The External Effects of Bank Executive Pay: Liquidity Creation and Systemic Risk

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June 7, 2021

Abstract: We develop a conceptual framework that links the compensation incentives of bank executives to the risk and return externalities generated by banks but borne by society. Using 1994 to 2016 data from large U.S. commercial banks, we find that CEO pay-performance incentives reduce both negative systemic risk externalities and positive liquidity creation externalities, while pay-risk incentives increase both externalities. Our findings offer support for Federal Reserve guidelines that encourage greater reliance on long-term equity-based compensation, and they infer a regulatory tradeoff: Bank executive pay rules aimed at reducing systemic risk will result in reduced system-wide liquidity creation as well.

Key words: Executive pay incentives, externalities, liquidity creation, systemic risk

* The authors thank the editor, Christa Bouwman, and two anonymous reviewers for reading and improving this article. Allen Berger, Mark Flannery, Philipp Hartmann, Luc Laeven, George Pennacchi, Giorgia Piacentino, Gokhan Torna, and Lucy White also contributed valuable insights and suggestions, as did seminar participants at the Bank of Portugal, the Banque de France, the European Central Bank, the Federal Reserve Bank of Chicago, the Federal Reserve Bank of Kansas City, the International Finance and Banking Society, the University of Kansas, the Southern Finance Association, the University of South Carolina, Stony Brook University, and Villanova University.

1. Introduction

After the 2007-2008 financial crisis, lawmakers and policymakers imposed a flurry of new rules to reduce risk-taking at commercial banks. The headline regulations imposed tighter restrictions on financial leverage, liquidity positions, trading portfolios, and residential mortgages. In the U.S., regulators also issued qualitative, principles-based guidelines to encourage longer term equity-based compensation contracts for bank decision-makers (Squam Lake 2010, Federal Reserve 2016).[1] These guidelines favor "incentives-based compensation that appropriately balances risk and reward, is compatible with effective risk management and controls, and is supported by effective governance" as well as contracts that allow the "deferral, downward adjustment and forfeiture, and clawback" of compensation for senior executive officers and other significant risk-takers employed by the banks (Federal Reserve 2016).

The objectives of these pay guidelines are two-fold: To reduce the incentives for bank decision-makers to take excessive risk that could lead to bank insolvency, and by doing so reduce the negative spillover effects of bank risk-taking on financial markets, other banks, and the macro-economy. Regarding the latter objective, little is known about how the incentives embedded in bank executive pay contracts influence these negative externalities; the literature on bank executive pay has focused chiefly on the risk profiles of the banks themselves, and not on the spillover effects of this risk-taking.

Our study investigates whether and how the compensation incentives of CEOs at large U.S. commercial banks influence the size and direction of the economic spillovers generated by their banks. We begin with the observation that banks can generate both negative economic spillovers (namely, systemic risk) and positive economic spillovers (namely, liquidity creation) and that a thorough investigation requires us to include both types of externalities in our analysis. Because externalities are unpriced, extra-market phenomena, they are difficult to measure. Much progress has been made on this front in recent years, but existing algorithms for measuring systemic risk and liquidity creation are inadequate for our research

[1] In contrast, European regulators have in some cases taken a rules-based approach, such as placing quantitative restrictions on the amount of bonus payments to bank executives and the timing with which managers are permitted to receive those payments (European Parliament Capital Requirements Directive IV, 2013).

purposes: They do not fully isolate the bank-generated risk borne privately by bank shareholders from the bank-generated risk that spills over as a negative externality. Nor do they fully isolate the bank-generated value captured by bank shareholders from the bank-generated value that spills over as a positive externality. Empirically separating these public and private phenomena is a key contribution of our study.

In the first stage of our analysis, we devise a straightforward method to capture the portions of standard systemic risk measures that are orthogonal to the private risks borne by bank shareholders, and similarly, the portion of standard liquidity creation measures that are orthogonal to the private returns earned by bank shareholders. In the second stage of our analysis, we test whether and how bank executive compensation incentives influence these 'pure' measures of negative and positive social spillovers. Our two-stage framework has a pleasing and important feature for estimation: Because economic externalities are by definition unintentional byproducts and hence carry no weight in either managers' or shareholders' objective functions, managers' compensation contracts should be strictly exogenous regressors in the second-stage regressions.

Conceptually, externalities are linked to executive pay incentives through the bank production function. Banks create liquidity for their creditor clients by holding illiquid loan contracts, and create liquidity for their debtor clients by financing these assets with callable deposit contracts. This arrangement generates profits for bank shareholders via an interest rate margin. But because the newly created deposit contracts serve as money in the economy, and because the newly created credit generates additional new deposits elsewhere in the banking system, this profit-seeking activity increases the liquidity available for economic agents beyond the clientele of the issuing bank. (This propagation of liquidity throughout the economy is described by macroeconomists in terms of the money creation multiplier and the velocity of money.) Thus, actions taken by banks in pursuit of private profits lead to positive social externalities, i.e., liquidity creation spillovers.

This production function exposes the bank to credit risk, interest rate risk, and illiquidity risk. In the classical case, depositors might withdraw their funds when they learn or fear that their bank is approaching insolvency or illiquidity; if depositors at other banks interpret this bank-specific run as a signal of a more general problem in the economy, a contagious run can result in an economy-wide reduction in liquidity, credit and economic activity. In its modern analog (in which retail deposits are insured), non-deposit creditors can cause the collapse of an already weak financial institution by refusing to roll over their short-term credit contracts, contagious fear leads to a collapse of short-term credit markets, and death-by-illiquidity spreads to other financial institutions. Thus, the risks taken by banks in pursuit of private profits lead to negative social externalities, i.e., systemic risk spillovers.

It is important to note that no extant studies of systemic risk or liquidity creation have attempted to empirically distinguish between the private and public incidence of these phenomena. Nevertheless, at least one study recognizes that these phenomena are not fully internalized by the banks that create them, and hence they are partially composed of economic externalities. Adrian and Brunnermeier (2016, §II.B.) write: "…systemic risk relates to spillovers that amplify initial adverse shocks… Many of these spillovers are externalities. That is, when taking on the initial position with low market liquidity funded with short-term liabilities—i.e., with high liquidity mismatch—individual market participants do not internalize the subsequent individually optimal response in times of crises that imposes (pecuniary) externalities on others."

Our two-stage methodology employs standard measures of executive pay incentives, systemic risk, and liquidity creation. Following Guay (1999) and Core and Guay (2002), we use pay-performance sensitivity (delta) and pay-risk sensitivity (vega) to measure the compensation incentives faced by bank CEOs. Following Acharya, et al. (2017), we measure the systemic expected shortfall (SES) of each bank, and then extract from this measure the systemic risk externality that is orthogonal to banks' private risk exposures. Following Berger and Bouwman (2009), we measure the gross liquidity created by each bank, and then extract from this measure the liquidity creation externality that is orthogonal to banks' private returns. We estimate our models using annual panel data on large U.S. commercial banking companies from 1994 through 2016.

We find that CEO pay-risk incentives (vega) are positively associated with both systemic risk externalities and liquidity creation externalities. The former result is straightforward and intuitive: Pay-risk incentives naturally lead to greater internal risk-taking, which in turn begets systemic risk spillovers. The latter result is less straightforward but is also intuitive: Because banks can create liquidity only by taking private risk—that is, making loans and issuing deposits exposes banks to credit risk and liquidity risk—then greater pay-risk incentives will result in more liquidity creation spillovers. Conversely, we find that CEO pay-performance incentives (delta) are negatively associated with both systemic risk externalities and liquidity creation externalities. Again, these are intuitive results: Pay-performance incentives concentrate the manager's personal wealth in the firm, which increases her effective risk aversion and causes her to reduce investment in risky liquidity-creating activities. In turn, less internal risk-taking begets fewer systemic risk spillovers.

