific mechanism that gives rise to strategic complementarities in banks' risky activities, they are all premised on the notion that banks – or, more specifically, banks' *executives*– can draw reasonable inferences about the actions that other banks' executives will take. We argue that compensation contracts that encourage risk-taking facilitate this inferential process. This idea follows from prior research that shows how executives' incentive-compensation contracts can also serve as a commitment mechanism that facilitates coordination of their decisions in strategic settings (e.g., Fershtman and Judd, 1987; Aggarwal and Samwick, 1999). 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.[7] In our setting, by serving

[7] 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' eq-

as a credible and visible commitment mechanism, bank managers' compensation contracts allow them to infer the risky activities that other managers are encouraged to take and incorporate these expectations when formulating their own risk-taking decisions, which can reinforce strategic complementarities in their activities. We hasten to note that strategic complementarities can take several forms that we do not attempt to disentangle empirically: (i) individual banks' actions induce other banks to follow, (ii) individual banks follow other banks' risk-taking activities, (iii) banks collectively coordinate on public signals (e.g., asset returns) and take risks.

Collectively, we argue that vega can encourage bank managers to engage in risky activities that contribute to systemic risk. The foregoing theories and arguments point to multiple channels through which bank managers' risk-taking activities can manifest as systemic risk. Accordingly, we develop multiple complementary empirical tests that are designed to capture the collective effects of these channels (i.e., strategic complementarities or contagious activities).

3 Variable Measurements and Research Design

3.1 Dependent Variable Measurements

3.1.1 Systemic Risk Measures

Our first set of tests relies on two commonly-used measures of systemic risk: (i) marginal expected shortfall, and (ii) conditional value at risk, or $\Delta CoVaR$. 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&P 500's 5% worst days during year t, multiplied by negative one so that larger values of MES correspond to greater systemic risk.

uity 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.

$\Delta CoVaR$ 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:

$$Ret_{i,t} = \alpha_i^q + \gamma_i^q M_{t-1} + \epsilon_{i,t}^q \quad (1)$$

$$Ret_{sys,t} = \alpha_{sys|i}^q + \gamma_{sys|i}^q M_{t-1} + \beta_{sys|i}^q Ret_{i,t} + \epsilon_{sys|i,t}^q, \quad (2)$$

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 ten-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 Equation (1) and Equation (2), we construct both VaR

and $CoVaR$ as follows:

$$VaR^q_{i,t} = \hat{\alpha}^q_i + \hat{\gamma}^q_i M_{t-1} \tag{3}$$

$$CoVaR^q_{i,t} = (VaR^q_{sys,t} | Ret_{i,t} = VaR^q_{i,t}) = \hat{\alpha}^q_{sys|i} + \hat{\gamma}^q_{sys|i} M_{t-1} + \hat{\beta}^q_{sys|i} VaR^q_{i,t} \tag{4}$$

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

$$\Delta CoVaR^{1\%}_{i,t} = \hat{\beta}^{1\%}_{sys|i}(VaR^{1\%}_{i,t} - VaR^{50\%}_{i,t}) \tag{5}$$

Since $\Delta CoVaR^{1\%}_{i,t}$ 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 the measure by negative one so that larger values correspond to greater systemic risk.[8]

Although these are arguably the most common measures of systemic risk, they present several potential limitations for purposes of studying the effects of bank executives' contractual incentives. First, because these measures are based on *ex post* realized returns, they are also influenced by a variety of factors (e.g., disclosure, informed trading, sentiment, and other features of their firm's information environment) that do not necessarily reflect bank managers' risk-taking decisions. Second, extreme negative outcomes for the banking system (i.e., the left tail) occur infrequently, if ever, during economic expansions. Consequently, measures of systemic risk based on realized returns may be "too coarse" to detect a relation between bank managers' contractual incentives and systemic risk if any extreme negative outcomes of their risk-taking decisions manifest with a (potentially long) lag or primarily during economic downturns. In light of these and other potential concerns, we also examine

[8] 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, correlated investments such as similar lending exposures). However, we hasten to add that 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.

whether any effect of vega on systemic risk varies over the business cycle in Section 5.1.2.

3.1.2 Bank activity measures

Our second set of analyses complements our previous tests by focusing on specific activities that contribute to the build-up of systemic risk during economic expansions. Examining these measures allows us to more directly isolate managers' *ex ante* risk-taking decisions rather than rely exclusively on empirical measures based on *ex post* realized negative outcomes, which as discussed in the previous section, may occur too infrequently or with too long of a lag to detect any effect of vega on systemic risk.

We first examine two capital measures. The first is the ratio of total equity to total assets ($Capital$). The second is the Tier 1 risk-based capital ratio ($Tier1$), which explicitly considers the riskiness of bank assets, defined as the ratio of Tier 1 capital to risk-weighted total assets. Although lower capital ratios do not necessarily lead to greater systemic risk *per se*, changes in the ratio–from either a reduction in the amount of capital or an increase in the riskiness of assets–are symptomatic of a bank's risk-taking activities that can potentially become systemic, particularly when banks take correlated risks (Acharya, 2009).

We next focus on specific activities on both the asset and liability side of the balance sheet that are likely to contribute to systemic risk. In particular, we examine activities that increase the magnitude and correlation of banks' losses during economic downturns or that lead to a greater risk of contagious bank defaults (e.g., due to information and illiquidity spillovers). On the asset side of the balance sheet, 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 documents 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 generally result in higher realized loss rates compared to other types of loans (e.g., mortgages) and accordingly, are generally considered to be riskier (DeYoung et al., 2013).

We also examine investments in non-agency mortgage-backed securities (MBSNA). Non-agency mortgage-backed securities are those that are not guaranteed by a government agency or government sponsored enterprise (i.e., Ginnie Mae, Frannie Mae, and Freddie Mac) and were thought to contribute to the most recent financial crisis. Moreover, Longstaff (2010) shows that subprime mortgage-related securities contributed to contagion during the 2007-2009 financial crisis by decreasing market liquidity and increasing risk premiums across markets. We define $MBSNA$ as the proportion of non-agency mortgage-backed securities in a bank's total available-for-sale investment portfolio.

Finally, banks are also exposed to contagion on the liability 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.