We uncover some of the business decision channels through which CEO pay incentives drive systemic risk and liquidity creation spillovers by decomposing each of these externalities into their component parts. By construction, the SES measure decomposes naturally into financial risk (leverage) and business risk (industry downside tail risk, or marginal expected shortfall). Faced with vega-induced incentives toward risk-taking, managers respond by increasing financial risk and, to a lesser extent, by increasing business risk; conversely, when faced with delta-induced incentives toward risk aversion and shareholder alignment, managers respond by reducing financial leverage. By construction, the liquidity creation measure decomposes naturally into various on-balance sheet and off-balance sheet components. Only the off-balance sheet channel—in particular, the off-balance sheet credit commitments channel—is statistically related to CEO wealth incentives. Faced with higher vega, managers respond by increasing credit commitments; conversely, when faced with higher delta, managers respond by reducing credit commitments. These patterns are economically intuitive, as credit commitments expose banks to at least four categories of risk: Credit risk, liquidity risk, interest rate risk, and increased effective financial leverage.

Our results help inform public policy. The estimated increases in systemic risk externalities in response to higher CEO delta are economically substantial; this lends support to Federal Reserve (2016) and European Parliament (2013) policies that stress long term, equity-based compensation for bank decision-makers. In contrast, the estimated reductions in systemic risk externalities in response to lower CEO vega are relatively small; this suggests that limiting executive stock options grants—an approach that had initially gained substantial popular favor (e.g., AFL-CIO, 2011)—is unlikely to meaningfully reduce systemic risk. Importantly, our results remind us that policy gains seldom occur without at least some costs. Efforts by regulators to reduce systemic risk externalities, with rules that encourage delta and/or restrict vega, will likely also result in nontrivial reductions in external liquidity creation.

We advance the literature on managerial pay incentives in several ways. Numerous previous studies have verified economic theory by demonstrating strong empirical associations between bank CEO pay incentives and the resulting risks and returns to bank shareholders (e.g., Chen, Steiner, and Whyte 2006; Cheng, Hong and Scheinkman 2010; Minnick, Unal and Yang 2011; Hagendorff and Vallascas 2011; DeYoung, Peng and Yan 2013; Bai and Elyasiani 2013). We break new ground by providing empirical evidence that the effects of CEO compensation incentives can ultimately spill over in material ways beyond the boundaries of the bank and its private stakeholders. We also break new methodological and conceptual ground in this area. Our model builds on the observation of Benoit, et al. (2013) that systemic risk measures can be expressed as transformations of market risk measures, as well as on the observation of Berger and Bouwman (2009) that liquidity creation is a function of return-generating banking activities. In our framework, successful orthogonalization of standard systemic risk and liquidity creation measures on private risk and return variables can generate relatively clean measures of social risk and social return spillovers. Given the textbook definition of an externality, identification should not be troubled by concerns over endogeneity: Because the costs or benefits of firm-generated externalities redound to society and not to the firm, the compensation incentives of firm executives are exogenous to those externalities.

We remain silent on the question of whether executive pay incentives either dampen or amplify agency problems between bank shareholders and bank managers. We are interested not in how executive pay incentives influence principal-agent problems between bank managers and their internal stakeholders—a large previous research literature on those questions exists—but rather how executive pay incentives influence principal-agent problems between the banking industry and the non-bank portion of the economy. We would expect our results to be largely unaffected by the degree of manager-shareholder misalignment: Bank business decisions aimed at enriching managers at the cost of shareholders are primarily transfers of wealth from one private party to another private party, leaving our private versus public dichotomy undisturbed. And as pointed out by Bebchuk and Spamann (2009), banks generate spillover costs even in the absence of manager-shareholder misalignment: The highly levered nature of commercial banks leads to moral hazard incentives in any case, and the risks that banks take in response to those incentives can generate negative externalities that justify prudential bank regulation.

The rest of the paper proceeds as follows: In Section 2 we develop an estimable analytic framework that links market externalities generated by banks to the pay incentives of bank executives. In Section 3 we describe the data and review standard empirical measures for the key variables in our analysis: executive compensation incentives, liquidity creation, and systemic risk. In Section 4 we detail the orthogonalization process used to generate our externality variables, and in Section 5 we present the full set of estimates from our two-stage analytic framework. In Section 6 we test for business decision channels through which CEO pay incentives may be resulting in market externalities. In Section 7 we conduct a variety of robustness tests, and in Section 8 we offer empirical support for some of our modeling assumptions. We discuss the implications of our results for bank regulatory policy in Section 9. Section 10 concludes.

2. Analytic framework

To date, both the modern theoretical literature on executive compensation (starting with Jensen and Meckling 1976) as well as the related empirical literature have focused on private outcomes, those being returns to shareholder's returns and the personal utilities of managers. In contrast, we focus on the positive and negative externalities that spill over beyond the boundaries of the firm, which are public outcomes. Because externalities are by definition extra-market processes, they are difficult to measure and value. We use recent advances in measuring liquidity creation (Berger and Bouwman 2009) and systemic risk (Acharya, et al., 2017) as starting points for estimating the values of positive and negative externalities generated by banking companies.

We begin with the standard notion that the firm's managers may act in their own self-interest rather than making decisions that maximize firm value (Berle and Means 1932), and that shareholders attempt to counter these principal-agent problems by designing compensation contracts to incentivize managers to make value-maximizing business decisions. We assume that these incentive contracts successfully align the managers' interests with those of the shareholders. Simplifying to a one-period framework, we can express the results of this corporate governance problem as

$$\pi = \pi(X(delta, vega)) \tag{1}$$

$$\sigma^{\pi} = \sigma^{\pi}(X(delta, vega)) \tag{2}$$

where we characterize the financial incentives embedded in manager compensation contracts as *delta* (pay-performance sensitivity) and *vega* (pay-risk sensitivity), the business decisions made by these incentivized managers as $X(delta, vega)$, and shareholder returns π and shareholder risk σ^{π} as the private wealth outcomes that result from those business decisions. We leave the details that lay within this chain of events un-modeled, as they are not necessary for our purposes.[2]

Our interest lies in whether bank managers, conditioned by their compensation incentives to make privately optimal business decisions, unintentionally cause the production of positive and/or negative externalities. To illustrate, assume that a bank makes a small- or middle-market business loan and finances that loan by issuing demand deposits. These business decisions are made with a clear objective of generating shareholder returns from the interest margins, fees and operating expenses associated with the loan and deposit contracts. But agents outside of the bank also benefit from this process of financial intermediation. The money that is created in the process of issuing customer deposits and funding customer credit will circulate in the economy, where it can be used free-of-charge to facilitate transactions among other agents who are not customers of the bank. These liquidity creation externalities, which can be thought of as *public returns*, are byproducts of the *private return*-seeking actions of bank management.

[2] In the Internet Appendix, we provide a stylized model of how the features of executive compensation contracts (salary, stock grants, and stock options grants) map into managerial compensation incentives (delta, vega) and hence influence managerial risk aversion.

Bank shareholders derive no more or no less value from this external liquidity creation than does any other member of society; as a result, these liquidity spillovers do not figure into the bank's private shareholder value maximization problem. The total amount of liquidity created by the bank is simply the sum of the internalized or private liquidity creation and the external or public liquidity creation. Because both the internal and external portions of this sum are functions of the same managerial business decisions, we can express total liquidity creation L as

$$L = L(X(delta,\ vega)) \tag{3}$$

Berger and Bouwman (2009) provide a tractable method for calculating the total liquidity L created by an individual bank during a given span of time. We propose using the following straightforward regression approach to separate L into its internalized and externalized components:

$$L^M{}_i \ = \ a \ + \ b \cdot \pi_i \ + \ \varepsilon^L{}_i \tag{4}$$

where L^M is any available empirical measurement of total liquidity creation, π is private shareholder returns, ε^L is the ordinary least squares residual term, and i indexes banks. By definition, OLS residuals are orthogonal to the right-hand side regressors. Hence, if L^M is a reasonable measure of total liquidity creation and if private returns π is correctly specified, then the estimated $\hat{\varepsilon}^L$ will be natural measures of external liquidity creation.

With the estimated liquidity creation externalities $\hat{\varepsilon}^L$ in-hand, we can then test whether and how these positive spillovers are influenced by the contractual wealth incentives of bank managers:

$$\hat{\varepsilon}^L{}_{i,t} = \ \alpha \ + \ \gamma \cdot delta_{i,t\text{-}1} \ + \ \lambda \cdot vega_{i,t\text{-}1} \ + \ \delta \cdot controls_{i,t} \ + \ \mu_{i,t} \tag{5}$$

where time t is measured in years as compensation contracts are typically repriced annually. Identification in this second-step regression should be free of endogeneity concerns: Assuming that managerial contracts (and hence *delta* and *vega*) are written only with private returns π in mind, then public returns $\hat{\varepsilon}^L$ are consumed outside the firm and shareholders care little about them. Because $\hat{\varepsilon}^L$ is orthogonal to private returns, then *delta* and *vega* should be uncorrelated with the error term $\mu_{i,t}$.