3.2 Model Specification

We are interested in understanding whether vega encourages bank executives to pursue activities that contribute to (the build-up of) systemic risk. We estimate the following specification:

$$Risk_{i,t+s} = \delta_t + \beta_1 Vega_{i,t-1} + \beta_2 Delta_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 BTM_{i,t-1} + \epsilon. \tag{6}$$

$Risk_{i,t+s}$ 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. 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 specific bank activities they are designed to encourage.

We focus on risk-taking incentives from bank executives' equity (i.e., stock and option) portfolios. The primary independent variable of interest is $Vega$ because, as explained previously, it provides a theoretically unambiguous source of risk-taking incentives. $Vega_{i,t-1}$ and $Delta_{i,t-1}$ are the portfolio vega and delta of the five highest-paid executives of bank i in year $t-1$.[10] Portfolio vega is the change in the risk-neutral (i.e., Black-Scholes) value of the executive's option portfolios for a 0.01 change in the standard deviation of the underlying stock returns. Similarly, portfolio delta is the change in the risk-neutral value of the executive's stock and option portfolios for a one percent change in the underlying stock price. Following prior studies (e.g., Armstrong and Vashishtha, 2012; DeYoung et al., 2013), we use the natural logarithm of both vega and delta in our analyses.[11]

We include control variables that are likely to be correlated with both executives' equity

[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] We note that compensation practices of the five highest-paid executives likely capture the bank's general risk-taking appetite and as such, have implications for the risk-taking of employees who are more directly involved in their bank's risky activities (e.g., lending).

[11] 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 twelve 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).

incentives and their firms' risk based on prior literature. Specifically, larger banks are likely to have different risk profiles and therefore may provide their executives with different risk-taking incentives, so we control for bank size using the natural logarithm of total assets ($Size$). To capture differences in banks' investment opportunities, we include the book-to-market ratio (BTM). Finally, we include year fixed effects to control for secular changes in risk that are common to all banks (e.g., economic conditions across the business cycle).[12]

One potential concern with Model (6) 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. For example, a bank that has a relatively riskier loan portfolio might offer compensation contracts with greater risk-taking incentives to attract a certain type of (e.g., more risk-tolerant) executive. In this case, a positive relation between executives' vega and their bank's risk would not represent a causal effect, which we are interested in isolating, but rather would result from a spurious relation due to executives' correlated omitted risk-tolerance. In other words, holding the executive-bank match fixed, changing bank executives' vega would not result in changes in their risk-taking behavior.

This form of endogenous selection is particularly problematic due to its two-sided nature: both unobserved executive and bank characteristics can affect banks' risk. 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 may not be a valid instrument if executives endogenously select into (i.e., match with) banks that are either less exposed to the shock or take actions in response to the shock (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 un-

[12]We do not add control variables that could be the outcomes of greater risk-taking incentives. For example, we do not control for investments in non-agency mortgage backed securities, which we view as a type of activity that potentially contributes to systemic risk. Controlling for outcome variables biases OLS coefficient estimates (Angrist and Pischke, 2008). Further, we use modified control function regressions, described in section 3.3, to address potential endogeneity concerns.

likely 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 matching. The next section describes the details of this technique.

3.3 Modified Control Function Regression

3.3.1 Identification

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 results in 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 of addressing endogeneity concerns. First, it does not rely on the conditional independence assumption 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). Second, it does not depend on a valid exclusion restriction that 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.

The modified control function regression starts with a typical two-stage regression specification. Recall that $Vega_{it}$ represents the equity portfolio vega of the bank's senior (i.e., five highest-paid) executives, and $Risk_{it+s}$ represents the risk of bank i in year $t+s$. $Vega_{it}$

and $Risk_{it+s}$ are specified by the following first- and second-stage models:

$$Vega_{it-1} = \alpha X_{it-1} + \xi_{it-1} \tag{7}$$

$$Risk_{it+s} = \beta_1 Vega_{it-1} + \Gamma' X_{it-1} + \eta_{it+s} \tag{8}$$

where β_1 is an estimate of the causal effect of $Vega$ on bank risk, X_{it} represents the same vector of observable characteristics as in (6) including intercepts, and ξ_{it-1} and η_{it+s} are unobserved factors that affect $Vega_{it-1}$ and Risk_{it+s}, respectively.[13]

If η_{it+s} is correlated with ξ_{it-1}, the coefficient estimates from an OLS regression of $Risk$ on $Vega$ will be biased. Denoting the correlation coefficient between η_{it+s} and ξ_{it} as ρ, the modified control function regression approach decomposes the error term η_{it+s} as follows:

$$\eta_{it+s} = \rho \frac{\sigma_\eta}{\sigma_\xi} \xi_{it-1} + \omega_{it+s} \tag{9}$$

where $\rho = \dfrac{cov(\eta_{it+s}, \xi_{it-1})}{var(\xi_{it-1})}$. The decomposition is achieved by projecting (i.e., regressing) η_{it+s} on ξ_{it-1} and, importantly, does *not* assume that η_{it+s} and ξ_{it-1} follow a joint normal distribution. By construction, ω_{it+s} is uncorrelated with $Vega_{it-1}$ conditional on X_{it-1}. Substituting (9) into the risk-taking equation (8) illustrates how the identification strategy works:

$$Risk_{it+s} = \beta_1 Vega_{it-1} + \Gamma' X_{it-1} + \eta_{it+s} \tag{10}$$

$$= \beta_1 Vega_{it-1} + \Gamma' X_{it-1} + \rho \frac{\sigma_\eta}{\sigma_\xi} (Vega_{it-1} - \alpha X_{it-1}) + \omega_{it+s} \tag{11}$$

In equation (11), the new error term, ω_{it}, is uncorrelated with $Vega_{it-1}$ conditional on X_{it-1}.

[13] We do not require that the coefficient estimates on X_{it-1} (i.e., Γ) have causal interpretations. The error terms in equations (7) and (8) can be interpreted as the true structural error terms that are orthogonalized with respect to X. Thus, by construction, $\text{E}(\epsilon_{it-1}|X) = 0$ and $\text{E}(\eta_{it+s}|X) = 0$. In other words, we only focus on one endogenous variable, namely $Vega$, and avoid the complexity of modeling a system of endogenous relations, which may have unknown effects on the properties of the modified control function estimator.