Returning to our example, a bank seeking to earn private returns by funding business loans with demand deposits is also exposing its shareholders to risk: Making the business loan (as opposed to investing in a Treasury security) exposes shareholders to credit risk, and funding the loan with demand deposits (as opposed to fixed maturity finance) exposes shareholders to both liquidity risk and interest rate risk. Simultaneously, these internal business decisions can also impose risks on agents outside of the bank. Bad outcomes regarding its own credit risk (its loans default), liquidity risk (its depositors run), and interest rate risk (its margins collapse) can result in collateral damage to other financial institutions. Some of the damage suffered by other financial institutions will be direct, e.g., capital losses on equity and debt securities issued by the distressed bank, capital losses on derivatives contracts priced on the underlying value or risk of the distressed bank, or counterparty losses on bilateral financial contracts with the distressed bank. Damage to other financial institutions can also occur indirectly, for example, due to disruptions in financial markets caused by the distressed bank, or from contagion-like losses on financial arrangements with third parties who themselves are directly exposed to the distressed bank. These indirect risk outcomes can be considered systemic risk externalities, or *public risks*, as they are byproducts of *private risk* outcomes from business decisions that spill over to parties not directly associated with the distressed bank.

We can express the chain of events that leads to the generation of systemic risk as:

$$S = S(X(delta, vega)) \tag{6}$$

Although private risk σ^π and public risk S are theoretically separable concepts, they are difficult to measure separately. Benoit, et al. (2013) show that systemic expected shortfall (SES) and other measures of systemic risk can be expressed as transformations of market risk measures (such as systematic risk, or beta) and demonstrate that empirical rankings of U.S. banks by systemic risk and market risk are similar. In the words of Guntay and Kupiec (2014), these measures of systemic risk "are contaminated by systematic risk." We propose using the following straightforward regression to separate measured systemic risk into its internalized and externalized components:

$$S^M_i = a + b \cdot \sigma^\pi_i + \varepsilon^S_i \tag{7}$$

where S^M is measured systemic risk, σ^π is private shareholder risk, ε^S is the ordinary least squares residual term, and i indexes banks. By definition, OLS residuals are orthogonal to the right-hand side regressors. Hence, if S^M is a reasonable measure of systemic risk and if private risk σ^π is correctly specified, then the estimated $\hat{\varepsilon}^S$ will capture the systemic risk externality.

With the estimated systemic risk externalities $\hat{\varepsilon}^S$ in-hand, we can test whether and how these negative spillovers are influenced by the contractual wealth incentives of bank managers:

$$\hat{\varepsilon}^S_{i,t} = \alpha + \gamma \cdot delta_{i,t-1} + \lambda \cdot vega_{i,t-1} + \delta \cdot controls_{i,t} + \nu_{i,t} \tag{8}$$

As in (5), identification in this second-step regression should be free of endogeneity concerns: Assuming that managerial contracts (and hence *delta* and *vega*) are written only with private risk σ^π in mind, then the public risk $\hat{\varepsilon}^S$ is consumed outside the firm and shareholders care little about it. Because $\hat{\varepsilon}^S$ is orthogonal to private risk, then *delta* and *vega* should be uncorrelated with the error term $\nu_{i,t}$.

Identification in the above framework depends squarely on the implementation of regression equations (4) and (7), which we use to separate measured liquidity creation L^M and measured systemic risk S^M into their orthogonal private (the fitted values $\hat{L}^M$ and $\hat{S}^M$) and public ($\hat{\varepsilon}^L$ and $\hat{\varepsilon}^S$) components. Clearly, these equations are not the true models of liquidity creation and systemic risk generation. For example, we purposely mis-specify equation (4) by omitting from π any of the variables in the true model that measure public returns (i.e., positive externalities). Given these omitted variables, the coefficient *b* will be biased (i.e., *b* is not coefficient on π from the true model) and hence the residuals ε^L will also be biased (i.e., ε^L are not the residuals that would obtain from a well-specified model). However, it is not our objective to estimate the true model, and the vector of estimated OLS residuals $\hat{\varepsilon}^L$ has the property that we desire: corr($\hat{\varepsilon}^L$,π)=0. It is crucial, of course, that we generously specify the vector π with multiple measures of private returns; as we purge greater amounts of private return from L^M, the ε^L become purer measures of liquidity creation spillovers.[3] Parallel arguments apply for equation (7).

A notable concern arises if managers make business decisions with the objective of increasing their chances of receiving a government bailout during an economic crisis. For example, a bank might coordinate its business policies with other banks, and this so-called 'herding behavior' will create a 'too-many-to-fail' scenario (Acharya and Yorulmazer 2007). In such a scenario, systemic risk becomes an intentional objective of bank managers' business policy choices and we can no longer assume that business decisions are being made exogenous of systemic risk. These phenomena are most likely to occur at very large banks and among banks with highly correlated financial performances. We conduct ancillary tests to determine the importance of such behavior in our data and find little evidence that it is driving our results.

Finally, we emphasize that managerial pay incentives are transformed into externalities through only two channels in our framework: business decisions that generate private risk σ^π and private returns π. Transmission channels other than these are possible if the *delta* and *vega* incentives do not align management's return and risk objectives with those of shareholders. However, our objective is to shed light on the principal-agent problems between the private firm and the external public, not between the private firm manager and the private firm shareholders. In this endeavor, we abstract away from internal agency conflicts, and restrict our framework to just these two transmission channels.

[3] Because we are not performing inference in equation (2), we are unconcerned with the statistical significance of the coefficients; multicollinearity is to be expected. Because we are not attempting to estimate the true model, we are unconcerned with goodness-of-fit; low adjusted R-square statistics are to be expected.

3. Data and variables

We estimate our model using an unbalanced panel of 1,211 firm-year observations of 168 different U.S. commercial banking companies (SIC code 6020) between 1994 and 2016. We obtain the information necessary to construct the CEO compensation variables (delta, vega) from the Execucomp database. We obtain bank affiliate-level data on liquidity creation from Christa Bouwman's website and then aggregate these data up to the bank holding company level.[4] From the Center for Research in Securities Prices (CRSP) database we obtain data necessary to construct our measures of systemic risk, systematic risk, and other stock return-related variables. From the Federal Reserve Y-9C financial statement database we obtain the data necessary to construct our measures of accounting-based returns and risks, as well as a number of control variables. We construct an index of annual economic conditions for each banking company based on data from the Federal Reserve Bank of Philadelphia's Coincident Index of Economic Conditions and the Federal Deposit Insurance Corporation's Summary of Deposits database. The time series boundaries of our dataset are determined by the Summary of Deposits database, which starts in 1994, and the data on Christa Bouwman's website, which at the time of original estimation ended in 2016. The cross sectional depth of our dataset is determined by the Execucomp database, which contains data on only 39 to 74 commercial banking companies in any given year. Definitions and summary statistics for all the variables used in our tests can be found in Tables 1 and 2.

3.1. Compensation incentives.

The two primary test variables in our model are *Delta* and *Vega* (Guay 1999, Core and Guay 2002). *Vega* is the pay-risk sensitivity of the bank CEO, i.e., how the CEO's personal wealth changes (in thousands of 2016 dollars) with an increase in the volatility of her bank's stock returns. We calculate *Vega* as the partial derivative of the bank's stock option value with respect to a 0.01 change in the bank's stock return volatility, multiplied by the number of options owned by the CEO. We use the Black-Scholes (1973) model modified by Merton (1973) to calculate the value of stock options. *Delta* is the pay-performance sensitivity

[4] See https://sites.google.com/a/tamu.edu/bouwman/data.

of the bank CEO, i.e., how the CEO's personal wealth changes (in thousands of 2016 dollars) with an increase in her bank's stock price. We calculate *Delta* as (a) the bank's stock price multiplied by 1% and then multiplied again by the number of shares owned by the CEO, plus (b) the partial derivative of the bank's stock option value with respect to stock price multiplied by 1% of the current stock price and then multiplied again by the number of stock options owned by the CEO.

The distributions of *Delta* and *Vega* are highly skewed to the right (see Table 2), which indicates that the dollar incentives given to CEOs *via* stock grants and stock options increase at an increasing rate with banking company size. We make three adjustments to cope with this. First, we winsorize *Delta* and *Vega* (as well as all of the other variables used in our tests) at the 1st and 99th percentiles of their sample distributions. Second, we apply the natural log transformation to both *Delta* and *Vega* prior to estimation. Third, we interpret the economic magnitudes of the estimated coefficients based on standard deviation changes in the regression variables *lnDelta* and *lnVega*, rather than on changes in the underlying levels of *Delta* and *Vega*.

In general, studies of non-financial firms have found that risk-taking decreases with pay-performance sensitivity in CEO compensation, and increases with pay-risk sensitivity in CEO compensation (e.g., Smith and Stulz 1985, Cohen, et al. 2000, Knopf, Nam and Thornton 2002, Rajgopal and Shevlin 2002, Coles, Daniel, and Naveen 2006). Researchers have only more recently turned to executive compensation incentives in the banking industry. Chen, Steiner, and Whyte (2006) found that option-based compensation at U.S. banks during the 1990s was positively associated with market-based risk measures. Cheng, Hong and Scheinkman (2010) found that the residual pay to bank executives (the portion of total compensation not explained by bank size) is also positively related to market-based risk. Minnick, Unal and Yang (2011) found that banking companies run by executives with high pay-performance sensitivity (delta) are less likely to make value-reducing acquisitions, while Hagendorff and Vallascas (2011) found that acquisitions made by bank executives with high pay-performance sensitivity and/or low pay-risk sensitivity (vega) tend to reduce distance-to-default. DeYoung, Peng and Yan (2013) documented an increase in bank CEO vegas following banking industry deregulation, and found that bank

CEOs that were awarded higher vega contracts subsequently chose riskier business policies. Similarly, Bai and Elyasiani (2013) found evidence of increased risk-taking at banks with high CEO vegas.

3.2. Liquidity creation.

Economic theory has long recognized that banks create liquidity through their normal course of doing business: by making and holding illiquid loans, by issuing demandable deposit liabilities, and by providing liquidity insurance via off-balance contracts (e.g., Diamond and Dybvig 1983; Holmstrom and Tirole 1998; Kashyap, Rajan, and Stein 2002). But empirical methods for measuring bank liquidity creation have only more recently evolved. Deep and Schaefer (2004) proposed the LT gap, a simple measure of liquidity transformation equal to (liquid liabilities – liquid assets)/total assets. Berger and Bouwman (2009) proposed a more inclusive method that considers longer term, illiquid assets and liabilities as well as financial contracts that do not appear on the balance sheet. We use the latter of these two approaches to measure the total liquidity creation per dollar of assets, *TLCA*, as the primary measure of liquidity creation in this study. While the Berger and Bouwman (2009) measure is indeed the more comprehensive of the two approaches, it is also quite complicated. We provide only a brief overview of this measurement method here. Readers interested in more detail can refer to the initial study.

The process begins by classifying all bank assets and liabilities as either 'illiquid' or 'liquid' or 'semi-liquid'. On the left-hand side of the balance sheet, illiquid assets such as small business loans indicate that the bank has taken an illiquid position in exchange for increasing the liquidity of its borrowers. In contrast, liquid assets such as cash or government securities indicate that the bank has retained liquidity rather than extending liquidity. Weights of 0.5 and -0.5 are applied, respectively, to the dollar values of illiquid assets and liquid assets. On the right-hand side of the balance sheet, liquid items such as transactions deposits indicate that the bank has financed its assets while accepting liquidity risk. In contrast, illiquid items such as subordinated debt or equity indicate that the bank has financed its assets without accepting liquidity risk. Weights of -0.5 and 0.5 are applied, respectively, to the dollar values of illiquid liabilities/equity items and liquid liability items. Off the balance sheet, items such as unused loan commitments are considered illiquid positions and their asset-equivalent values are weighted by 0.5, while items such as derivatives contracts are considered liquid positions and their asset-equivalent values are weighted by -0.5. Any item that cannot be clearly categorized as liquid or illiquid (i.e., semi-liquid items) receives a zero weight.

Total liquidity creation *TLC* can be calculated in straightforward fashion as the sum of all the weighted balance sheet and off-balance sheet items. While these measures are crude and the approach is somewhat ad hoc, the underlying logic is rooted in economic theory: A bank that issues $100 of transactions deposits (0.5×$100) and uses those funds to make $100 of business loans (0.5×$100) *creates* $100 worth of liquidity. In contrast, a bank that issues $100 of equity securities (-0.5×$100) and uses those funds to purchase $100 of U.S. Treasuries (-0.5×$100) *consumes* $100 worth of liquidity. Dividing *TLC* by total bank assets yields liquidity creation per dollar of assets *TLCA*.

3.3. Systemic Risk.

Systemic estimated shortfall (*SES*) is one of the seminal approaches for measuring systemic risk, and it is the primary measure of systemic risk used in this study. Acharya, et al. (2017) define *SES* as the propensity of a bank to be undercapitalized when the banking system as a whole is undercapitalized. Logically, this propensity should increase with a bank's financial leverage (i.e., its proximity to being undercapitalized) as well as with the bank's expected losses during a financial crisis (i.e., its valuation in the tail of the banking system's loss distribution). A bank's *financial leverage* (*LEV*) is measured as the market value of its assets divided by the market value of its equity. A bank's expected losses during a crisis, the *marginal expected shortfall* (*MES*), is measured as the negative of its average daily stock returns on the 5 percent of the trading days each year during which the banking system suffers its largest valuation losses. The authors regressed the cumulative percentage stock returns of large U.S. financial institutions during the financial crisis (July 2007 through December 2008) on the values of *LEV* and *MES* for those banks during the twelve months leading up to the crisis, which generated the following cross sectional formula:

$$SES_{i,crisis} = 0.15*MES_{i,crisis-1} + 0.04*LEV_{i,crisis-1} \tag{9}$$

We use the estimated parameters in (9) to calculate annual fitted value measures of *SES* for every bank-year observation in our data.[5]

There is no standard definition of systemic risk nor is there a standard approach for systemic risk measurement.[6] It is instructive to compare our chosen SES approach to the ΔCoVaR approach of Adrian and Brunnermeier (2016), another of the seminal approaches to measuring systemic risk. CoVaR is the value at risk in the financial system conditional on the value at risk of an individual bank *i*. The authors estimate CoVaR^i_q as the fitted value from a quantile regression of the financial system's value at risk (VaR) on bank *i*'s VaR, evaluated at quantile *q* of *i*'s returns. Then ΔCoVaR^i_q is simply the predicted change in CoVaR^i_q when bank *i*'s returns decline from the median return quantile (i.e., normal returns) to an extreme tail return quantile (i.e., very large losses). As stated by the authors, this measure has only cross-sectional variation; time series variation can be added by pre-conditioning financial system's VaR and bank *i*'s VaR on a set of macroeconomic state variables (e.g., market interest rates, change in market rates, market-average credit risk spreads, equity market volatility). The authors estimate their models using weekly and quarterly data over 1971-2013; they show that ΔCoVaR estimated using pre-crisis data predicts more than one-third of the lost value in the financial system during 2007-2009.

In our panel estimation models, it is essential that bank-year observations exhibit within-bank time series variation in the systemic risk externality variable.[7] Bank-year observations of SES contain both cross sectional and time series variation, and both types of variation are derived from bank-level characteristics that change over time (*MES*, *LEV*). In contrast, the time series variation in bank-year observations of ΔCoVaR comes exclusively from macroeconomic state variables that do not vary across banks. In addition, SES is decomposable into business policy effects (*MES*) and financial policy effects (*LEV*), which allows

[5] The original estimates can be found in Table 4 and Appendix B of Acharya, et al. (2017). The authors also include a constant term and dummy variables for non-bank financial institutions. As including these terms are meaningless for our purposes, we drop them from our equation (9).
[6] See Brunnermeier and Oehmke (2012) for a survey of the literature.
[7] Expressed another way: If the time series variation in our systemic risk measure is driven entirely by macroeconomic state variables, then that variation will be absorbed into the time fixed effects.

us to test the channels through which managerial compensation incentives might be driving the creation of negative risk externalities. Hence, SES is the more appropriate measure for the purposes of our study.