When the standard deviation ratio, $\frac{\sigma_\eta}{\sigma_\xi}$, is a constant, β_1 is not identified because the term $Vega_{it} - \alpha X_{it-1}$ is collinear with the regressors $Vega_{it}$ and X_{it-1}. However, when $\frac{\sigma_{\eta,it}}{\sigma_{\xi,it}}$ varies across observations (i.e., i, t, or both) and its interaction with ξ_{it} is not collinear with $Vega_{it-1}$, variation in $\frac{\sigma_{\eta,it}}{\sigma_{\xi,it}}(Vega_{it} - \alpha X_{it-1})$ can identify both ρ and β_1.

The intuition behind modified control function regressions can be illustrated with the following example.[14] Consider two banking markets, denoted A and B, that each consist of multiple banks. For illustrative purposes, we assume homoskedasticity of η_{it+s} (i.e., the variance of η_{it+s} is the same for banks in both markets) and focus on how the differences in the variance of ξ_{it-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 with each other, or differences in how banks operate in these two markets. Estimating two separate OLS regressions using observations in market A and market B provides two separate coefficient estimates for $Vega$, labeled $\hat{\beta}^A = \beta_1 + \rho\frac{\sigma_\eta}{\sigma_{\xi,A}}$ and $\hat{\beta}^B = \beta_1 + \rho\frac{\sigma_\eta}{\sigma_{\xi,B}}$, 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 $\rho\sigma_\eta\left(\frac{1}{\sigma_{\xi,A}} - \frac{1}{\sigma_{\xi,B}}\right)$, 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.

Two points are worth noting. First, the modified control function method achieves identification by estimating a constant causal effect and a single correlation coefficient between the structural error terms in the two equations. Although these assumptions are implicit in the research designs of most prior studies that use either OLS or IV estimation, assuming a single common correlation coefficient is not necessarily innocuous and imposes structure

[14] 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.

on the nature of the endogenous relationship between the treatment and the outcome of interest. If there is reason to suspect that ρ varies systematically with certain observables, the researcher has to specify *a priori* how ρ varies, which is also required by alternative econometric methods, including OLS. The intuition is similar to that for 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, it is difficult to develop accurate assumptions about how ρ varies in the cross-section. For the same reason, we do not draw inferences regarding the sign of ρ. As ρ captures the correlation between *unobservable* factors that drive risk-taking activities and vega, testing hypotheses regarding the sign of ρ requires researchers to specify how ρ varies in the cross-section which, by definition, is unknown. In other words, the modified control function approach is useful precisely when the researcher lacks detailed, *a priori* knowledge about the unobserved factors.

Second, the modified control function approach is not always a viable way to address endogeneity concerns, nor should it be viewed as a replacement for instrumental variables. However, we believe that this method can be useful in settings, such as ours, in which it is difficult to find a valid instrument due to two-sided endogenous matching.

3.3.2 Implementation

As illustrated in the previous section, identification of the causal effect relies on variation in the standard deviation ratio, $\frac{\sigma_\eta}{\sigma_\xi}$. 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:

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

where m denotes a market.[15]

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 ratios, 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 $\frac{\sigma_\eta}{\sigma_\xi}$ potentially varies across geographic markets and time. We provide evidence that supports our assumption that the standard deviation ratios do, in fact, vary across markets in Section 5.1.1. It is also important to reiterate that the modified control function regression does not require the determinants of the variance ratios to be exogenous. As our example illustrated, the only requirement is that the variance ratios *differ* in the cross-section, and this can occur for reasons that are either endogenous or exogenous with respect to the model.

Estimating the variance of ξ and η in each market presents a practical issue. More observations in a market allow for more accurate variance estimates, but leave fewer variances to identify ρ. Consequently, standard errors can be large, which biases against finding significant coefficients. As such, when illustrating the method, we perform statistical tests across the OLS and modified control function regressions to assess the power of our tests. We also estimate bootstrapped standard errors to address the concern that statistical significance may be an artifact of influential observations. Another issue is that the coefficient estimates from the second-stage model require estimating the residual η, which in turn, depends on the coefficient estimates. We use an iterative approach to overcome this inherent circularity. Specifically, for each iteration, we first obtain the estimated residuals based on the coefficient

[15] Klein and Vella (2010) use a more flexible semi-parametric approach that assumes that $\frac{\sigma_\eta}{\sigma_\xi}$ depends on the vector of control variables.

estimates from the previous iteration, and update the coefficient estimates using the new residuals. We repeat this procedure until convergence is achieved.[16]

4 Sample Selection and Descriptive Statistics

4.1 Sample Selection and Data

Our sample is comprised of observations with required data at the intersection of Compustat, CRSP, Execucomp, and FR Y-9C regulatory reports during the period 1995 - 2016. We use Execucomp data to calculate the contractual incentive measures, $Vega$ and $Delta$, and Compustat and CRSP data to measure the control variables ($Size$ and BTM).

For the systemic risk measures, 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] Our tests that examine specific bank activities require more detailed loan, investment, and deposit variables, which we gather from the FR Y-9C regulatory reports. Given that we use one-, two-, and three-year ahead measures of systemic risk, our final sample period in our analyses is 1995 - 2013 and includes 1,270 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 and specific bank activity measures. The table shows that the average loss on the worst 5% days for the S&P 500 during the year is 2.99% (MES), while the mean of $\Delta CoVaR^{1\%}$ is 3.9%. The average Tier 1 capital ratio is 11.6%

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

[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.

and the average unadjusted capital ratio is 9.4%, suggesting that the banks in our sample are, on average, well capitalized during our sample period.[18] Moreover, approximately 6% of banks' investment portfolios are comprised of $MBSNA$, on average, while close to 69% of bank deposits are shorter-term (non-time deposits). Finally, approximately 21% of banks' loan portfolios are comprised of $CommLoans$.

[Insert Table 1]

The second 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 $290,065 increase in the average risk-neutral value of bank executives' option portfolio. Similarly, a 1% increase in stock price increases the option portfolio value by $965,350 on average (*delta*).[19] The final panel presents descriptive statistics for the bank characteristics. The average book-to-market ratio is 66.3% and the mean (median) of total assets is $74 billion ($12 billion) (untabulated).