4. First-stage estimates

We estimate the first-stage equations (4) and (7) for our full sample of 1,211 bank-year observations, using pooled OLS and no right-hand side variables other than the vectors π and σ^{π}. Because these first-stage estimations are orthogonalization exercises from which we draw no statistical inference, there is no *a priori* reason for adding structure. Including fixed effects terms in the first-stage regressions would absorb the time-invariant and bank-invariant variation in *TLCA* and *SES*, some of which (i.e., the external portions of *TLCA* and *SES*) we wish to capture in the spillovers ε_{TLCA} and ε_{SES}. In the Internet Appendix, we show that our first-stage results are materially unchanged when we include year and/or bank-CEO fixed effects.

A crucial presumption in our analysis is that the first-stage regression (4) strips a substantial amount of private returns π from the initial measure of liquidity creation *TLCA*, and likewise that the first-stage regression (7) strips a substantial amount of private risk-bearing σ^{π} from the initial measure of systemic risk *SES*, so that the first-stage residuals $\hat{\varepsilon}^{TLCA}$ and $\hat{\varepsilon}^{SES}$ contain mainly information on return and risk externalities. We cannot formally test the soundness of this presumption because the true externalities cannot be observed. However, we can and do examine the first-stage regression results for evidence that a substantial amount of orthogonalization has occurred.

Table 3 displays the results from the first stage of the liquidity creation model. We populate the private returns vector π with six variables that are broadly representative of the population of firm return measures: Return on equity (*ROE*), return on assets (*ROA*), the market-to-book ratio (*Market-to-Book*), net interest income scaled by assets (*Interest Margin*), the annual change in market capitalization scaled by assets (*ΔMktCap/Assets*), and the annual share price return predicted from a three-factor market model (*Expected Return*). In Panel A, we add these six variables one-at-a-time in decreasing order of their correlations with *TLCA* (see Panel C), beginning with *Interest Margin*. In Panel B we began once again with *Interest Margin*, but then added the remaining five variables one-at-a-time for each of the 120 possible sequences of those variables; the sequence that was most concave in adjusted-R^2 is displayed in Panel B. Following the same methodology, in Table 4 we show the results from the first stage of the systemic risk model. We populate the risk-bearing vector σ^{π} with six variables that are broadly representative of the population of firm risk measures: The standard deviation of *ROE*, the standard deviation of *ROA*, an accounting-based measure of insolvency risk (*Z Score*),[8] systematic risk from a three-factor model (*Beta*), the standard deviation of idiosyncratic return from a three-factor model (*Std(Idio. Return)*), and the standard deviation of equity returns (*Std(Returns)*).[9] We use the residual values from the column 6 regressions in these two tables as our measures of external liquidity creation ε_{TLCA} and external systemic risk ε_{SES}.

Figure 1 summarizes the relative statistical fits of the four regression sequences shown in Tables 3 and 4. Each of the four graphs is either concave or nearly concave, and in each case the incremental improvement in statistical fit from adding the sixth variable is very small. The clear implication is that adding private return and private risk variables beyond those we have already considered would not meaningfully reduce the amount of *TLCA* or *SES* variation left in the regression residuals.

We are relatively uninterested in the signs and statistical significance of individual coefficients in these first-stage models. In some cases we observe discrete jumps in the regression standard errors that are indicative of multicollinearity, while in other cases we observe coefficients with economically non-intuitive signs. Neither outcome is surprising, given the strong correlations among each set of first-stage regressors shown in the two Panel Cs. Moreover, neither outcome is worrisome for our purposes, as we are not testing hypotheses in the first-stage of the model.

It is instructive to visualize the results of the first-stage orthogonalizations. The right-hand side of Figure 2 displays the annual means for the estimated liquidity creation residuals ε_{TLCA} and the estimated systemic risk residuals ε_{SES}, while the left-hand side of the figure displays the annual means for the

[8] We use the accounting-based Z score rather than the market-based Distance-to-Default measure because the latter is conceptually similar to systemic risk (see International Monetary Fund 2011, Saldias 2013, and Anginer, Demirguc-Kunt and Zhu 2014). Hence, using the latter would run the risk of overidentification in the first stage of the model.
[9] We use a three-factor market model to estimate *Beta* and *Std(Idio. Return).* The three factors are daily returns on a CRSP value-weighted market portfolio, daily 3-month T-Bill yields, and daily 2-year to 10-year Treasury spreads.

underlying parent variables *TLCA* and *SES*. By definition, both sets of residuals are centered around zero. Although *TLCA* is relatively flat over time, the associated residual ε_{TLCA} exhibits a noisy upward trend, an indication that the external liquidity creation per dollar of assets generated by the banks in our data was increasing over time. We will control for this by using year fixed effects in the second-stage model. The data for *SES* and ε_{SES} move in roughly parallel fashion over time.

5. Baseline results

We estimate the second-stage equations (5) and (8) using OLS with year and bank-CEO fixed effects. The test variables are the one-year lagged values of *lnDelta* and *lnVega*, and statistical inference is performed using standard errors clustered at the bank-CEO level.[10] Because nearly all bank financial statement variables are choice variables for bank management, and hence potentially endogenous to CEO pay incentives, we specify the *controls* vector using just three arguably exogenous variables. Lagged bank size (*lnAssets*) is a standard control variable in empirical banking studies and is relatively persistent on a year-to-year basis. Lagged CEO tenure at the bank (*lnCEOtenure*) has been used an instrument in previous studies of executive pay and firm risk-taking. The Philadelphia Fed's Coincident Index of State Economic Conditions, which we weight for each bank based on the distribution of its deposits in each state (*Econ Index*), controls for both cross-sectional and time-series variation in the macro-economic conditions facing each bank. We have no *a priori* expectations about the signs of the coefficients on these variables. The year and bank-CEO fixed effects provide additional time-series and cross-sectional explanatory power. We also note that, because our dependent variables are residuals from first-stage processes, the six control variables used in the first-stage estimations are indirectly controlled for in the second-stages estimations.

5.1. Liquidity creation model. Columns 1 and 2 in Table 5 show the baseline results for the two-stage liquidity creation model. The first-stage regression explains 12% of the variation in *TLCA*. We are

[10] We use bank-CEO fixed effects and cluster standard errors at the bank-CEO level because compensation packages, executive incentives, and executive preferences can change substantially upon the hiring of a new CEO. In the Internet Appendix, we show that our second-stage results are robust to other effects specifications and clustering approaches.

unconcerned by this relatively low statistical fit—indeed, a very high first-stage R^2 would pose a greater concern, as it might indicate that we were absorbing not only private return variation but also a portion of the external returns that we wish to leave in the regression residuals. While the first-stage equation was not designed with statistical inference in mind, it is instructive to note *Interest Margin* is the most statistically precise of the six private return coefficients. This is a sensible result, as a bank's interest margin captures most directly the financial flows (interest revenues and interest expenses) thrown off by the two primary components of bank liquidity generation (loans and deposits). It is also economically significant: A one-standard deviation increase in *Interest Margin* is associated with an 11.9% increase in *TLCA*.[11]

lnDelta is statistically negative in the second-stage regression. A one-standard deviation increase in *lnDelta* is associated a 0.19 standard deviation decrease in external liquidity creation ε_{TLCA}.[12] The coefficient on *lnVega* is statistically positive, with a one-standard deviation increase in *lnVega* associated with a 0.14 standard deviation increase in ε_{TLCA}. The directions of these effects are consistent with economic logic as well as with the stylized theoretical framework presented in the Internet Appendix: An increase in vega or decrease in delta increases managers' incentives to take risk; this higher desired level of risk can be accomplished by increasing the bank's liquidity-generating activities (which generate credit risk, liquidity risk, and/or interest rate risk); and, as an unpriced byproduct of these private business decisions, external liquidity creation also increases.