5 Results

5.1 Vega and Systemic Risk

5.1.1 OLS and Modified Control Function Estimation

We begin by examining the relation between vega and the two measures of systemic risk: MES and $\Delta CoVaR^{1\%}$. Figure 1 illustrates the relation between vega and systemic risk for the full sample. We rank banks into deciles according to their executives' vega and plot the average MES (left y-axis) and $\Delta CoVaR^{1\%}$ (right y-axis) for each decile. To allow for a potential lag in the relation, systemic risk is measured one year after vega. The figure shows

[18] For example, U.S. banks are required to maintain a minimum Tier 1 capital ratio of 6%.

[19] The values of *vega* and *delta* are larger relative to prior studies (e.g., DeYoung et al., 2013) given that we examine the collective risk-taking incentives of the top five executives rather than only the CEO.

a positive relation between vega and MES. The same pattern exists using $\Delta CoVaR^{1\%}$ to measure systemic risk.

[Insert Figure 1]

Table 2 presents OLS estimates of the relation between vega and systemic risk. 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 similar 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.

Across all six columns, we document a positive and significant coefficient on vega. In terms of economic significance, using the one-year-ahead systemic risk measures in columns (1) and (4), a one-standard deviation increase in vega (1.800) is associated with an increase in systemic risk of 0.18% (0.098%*1.8) for MES and 0.30% (0.165%*1.8) for $\Delta CoVaR^{1\%}$. This corresponds to approximately 8% and 16.9% of the sample standard deviation of MES and $\Delta CoVaR^{1\%}$, respectively. The magnitudes are relatively similar for systemic risk measured over other horizons. Although the OLS estimates provide evidence of a positive relation between bank executives' vega and their banks' systemic risk, our next set of tests examines whether the endogenous matching of executives and banks explains some, if not all, of this relation.

[Insert Table 2]

In Table 3, we present estimates from the modified control function regressions that examine whether bank executives' vega has an effect on systemic risk. Once again, columns (1)-(3) provide estimates using MES as the dependent variable and columns (4)-(6) present results using $\Delta CoVaR^{1\%}$ as the dependent variable using different horizons of systemic risk. We again present 90% confidence intervals below the coefficient estimates based on 200 bootstrapped samples.

[Insert Table 3]

Across all six columns, we find no evidence that the coefficient on vega is statistically distinguishable from zero at the 10% level. Moreover, the economic magnitude of the coefficient on vega from the modified control function approach is smaller than its OLS counterpart. For the one-year-ahead measures, a one standard deviation increase in vega (1.800) is associated with an increase in systemic risk of 0.06% for MES and 0.14% for $\Delta CoVaR^{1\%}$. These estimates correspond to approximately 2.8% and 8.1% of the respective standard deviations of MES and $\Delta CoVaR^{1\%}$.

As discussed in section 3.3, the modified control function regression includes the ratio of the standard deviations of the first- and second-stage residuals interacted with the first-stage residuals as an additional regressor. The regression coefficient on this interaction equals the correlation coefficient between the two residuals. In theory, the correlation coefficient is identified as long as there is variation in the standard deviation ratio (i.e., the variance is not zero). However, in practice, as with any regression, sufficient variation in a regressor is crucial for a high-powered test. Thus, one potential concern is that the modified control function approach might have low power in our research setting, which could yield attenuated estimates of the correlation coefficient ρ and the effect of vega on systemic risk, namely β_1.

[Insert Figure 2]

To investigate this potential concern, Figure 2 displays the kernel density of the standard deviation ratios across markets (i.e., OCC region-years). The left panel reports one-year-ahead MES (i.e., column (1) of Table 3), and the right panel reports $\Delta CoVaR^{1\%}$ (i.e., column (4) of Table 3). Both plots indicate large variation in the ratios across markets.[20] In further untabulated analyses, we confirm that the coefficient estimates from the OLS regressions are significantly larger than their counterparts from the modified control function

[20] We do not interpret the magnitude of the ratio as it has no economic meaning. To save space, we do not present plots of standard deviation ratios based on other columns, but note that they also exhibit significant variation across markets.

regressions at the 1% level.[21] These two pieces of evidence suggest that the different results across the OLS and modified control function regressions cannot be attributed 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 an endogenous relation and, consequently, likely overstates the economic magnitude of its true causal effect. In light of this evidence that suggests that endogeneity is a valid concern in our research setting, we use the modified control function approach for our remaining analyses.

5.1.2 Boom vs. Bust

Our next set of tests examines 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 downturns. 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 a financial crisis.[22] Their model implies that negative outcomes–including financial distress–from risk-taking are more likely to manifest during economic downturns. 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 measured during economic contractions.

[Insert Figure 3]

[21] 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.

[22] 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. They also explain how lending booms increase the likelihood of a banking crisis, which is consistent with the eventual realization of negative outcomes stemming from actions taken during the preceding boom (e.g., increased lending to lower quality borrowers). Ruckes (2004) shows that competition can influence lending standards, leading to more risk-taking during economic expansions when credit standards are lower.

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 further exacerbate systemic risk during economic downturns. We identify economic downturns as occurring during the years 2001, 2008, or 2009 and construct an indicator, $Bust$, that equals one if systemic risk is measured during any of these years and zero otherwise.[23] The dashed blue line presents the relation between vega and one-year ahead systemic risk measured during economic expansions, while the solid red 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.[24]

[Insert Table 4]

Table 4 presents results from estimating the modified control function regression 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 coefficient on vega to differ with $Bust$.[25] We again present 90% confidence intervals beneath coefficient estimates based on 200 bootstrapped samples. Table 4 provides consistent evidence of a positive coefficient on the interaction $log(vega) * Bust$ in all six specifications, all of which are statistically significant at the 10% level. Collectively, these results suggest that bank executives' equity

[23] We define downturn years as those with at least 6 months out of the year classified as a contraction by the NBER.

[24] Moving from the lowest to the highest decile of vega, MES ($\Delta CoVaR^{1\%}$) increases monotonically during economic expansions from 2.2% to 2.6% (from 2.9% to 4.9%). There is a much larger increase–both in absolute and relative magnitude–in MES ($\Delta CoVaR^{1\%}$) during economic contractions, from 5.8% to 7.4% (from 4.5% to 8.2%).

[25] As long as the endogenous relation can be characterized as $\eta_{it+s} = \rho \frac{\sigma_\eta}{\sigma_\xi} \xi_{it-1} + \omega_{it+s}$, no further adjustments to the regression model are needed. In theory, we can also allow ρ to vary with $Bust$. Although this would arguably result in a more flexible specification, as discussed in Section 3.3, 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 twelve markets for the bust periods (i.e., four regions times three years), preventing us from drawing meaningful inferences. Thus, we do not interact ρ with $Bust$.

portfolio vega leads to greater systemic risk at their banks, which largely manifests during economic downturns.

In terms of economic magnitude, a one standard deviation increase in vega (1.800) corresponds to an increase in MES ($\Delta CoVaR^{1\%}$) of 0.10, 0.13, and 0.08 percentage points (0.18, 0.11, and 0.13 percentage points) if the economy is expanding one-, two-, or three-years ahead. In contrast, based on the coefficients on the interaction term, a one standard deviation increase in vega corresponds to an *additional* 0.33, 0.52, and 0.56 percentage points (0.44, 0.53, and 0.64 percentage points) increase in MES ($\Delta CoVaR^{1\%}$) if the economy is in contraction one-, two-, or three-years ahead.

Overall, the evidence from Figure 3 and Table 4 is consistent with the theoretical prediction that systemic risk accumulates during economic expansions and subsequently manifests during economic downturns (Acharya and Naqvi, 2012). In the next section, we develop a series of supplemental tests to shed additional light on this phenomenon by investigating the relation between vega and specific bank activities that have the most potential to contribute to the build-up of systemic risk.

5.2 Vega and Specific Bank Activities

5.2.1 Leverage and Risk-Adjusted Capital Ratio

We first examine whether bank executives' vega influences their capital structure decisions and, in particular, encourages them to choose greater leverage (or lower capital ratios) measured as either $Capital$ or $Tier1$. The results are presented in Table 5. Column (1) provides no evidence of a negative relation between bank executives' vega and their banks' total equity-to-asset ratios. Although the coefficient estimate on vega is negative, it is not statistically significant at the 10% level. Column (2) shows that vega exhibits a statistically significant negative relation with Tier 1 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. Specifically, since riskier assets receive a higher risk-weight in the denominator of the Tier 1 capital ratio, our evidence suggests that vega causes managers to increase the riskiness of their bank's assets without a commensurate increase in capital.[26] Our estimates imply that a one-standard deviation increase in bank executives' vega leads to a 0.68 percentage point decline in their bank's Tier 1 capital ratio, which corresponds to 22.5% of the variable's sample standard deviation. Overall, our findings in Table 5 provide evidence that vega encourages bank executives to increase the riskiness of their bank's assets leading to a decrease in the risk-adjusted capital ratio, but not necessarily the amount of leverage (i.e., the total equity-to-assets ratio). Further, these findings suggest that examining the specific activities encouraged by vega is important given that changes in overall leverage do not account for the nature of the underlying activities.

[Insert Table 5]

5.2.2 Procylical and contagious activities

Our final set of tests examines whether vega encourages bank executives to invest in certain types of assets or rely on certain types of financing that have the most potential to contribute to systemic risk. We first examine the relation between vega and C&I loans ($CommLoans$). The results are presented in column (1) of Table 6 and show that bank executives' vega has a significant positive relation with their bank's C&I lending, measured as the proportion of C&I loans to total loans. Our estimates imply that a one standard deviation increase in vega leads to a 3.6 percentage point increase in a bank's proportion of $CommLoans$.

[Insert Table 6]

We next examine $MBSNA$ and present the results in Table 6. Column (2) reports a positive and significant coefficient on vega, consistent with bank executives' vega encouraging

[26] Although most banks are consistently well above the threshold to be considered "well-capitalized", banks generally have internal capital ratio targets that exceed–and are therefore more stringent than–the regulatory thresholds (Berger et al., 2008).

them to make greater investments (as a proportion of their bank's investment portfolio) in MBSNA.Our estimates imply that a one standard deviation increase in vega leads to a three percentage point increase in the proportion of MBSNA in their bank's investment portfolio. On the liability side, we examine $STdep$ and present the results in column (3) of Table 6. 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 4.4 percentage point increase in $STdep$ as a source of financing.

Collectively, our results from examining several specific bank activities provide consistent evidence that bank executives' equity risk-taking incentives encourage them to adopt lending, investment, and financing policies that are highly procyclical and more susceptible to spreading contagion during economic downturns.[27] As discussed in Section 3.1.2, these particular activities put banks at a greater risk of distress during economic downturns and, consequently, potentially amplify banks' systemic risk.

6 Conclusion

Our paper provides evidence on whether bank executives' contractual incentives *cause* systemic risk using a novel approach developed by Klein and Vella (2010). We find that bank executives' portfolio vega *causes* systemic risk that manifests only during economic downturns. We also document that vega motivates bank managers to take actions that contribute to the build-up of systemic risk, including lower Tier 1 capital ratios, greater investment in commercial and industrial (C&I) lending and non-agency mortgage-backed securities, and more reliance on short-term deposits. Collectively, our results suggest that vega *causes* managers to take actions during economic expansions that result in greater systemic risk during

[27] In untabulated analyses, we find that all of our inferences based on the results reported in this section are qualitatively similar if we limit our sample to the "boom" periods of economic expansion. This provides further evidence that vega encourages certain activities during "boom" periods that do not manifest in *ex post* systemic risk measures until the subsequent "bust" that occurs during an economic downturn.

economic downturns.

We contribute to the systemic risk literature by documenting that features of managerial compensation contracts influence systemic risk. Prior research has primarily focused on the effects of specific risk-taking activities on systemic risk, rather than the underlying contractual incentives that give rise to these actions. We also provide insight into activities on both the asset and liability side of the balance sheet, which links together two streams of theoretical studies regarding systemic risk. Our findings also contribute to the literature on the effects of contractual incentives on bank risk-taking. Prior literature focuses on more general risk measures (e.g., systematic risk or idiosyncratic risk) and provides mixed evidence regarding the associations. We complement these studies by focusing on systemic risk, which is an important and unique risk for the banking industry, and by using a novel identification technique that accounts for endogenous matching between executives and banks.

These 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.