For comparative purposes, in column 3 we estimate a naïve single-equation approach in which the dependent variable *TLCA* is not orthogonalized to private returns. We find no statistical association between bank liquidity creation and either *lnDelta* or *lnVega* in this naïve model. Why might CEO compensation incentives be strongly related to the bank's external liquidity creation, but be unrelated to the bank's total liquidity creation? Let's assume an increase in CEO vega that gives her an incentive to take

[11] The calculation is (6.900*0.0077)/0.447 = 0.1189, where 6.900 is the coefficient on *Interest Margin*, 0.0077 is the standard deviation (converted from percent) of *Interest Margin*, and 0.447 is the mean of *TLCA*.

[12] The calculation is (-0.0221*0.56)/0.0655 = -0.1889, where -0.0221 is the coefficient on *lnDelta* and the standard deviations 0.56 and 0.0655 are the average de-meaned (within) standard deviations, respectively, of *lnDelta* and ε_{TLCA} reported in the final column of Table 2. Unless otherwise indicated, all other similar calculations follow this format.

more risk. She may accomplish this by changing the composition of bank liquidity creation, while leaving the total amount of bank liquidity creation unchanged: Credit risk can be increased by reallocating the existing loan portfolio from high quality borrowers to low quality borrowers; liquidity risk can be increased by reallocating existing business lending from term loans to credit lines; and interest rate risk can be increased by altering the durations of existing loans and deposits.[13] Moreover, large commercial banking companies have numerous ways to generate returns and risk, and many of those business lines (e.g., securities brokerage, securities trading, investment banking, insurance sales, risk management services, private wealth management) are unrelated to liquidity generation or net liquidity generation.

We estimate several variants of this two-stage model (unreported, see Internet Appendix). In one, we calculate *Delta* and *Vega* based on the aggregate compensation attributes of the top five managers, including the CEO, at each banking company, and then re-estimate both the liquidity creation and systemic risk models. In another, we use a 'securitization-adjusted' version of total liquidity creation (see Berger and Bouwman, 2009) that partially credits banks with liquidity creation for securitizing loans that they originate rather than holding them on their balance sheets.[14] The estimated coefficients on *lnDelta* and *lnVega* are materially unchanged from the baseline results in Table 5.

5.2. Systemic risk model. Columns 5 and 6 in Table 5 show the baseline results for the systemic risk model. The first-stage regression explains 22% of the variation in *SES*. *Beta* carries the most statistically precise of the six private risk coefficients and is also economically significant: A one-standard deviation increase in *Beta* is associated with an 11.1% increase in *SES*. This result is consistent with the observations of Benoit, et al. (2013), Guntay and Kupiec (2014) and others that systemic risk measures contain substantial information about systematic risk.

[13] It is straightforward to explain why a decrease in CEO delta could also result in this outcome.

[14] Although we include this robustness test, we feel that the concern is unwarranted. At any given point in time, a bank is creating liquidity only when it holds an illiquid loan. In contrast, when a bank sells a loan in exchange for cash—regardless of whether it is a straight loan sale or a loan sale into a securitization pool—the selling bank is no longer creating liquidity. Rather, the liquidity is now being created by the financial institution that purchased the loan or loan-backed security, because it traded a liquid asset (cash) in exchange for an illiquid asset.

In the second-stage regression, the coefficient on *lnDelta* is statistically negative and economically meaningful; a one-standard deviation increase in *lnDelta* is associated with a 0.42 standard deviation decrease in $\hat{\varepsilon}_{SES}$. The coefficient on *lnVega* is statistically positive but economically small; a one-standard deviation increase in *lnVega* is associated with an economically small 0.04 standard deviation increase in $\hat{\varepsilon}_{SES}$. These results imply that business decisions made by relatively less risk-averse (high-vega or low-delta) managers generate greater amounts of systemic risk externalities.

The *lnDelta* and *lnVega* coefficients are little changed in the naïve single-equation model shown in column 7. This is not to say that the first-stage equation did not remove substantial information about private risk from *SES*; far from it, given the first-stage adjusted-R^2 statistic of 0.217. Rather, it simply indicates that the distributions of the systemic risk externality ε_{SES} and the systemic risk variable *SES* are related similarly to CEO wealth incentives. Stated differently, a given change in managerial incentives will have a similar marginal impact on both public risk and private risk. Why might this be the case? Unlike *TLCA*, which Berger and Bouwman (2009) designed to measure private activity at banks but unavoidably also captures related spillover effects, *SES* was designed explicitly with spillover effects in mind. Hence, if extraneous private risk information is randomly captured in the process of constructing *SES*, removing this random information is less likely to substantially re-center the distribution.[15]

5.3. Potential joint effects

Before moving ahead, we must acknowledge a tacit restriction that is embedded in our baseline models. By estimating the *TLCA* and *SES* models separately, we are assuming that compensation-induced business decisions have independent and separable effects on the externality measures ε_{TLCA} and ε_{SES}. In other words, we are ruling out joint effects. For example, the CEO might react to higher vega by taking on more financial leverage, which all else equal will increase the bank's systemic risk externality. But if the bank achieves this leverage by issuing more transactions deposits (as opposed to issuing time deposits) then the CEO's actions will also increase

[15] We note that the *lnDelta* and *lnVega* coefficients have somewhat smaller magnitudes in the two-stage model than in the naïve one-stage model—32% smaller and 14% smaller, respectively—an indication that the first-stage orthogonalization did have an impact, albeit a small impact, on the structure of the data.

the bank's liquidity creation externality. If these joint effects are large enough, the coefficients on *lnVega* and *lnDelta* in Table 5 could be misleading.

We investigate the empirical importance of these potential joint effects in columns 4 and 8 in Table 5. In column 4, we augment the second-stage external liquidity creation (ε_{TLCA}) baseline regression by including the external systemic risk (ε_{SES}) variable on the right-hand side. If joint effects are strong—that is, if both ε_{TLCA} and ε_{SES} are substantially driven by the same set of business decisions—then a large part of the variation in ε_{TLCA} will be explained by ε_{SES} and the coefficients on *lnVega* and *lnDelta* will decline in magnitude and/or lose their statistical significance. The same logic applies in column 8, where the second-stage external systemic risk (ε_{SES}) baseline regression by including the external liquidity creation (ε_{TLCA}) variable on the right-hand side.

The positive coefficient on ε_{SES} in column 4 indicates that the two externalities on average move up and down together; this result is consistent with the notion that some business decisions do jointly create liquidity creation and systemic risk externalities. However, the coefficients on *lnDelta* and *lnVega* are little changed, consistent with our assumption that incentive-based changes in external liquidity creation do not substantially run through external systemic risk. We find similar results in column 8, where the coefficient on the added externality term is statistically positive but the coefficients on *lnDelta* and *lnVega* are little changed.[16]

6. Business decisions

We now turn to the channels through which actions taken by incentivized managers result in market externalities. We can derive these channels formally from our model. Substituting equations (1) and (3) into equation (4) and solving for the liquidity externality yields:

$$\varepsilon^{L} = L(X(delta,vega)) - b\cdot\pi(X(delta,vega)) - a \tag{10}$$

[16] In difference-in-means tests applied across columns 2 and 4, the p-values for the coefficients on *lnDelta* and *lnVega* are 0.08 and 0.47, respectively. For similar tests across columns 6 and 8, these p-values were 0.14 and 0.12, respectively.

where we have suppressed the subscripts *i* for simplicity. Taking the derivative with respect to executive compensation incentives, applying the chain rule, and rearranging yields the expression of interest:

$$\frac{\partial \varepsilon^L}{\partial(delta, vega)} = \left[\frac{\partial L}{\partial X} - b \cdot \frac{\partial \pi}{\partial X}\right]\left[\frac{\partial X}{\partial(delta, vega)}(delta, vega)\right] \tag{11}$$

The first bracketed expression is the change in external liquidity creation ε^L for a marginal change in business decisions *X* (i.e., the difference between the total liquidity created by the business decision $\partial L/\partial X$ and the liquidity intended to be created by the business decision $b \cdot \partial\pi/\partial X$). The second bracketed expression is the elasticity of business decision *X* with respect to executive wealth incentives *delta* and *vega*.

Now assume that managers have $K = (1,k)$ categories of business decisions *X* at their disposal. If executive wealth incentives *delta* and *vega* have separable effects on each business decision *k*, and each business decision *k* has a separable effect on external liquidity creation, then we can disaggregate (11) into *K* separate business decision-specific effects:

$$\frac{\partial \varepsilon_k^L}{\partial(delta, vega)} = \left[\frac{\partial L}{\partial X_k} - b \cdot \frac{\partial \pi}{\partial X_k}\right]\left[\frac{\partial X_k}{\partial(delta, vega)}(delta, vega)\right] \tag{12}$$

Proceeding in parallel fashion yields a similar expression for external systemic risk:

$$\frac{\partial \varepsilon_k^S}{\partial(delta, vega)} = \left[\frac{\partial S}{\partial X_k} - b \cdot \frac{\partial \pi}{\partial X_k}\right]\left[\frac{\partial X_k}{\partial(delta, vega)}(delta, vega)\right] \tag{13}$$

By construction, both *LTCA* and *SES* are separable across broad categories of business decisions. Following Berger and Bouwman (2009), we disaggregate *LTCA* into three broad areas of business activity: On-balance sheet activities, off-balance derivatives exposures, and off-balance sheet credit commitments. Following Acharya, et al. (2017), we disaggregate *SES* into two broad areas of risk exposure: *MES* captures the bank's sensitivity to market shocks and is associated mainly with banks' investment decisions, while *LEV* measures the bank's financial leverage and is associated mainly with banks' financing decisions.

The disaggregated results for liquidity creation are displayed in Table 6. Perhaps surprisingly, we find little evidence linking CEO wealth incentives to liquidity creation spillovers via on-balance sheet channels. The coefficients on *lnDelta* and *lnVega* are either statistically non-significant or carry an unintuitive sign in columns 2, 4 and 6. Rather, the association between CEO wealth incentives and external liquidity creation runs chiefly through off-balance sheet credit commitments (columns 8 and 12). By issuing revolving business credit facilities, consumer credit cards, and home equity lines of credit, banks incur future liquidity (drawdown) risk—as well as the future credit risk and interest rate risk accompanied by on-balance sheet activities—in exchange for immediate revenue from origination, upfront, facility and/or commitment fees. Our results suggest that banks become more willing to accept this intertemporal return-risk tradeoff when higher vega or lower delta increases CEO risk-taking incentives. A one-standard deviation increase in *lnVega* (decrease in *lnDelta*) is associated with a .165 standard deviation increase (.351 standard deviation increase) in external liquidity creation.

The disaggregated results for systemic risk, displayed in Table 7, indicate that financial risk (*LEV*) is the main channel through which CEO wealth incentives influence systemic risk externalities. By increasing CEO vega or cutting CEO delta, the bank provides incentives to expand financial leverage, which in turn generates larger systemic risk spillovers. The delta effects are far stronger than the vega effects: A one-standard deviation decrease in *lnDelta* is associated with a .432 standard deviation increase in external systemic risk, while a similar increase in *lnVega* is associated with just a .043 standard deviation increase in external systemic risk. An increase in CEO vega is also positively associated with increased exposure to negative industry shocks (*MES*), though this result is economically small and statistically weak.

In summary, banks respond to high-delta CEO contracts by writing fewer loan commitments and by levering down, respectively resulting in less liquidity creation spillover and less systemic risk spillover. In contrast, banks respond to high-vega CEO contracts by writing more loan commitments and levering up, respectively resulting in more liquidity creation spillover and more systemic risk spillover.

7. Alternative measures of systemic risk

All models of systemic risk are imperfect. As described above, SES is measured relative to a benchmark systemic event; as a result, estimates of SES necessarily become less accurate for years long before or long after the year in which the benchmark event occurred. Our annual 1994-2016 SES estimates are benchmarked to the financial crisis event in 2008, so our estimates of SES in the 1990s may be especially susceptible to measurement error. In Table 8 (columns 1 and 2) we re-estimate our baseline systemic risk model for the shorter 2000-2016 sample period. The coefficients on *lnDelta* and *lnVega* have the same statistically significant signs, but are now 14% and 22% larger, respectively, relative to the baseline model in Table 5. Hence, our baseline results are likely underestimates of the sensitivity of systemic risk spillovers to CEO wealth incentives.

The SRISK method of measuring systemic risk (Brownlees and Engle 2015) provides a second way to avoid this potential measurement error problem. Like SES, SRISK measures a bank's expected capital shortfall conditional on a systemic event and contains both cross-sectional and time-series variation, but SRISK does not rely on an actual benchmark systemic event. We estimate *SRISK* each year for each bank and normalize these estimates by bank assets.[17] The signs, statistical significance, and economic magnitudes of the *lnDelta* and *lnVega* coefficients are relatively robust to replacing *SES* with *SRISK* in our model (columns 3 and 4). A one-standard deviation increase in *lnDelta* (*lnVega)* is associated with a 0.32 standard deviation decrease (a 0.09 standard deviation increase) in external systemic risk.

ΔCoVaR estimations of systemic risk (Adrian and Brunnermeier 2016) exhibit no bank-specific time series variation, and hence are incompatible with our panel data modeling approach. Nevertheless, ΔCoVaR has two desirable characteristics not found in SES: It measures the *contribution* of an individual bank to system-wide risk (SES measures the *exposure* of an individual bank to a system-wide event) and it is parameterized using data from multiple business cycles (SES is parameterized using data from a single

[17] Like Brownlees and Engles (2015), we estimate monthly measures of SRISK for each bank, but then we calculate the annual measure that we need as the average of the monthly estimates. For purposes of tractability, we assume that equity returns of the bank and the market follow a bivariate normal distribution.

recession or crisis). We re-estimate our systemic risk model for two different ΔCoVaR approaches. First, we use Adrian and Brunnermeier's (2016) original ΔCoVaR approach (we refer to this as *classic-ΔCoVaR*) which generates a single estimate of systemic beta for each bank, with time series variation coming only from the macroeconomic state variables (see columns 5 and 6). Second, use Sedunov's (2016) *adapted-ΔCoVaR* approach which injects bank-specific time series variation into systemic beta by executing the estimations on five-year rolling windows of data (see columns 7 and 8).[18]

Neither of the *ΔCoVaR* specifications generate statistically significant coefficients on *lnDelta* or *lnVega*. This is consistent with an ancillary result reported in Sedunov (2016, page 84, footnote 28), who also found no statistical relationship between systemic risk and executive compensation. We offer two potential, mutually exclusive explanations for these results. First, as already pointed out, the general lack of bank-specific time series variation in *ΔCoVaR* may simply preclude us from finding statistically precise relationships between these measures and the *lnDelta* and *lnVega* measures. Second, and more intriguing, is the possibility that the business decisions made by bank managers in response to delta and vega impact their banks' *exposures* to systemic risk without affecting their banks' *contributions* to systemic risk. Our finding that externalities associated with financial leverage (*LEV*) are strongly related to delta and vega (see Table 7) is consistent with this notion; all else equal, a bank's financial leverage amplifies its exposure to exogenous earnings shocks.

8. Maintained assumptions

We now address two important assumptions of our framework: Is a liquidity creation spillover always a positive economic externality? And are systemic risk spillovers purely public outcomes?

There may be times when banks individually or collectively produce too much liquidity. Excess extensions of credit can result in asset bubbles, which are prone to rapid collapse and attendant macroeconomic distress; during such episodes, a marginal increase in liquidity creation could constitute a

[18] For both approaches, we use weekly bank asset returns, weekly asset returns on the banking sector, and macroeconomic state variables to estimate *ΔCoVaR*.

negative externality. To identify periods of potential excess liquidity creation, we apply a Hodrick-Prescott filter to a 1947-2017 time series of the change in total lending by U.S. commercial banks as a percentage of U.S. GDP. Not surprisingly, this identified 2006 and 2007 as the two largest positive outliers of our 1994-2016 sample period. We create a dummy variable *Credit Bubble*=1 for these two years, and interact it with *lnDelta* and *lnVega* in the second-stage liquidity creation regression.