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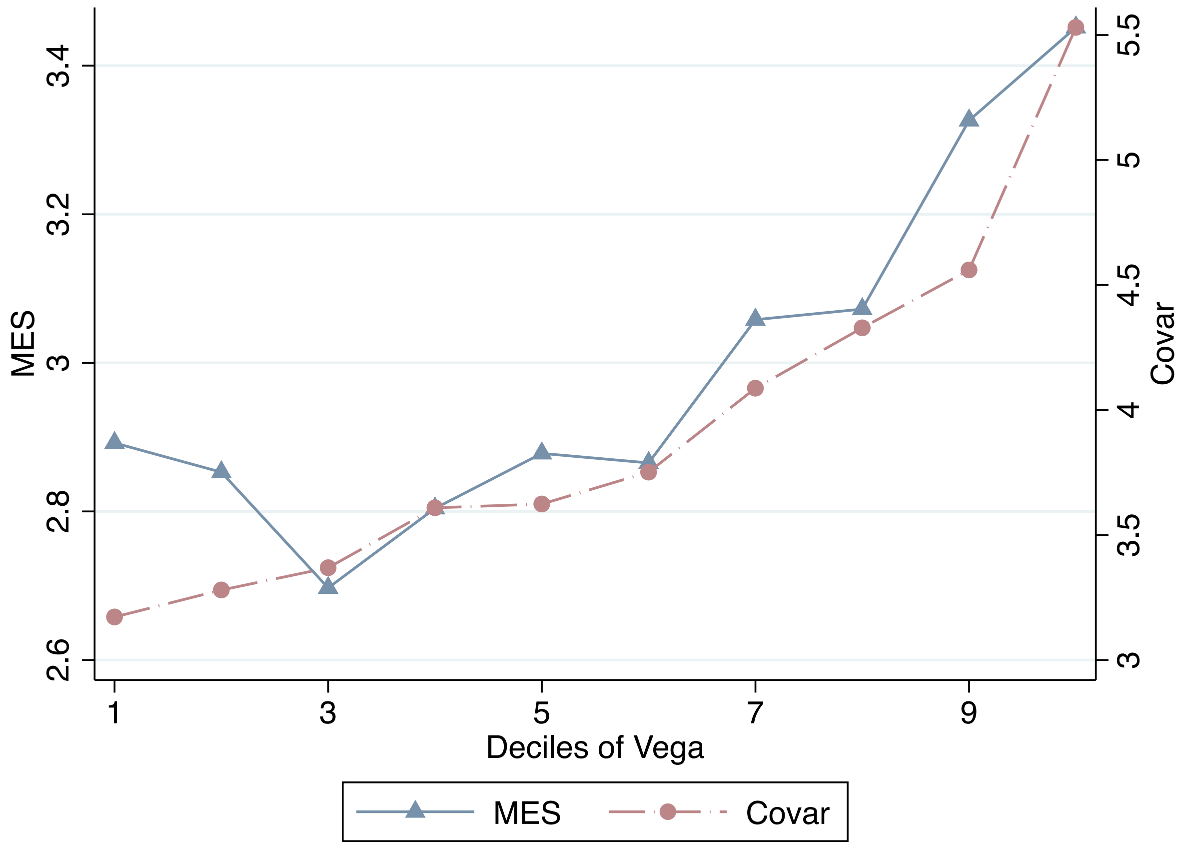
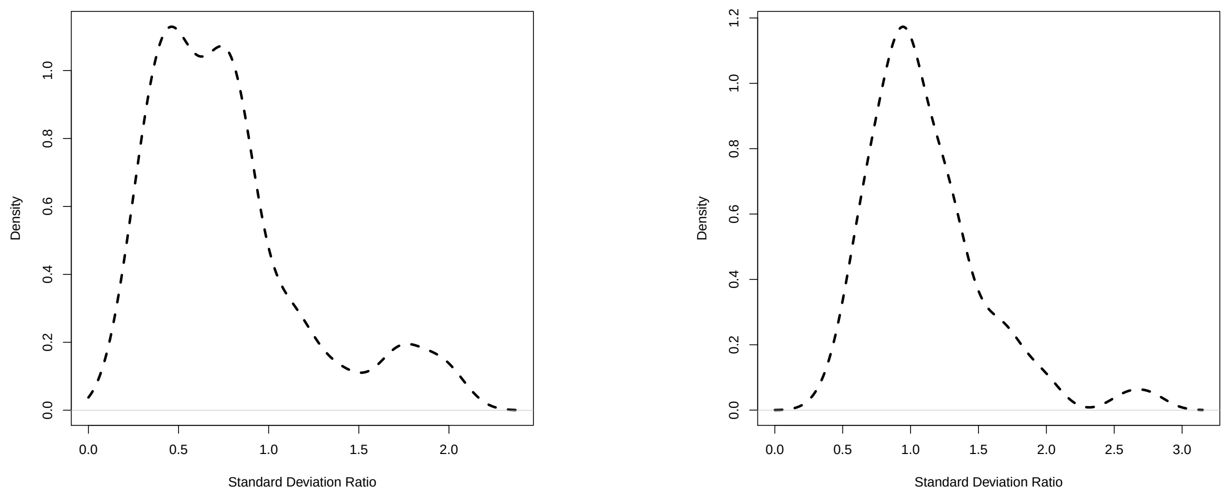
Figure 1: Vega and Systemic Risk



This figure presents the relations between vega and systemic risk measures, MES and $\Delta CoVaR^{1\%}$. 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 3.1. The vertical axis on the left represents MES (the straight line with triangles) and on the right $\Delta CoVaR^{1\%}$ (the dashed line with circles). The horizontal axis represents the deciles of vega. The measurement of systemic risk leads the measurement of vega by one year.

Figure 2: Density of Standard Deviation Ratios



(a) MES

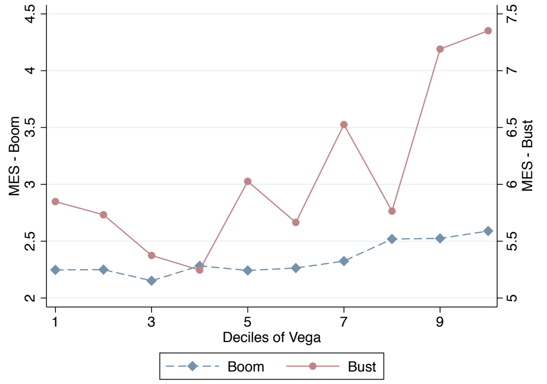
(b) CoVaR

This figure presents the kernel density of the ratios of the standard deviations of the first- and second-stage residuals based on equations (7) and (8), repeated below:

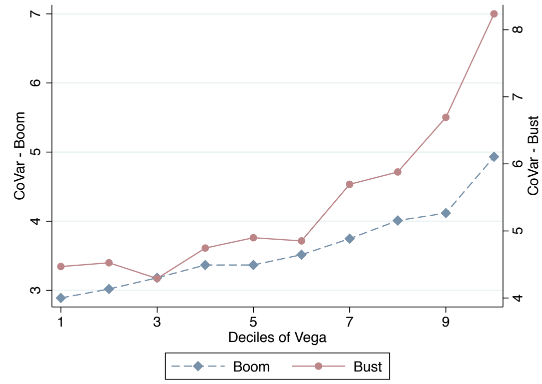
$$\begin{aligned} Vega_{it-1} &= \alpha X_{it-1} + \xi_{it-1} \\ Risk_{it} &= \beta_1 Vega_{it-1} + \beta X_{it-1} + \eta_{it+s}. \end{aligned}$$

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 3), and the right panel for the case where the dependent variable is $\Delta CoVaR^{1\%}$ (i.e., column (4) of Table 3).

Figure 3: Vega and Systemic Risk in Boom vs. Bust Periods



(a) MES



(b) CoVaR

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 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 3.1. 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 boom periods (the dashed line with diamonds) and on the right presents the systemic risk measure during bust periods (the solid line with circles). The horizontal axis represents the deciles of vega. The straight dot line represents systemic risk measured in economic downturns, namely year 2001, 2008, and 2009. The dashed diamond line represents systemic risk measured during economic expansions, namely years other than 2001, 2008, and 2009. The measurement of systemic risk leads the measurement of vega by one year.

Table 1: Descriptive Statistics

This table presents descriptive statistics. The sample period is 1995 - 2013. $log(vega)$ and $log(delta)$ are the log of portfolio level vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. 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 3.1. $Capital$ is the ratio of equity to total assets, multiplied by 100. $Tier1$ is the tier 1 risk-adjusted capital ratio, multiplied by 100. $CommLoans$ 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. $STdep$ is short-term deposits (total deposits less time deposits) scaled by total deposits, multiplied by 100. $Size$ is the log of total assets. BTM is the ratio of book equity to market value of equity. Continuous variables are winsorized at the 1st and 99th percentiles.

	N	Mean	SD	25%	50%	75%
Systemic risk measures and business activities						
MES	1270	2.985	2.192	1.527	2.242	3.675
$\Delta CoVaR^{1\%}$	1270	3.913	1.755	2.718	3.655	4.863
$Capital$	1270	9.387	2.337	7.786	9.242	10.852
$Tier1$	1270	11.589	3.013	9.414	11.215	13.196
$CommLoans$	1270	21.358	11.775	13.765	19.589	26.877
$MBSNA$	1270	6.013	10.498	0.000	0.875	7.214
$STdep$	1270	68.586	15.032	58.817	69.599	79.354
Compensation variables						
$vega$	1270	290.065	531.271	30.639	80.542	291.797
$delta$	1270	965.350	1379.078	140.946	439.163	1120.545
$log(vega)$	1270	4.393	1.800	3.455	4.401	5.677
$log(delta)$	1270	5.997	1.431	4.956	6.087	7.021
Bank characteristics						
$Size$	1270	9.710	1.465	8.613	9.388	10.563
BTM	1270	0.663	0.393	0.402	0.559	0.806

Table 2: Vega and Systemic Risk: OLS Regressions

This table presents OLS regression results of regressing the systemic risk measures on vega and control variables. 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 3.1. 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 portfolio level vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. $Size$ is the log of total assets. BTM is the ratio of book equity to market value of equity. 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) MES_t	(2) MES_{t+1}	(3) MES_{t+2}	(4) $\Delta CoVaR^{1\%}_t$	(5) $\Delta CoVaR^{1\%}_{t+1}$	(6) $\Delta CoVaR^{1\%}_{t+2}$
$log(vega)_{t-1}$	0.098	0.099	0.069	0.165	0.159	0.143
	[0.056, 0.136]	[0.057, 0.134]	[0.028, 0.105]	[0.115, 0.212]	[0.110, 0.206]	[0.094, 0.190]
$Size_{t-1}$	0.218	0.200	0.155	0.498	0.467	0.441
	[0.158, 0.271]	[0.139, 0.261]	[0.100, 0.211]	[0.418, 0.575]	[0.392, 0.550]	[0.372, 0.514]
BTM_{t-1}	0.685	0.326	0.172	-0.691	-0.685	-0.647
	[0.422, 0.964]	[0.088, 0.519]	[0.009, 0.347]	[-0.934, -0.448]	[-0.887, -0.481]	[-0.844, -0.452]
$log(delta)_{t-1}$	-0.028	0.003	0.039	0.283	0.292	0.286
	[-0.090, 0.034]	[-0.051, 0.057]	[-0.024, 0.100]	[0.210, 0.367]	[0.215, 0.373]	[0.209, 0.366]
R^2	0.823	0.811	0.809	0.538	0.529	0.542
Obs	1270	1270	1270	1270	1270	1270
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Vega and Systemic Risk: Modified Control Function Regressions

This table presents modified control function regression results of regressing the systemic risk measures on vega and control variables. 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 3.1. 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 portfolio level vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. $Size$ is the log of total assets. BTM is the ratio of book equity to market value of equity. 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) MES_t	(2) MES_{t+1}	(3) MES_{t+2}	(4) $\Delta CoVaR^{1\%}_t$	(5) $\Delta CoVaR^{1\%}_{t+1}$	(6) $\Delta CoVaR^{1\%}_{t+2}$
$log(vega)_{t-1}$	0.034	0.022	0.016	0.079	0.015	0.047
	[-0.035, 0.109]	[-0.049, 0.097]	[-0.075, 0.094]	[-0.059, 0.206]	[-0.114, 0.139]	[-0.089, 0.168]
$Size_{t-1}$	0.210	0.191	0.148	0.488	0.449	0.428
	[0.155, 0.264]	[0.133, 0.254]	[0.095, 0.208]	[0.413, 0.564]	[0.377, 0.528]	[0.359, 0.504]
BTM_{t-1}	0.740	0.386	0.210	-0.625	-0.579	-0.576
	[0.466, 1.029]	[0.146, 0.604]	[0.039, 0.403]	[-0.898, -0.359]	[-0.808, -0.338]	[-0.784, -0.356]
$log(delta)_{t-1}$	0.034	0.078	0.092	0.366	0.433	0.381
	[-0.039, 0.124]	[0.001, 0.161]	[0.000, 0.189]	[0.224, 0.533]	[0.298, 0.592]	[0.253, 0.529]
ρ	0.101	0.123	0.088	0.097	0.163	0.113
	[-0.050, 0.237]	[-0.010, 0.262]	[-0.093, 0.261]	[-0.069, 0.252]	[-0.006, 0.306]	[-0.062, 0.284]
R^2	0.823	0.812	0.810	0.539	0.533	0.544
Obs	1270	1270	1270	1270	1270	1270
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Vega and Systemic Risk: Boom vs. Bust

This table presents modified control function regression results of regressing the systemic risk measures on vega, the interaction between $log(vega)$ and $Bust$, and control variables, where $Bust$ 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) $\Delta CoVaR^{1\%}$. 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 3.1. 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 portfolio level vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. $Size$ is the log of total assets. BTM is the ratio of book equity to market value of equity. 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) MES_t	(2) MES_{t+1}	(3) MES_{t+2}	(4) $\Delta CoVaR^{1\%}_t$	(5) $\Delta CoVaR^{1\%}_{t+1}$	(6) $\Delta CoVaR^{1\%}_{t+2}$
$log(vega)_{t-1}$	0.056	0.071	0.042	0.102	0.059	0.071
	[-0.025, 0.150]	[-0.013, 0.166]	[-0.047, 0.137]	[-0.053, 0.236]	[-0.072, 0.186]	[-0.056, 0.193]
$log(vega)_{t-1} * Bust_t$	0.183			0.242		
	[0.023, 0.356]			[0.104, 0.407]		
$log(vega)_{t-1} * Bust_{t+1}$		0.291			0.296	
		[0.141, 0.454]			[0.126, 0.436]	
$log(vega)_{t-1} * Bust_{t+2}$			0.312			0.354
			[0.131, 0.495]			[0.203, 0.539]
$Size_{t-1}$	0.212	0.196	0.153	0.489	0.453	0.434
	[0.151, 0.268]	[0.136, 0.256]	[0.096, 0.213]	[0.413, 0.568]	[0.377, 0.533]	[0.367, 0.506]
BTM_{t-1}	0.697	0.300	0.136	-0.665	-0.655	-0.655
	[0.440, 0.987]	[0.070, 0.523]	[-0.036, 0.333]	[-0.934, -0.381]	[-0.867, -0.414]	[-0.859, -0.435]
$log(delta)_{t-1}$	-0.017	-0.017	0.025	0.306	0.342	0.312
	[-0.100, 0.086]	[-0.110, 0.081]	[-0.083, 0.133]	[0.154, 0.478]	[0.204, 0.483]	[0.190, 0.460]
ρ	0.015	-0.019	-0.029	0.024	0.069	0.036
	[-0.150, 0.186]	[-0.191, 0.146]	[-0.227, 0.175]	[-0.148, 0.192]	[-0.093, 0.230]	[-0.139, 0.198]
R^2	0.826	0.819	0.817	0.546	0.543	0.560
Obs	1270	1270	1270	1270	1270	1270
$Year\ FE$	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Vega and Leverage

This table presents modified control function regression results of regressing bank capital ratios on vega and control variables. The dependent variable is *Capital*, the ratio of equity to total assets, multiplied by 100, in column (1), and *Tier1*, the tier 1 risk-adjusted capital ratio, multiplied by 100, in column (2). *log*(*vega*) and *log*(*delta*) are the log of portfolio level vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. *Size* is the log of total assets. *BTM* is the ratio of book equity to market value of equity. 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) $Capital_t$	(2) $Tier1_t$
$log(vega)_{t-1}$	-0.066	-0.377
	[-0.297, 0.158]	[-0.659, -0.131]
$Size_{t-1}$	-0.271	-0.648
	[-0.419, -0.141]	[-0.811, -0.506]
BTM_{t-1}	-0.031	-0.078
	[-0.686, 0.667]	[-0.718, 0.785]
$log(delta)_{t-1}$	0.010	0.085
	[-0.217, 0.255]	[-0.174, 0.412]
ρ	0.009	-0.014
	[-0.131, 0.154]	[-0.147, 0.143]
R^2	0.232	0.405
Obs	1270	1270
Year FE	Yes	Yes

Table 6: Vega and Bank Operations

This table presents modified control function regression results of regressing the business activity measures, $CommLoans$, $MBSNA$, and $STdep$ on vega and control variables. $CommLoans$ 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. $STdep$ 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 portfolio level vega and delta, respectively, measured following Core and Guay (2002), for the top five bank executives. $Size$ is the log of total assets. BTM is the ratio of book equity to market value of equity. 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)
	$CommLoans_t$	$MBSNA_t$	$STdep_t$
$log(vega)_{t-1}$	2.022	1.680	2.450
	[0.815, 3.214]	[0.915, 2.539]	[0.970, 3.855]
$Size_{t-1}$	0.948	0.981	2.527
	[0.232, 1.653]	[0.435, 1.492]	[1.698, 3.427]
BTM_{t-1}	-1.401	-0.138	-8.201
	[-3.332, 0.868]	[-1.997, 1.775]	[-10.809, -4.909]
$log(delta)_{t-1}$	-0.959	0.514	-0.145
	[-2.175, 0.318]	[-0.270, 1.365]	[-1.426, 1.466]
ρ	-0.144	-0.200	-0.197
	[-0.284, -0.014]	[-0.338, -0.053]	[-0.319, -0.038]
R^2	0.069	0.122	0.306
Obs	1270	1270	1270
Year FE	Yes	Yes	Yes