The results are displayed in the first column of Table 9. The derivative $\partial\varepsilon_{TLCA}/\partial$*Credit Bubble* = 0.1757 indicates that the liquidity creation externality increased by a large 2.68 standard deviations on average during each of the bubble years. This is consistent with the consensus *ex post* wisdom that banks were providing too much credit in the years leading into the financial crisis. The stand-alone (non-bubble period) coefficients on *lnDelta* and *lnVega* are relatively unchanged from the baseline estimates. Moreover, neither of the conditional partial derivatives $\partial\varepsilon_{TLCA}/\partial$*lnDelta(Credit Bubble=1)* and $\partial\varepsilon_{TLCA}/\partial$*lnVega(Credit Bubble=1)* are statistically different from zero. This implies an environment in which liquidity creation was on an autopilot setting, uninfluenced by the wealth incentives of bank CEOs. Such a characterization is completely consistent with then-CitiGroup CEO Charles Prince's infamous 2007 statement that "As long as the music is playing, you've got to get up and dance."

Some banks might not ignore the systemic risk spillovers that they generate. For example, to increase their chances of receiving a government bailout during an economic downturn, banks might engage in 'herding' behavior in which they manage their business decisions to increase their co-movements (systemic risk exposures) with other banks. Very large banks might be especially likely to benefit from such behavior, because they are more likely to be bailed out during a 'too-many-to-fail' scenario. To test these notions, we interact *lnDelta* and *lnVega* with two different dummy variables: *Herding*=1 if the correlation of bank daily returns and banking industry daily returns exceeds the 90th percentile of the sample distribution, and *Over250*=1 if banks have more than $250 billion in assets (2016 dollars). The results, displayed in the second and third columns of Table 11, are not consistent with either herding behavior or too-many-to-fail behavior. The partial derivatives $\partial\varepsilon_{SES}/\partial Herding$ and $\partial\varepsilon_{SES}/\partial Over250$ are both statistically non-significant.[19]

9. Policy implications

To have meaningful implications for regulatory policy, the coefficients in our models must translate into macro-economically meaningful changes in market externalities. In Panel A of Table 10 we perform some back-of-the-envelope calculations to gross up our baseline bank-level liquidity externality results to the banking system level. Panel B shows a parallel set of calculations for systemic risk externalities.

Moving left-to-right across the first row of panel A, we begin by multiplying a one-standard deviation shock to *lnDelta* (0.56) by the estimated coefficient on *lnDelta* (-0.0221) from our baseline model. This results in an annual reduction in external liquidity creation of $0.0124 per dollar of assets for the average bank in our data. Multiplying by the average aggregate assets for the banks in our data (about $4.09 trillion), we find an annual aggregate reduction in external liquidity creation of $50.7 billion. Dividing this by the average annual aggregate liquidity created by the banks in our data (about $1.82 trillion) yields an economically meaningful 2.79% reduction in system-wide liquidity creation. Using the same method in the second row of Panel A, a one-standard deviation increase in *lnVega* results in a 2.05% increase in system-wide external liquidity creation. Thus, normal variation in CEO delta and CEO vega have substantial and absolutely similar effects on system-wide liquidity creation externalities.

We find more disparate results for external systemic risk in panel B. A one-standard deviation across-the-board increase in *lnDelta* results in an estimated 7.08% reduction in external systemic risk, while the same size increase in *lnVega* results in just a small 0.73% increase in external systemic risk. Thus, if our policy objective is to reduce systemic risk externalities, and if our policy instrument is bank executive compensation, then encouraging banks to award stock grants to their CEOs (increasing delta) would be a much more effective than discouraging banks from awarding stock option grants to their CEOs (decreasing

[19] Although the conditional partial derivatives $\partial\varepsilon_{SES}/\partial lnVega$ (θ=1) are no longer statistically significant in columns 2 and 3, they carry essentially the same economic magnitudes as the coefficients on *lnVega*.

vega). This set of results is consistent with the spirit of Federal Reserve guidelines (2016) that stress greater reliance on long-term equity-based compensation.

These calculations illustrate an important side effect of policies that aim to reduce harmful systemic risk externalities by regulating bank CEO contracts: Doing so likely also reduces beneficial liquidity creation spillovers. Let's assume that regulation calls for banks to increase *lnDelta* by one standard deviation via increased stock grants. According to our calculations, this will drive down systemic risk by 7.08% but will reduce system-wide liquidity creation by 2.79%. Banks will naturally want to offset the increase in CEO stock grants by reducing some other dimension of CEO remuneration. This could be accomplished by reducing CEO cash salary, which would likely have little additional impact on managerial incentives. But if the offset is accomplished by reducing SEO stock options, then there will be a further reduction in liquidity spillovers; for example, if the stock option offset required a one-standard deviation reduction in *lnVega*, liquidity spillovers would decline by another 2.05%. Thus, in this crude example, the overall cost of reducing system-wide systemic risk by 7.08% might be as much as a 5.04% reduction in the system-wide liquidity creation externality.[20]

10. Conclusions

A small body of research examines how bank executive compensation influences bank financial performance. But there is no evidence to date on the links between bank executive compensation and the positive and negative externalities generated by banks. We find statistically strong and economically meaningful evidence of such links at large U.S. commercial banking companies between 1994 and 2016. Increases in CEO pay-for-performance incentives (delta) are associated with economically substantial reductions in both systemic risk and liquidity creation externalities. Increases in CEO pay-for-risk incentives (vega) are associated with statistically significant albeit smaller increases in both externalities.

[20] To the best of our knowledge, Boyd and Heitz (2016) is the only other study that attempts to measure social cost tradeoffs related to systemic risk. They conclude that the social savings from scale economies achieved by large U.S. banking companies are insufficient to offset the social costs of systemic risk associated with these banks.

These results illustrate a vexing tradeoff for bank regulatory policy: A regulation that dampens a bank CEO's risk-taking incentives reduces her bank's exposure to systemic risk, but only at the cost of also reducing her bank's contribution to system-wide liquidity.

Measuring the social costs and benefits of externalities is difficult because, by definition, externalities are unintentional byproducts and are not priced by the market. Recent research provides us with quantitative starting points. Starting with the Berger and Bouwman (2009) measure of liquidity creation), we measure liquidity creation spillovers as the portion of the Berger and Bouwman measure that is orthogonal to the observable private returns to bank shareholders. And starting with the Acharya, et al. (2017) measure of systemic expected shortfall, we measure systemic risk spillovers as the portion of SES that is orthogonal to the observable private risk borne by bank shareholders. With our measures of positive and negative spillovers in-hand, we exploit the unintentional nature of spillover effects to identify the causal link between executive pay incentives and externalities. Because unpriced externalities are unintentional, they carry no weight in either manager or shareholder objective functions—in which case, executive compensation incentives become exogenous regressors in our models.

We engage in this research in hopes of informing the ongoing efforts of bank regulators to optimize macro-prudential guidelines for bank executive compensation. Some of these regulatory efforts have been more reactive than well-reasoned and are unlikely to have significant or long-lasting impacts. The tight restrictions on executive compensation following Troubled Asset Relief Program (TARP) capital infusions and the non-binding shareholder 'say-on-pay' rules imposed by the U.S. Securities and Exchange Commission (2011) may well fall into this category.[21] More thoughtfully considered efforts—such as the executive pay guidelines jointly issued by the various U.S. bank regulatory agencies (Federal Reserve 2016) that encourage long-term, equity-based compensation for bank executives—may have a better chance to bear fruit. Consistent with the intent of those guidelines, we show that equity-based pay incentives have substantially stronger effects on systematic risk than do options-based pay incentives. Nevertheless, in a

[21] The former originated with the Emergency Economic Stabilization Act of 2008. The latter originated with the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010.

post-crisis regulatory environment in which large bank executives enjoy less scope for risk-taking—e.g., tighter restrictions on financial leverage, balance sheet liquidity, and permissible banking activities—the links between executive pay incentives and social externalities may be different from those that we find during our 1994-2016 sample period.

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Table 1 – Variable Definitions

All variables are observed annually at the firm level between 1994 and 2016.

Assets	Total banking company assets.
Beta	Systematic risk. Coefficient on the market return variable in a three-factor market model estimated annually using daily data. The three factors are CRSP value-weighted stock market return, the 2-to-10 year Treasury yield spread, and the 6-month T-Bill rate.
CEO Tenure	Number of years the current CEO has held this job.
Adapted-ΔCoVaR	The change in the value at risk of the financial system conditional on an individual bank being under extreme events to its median state per the Sedunov's (2014) ΔCoVaR approach. See Sedunov (2014) for details.
Classic-ΔCoVaR	The change in the value at risk of the financial system conditional on an individual bank being under extreme events to its median state per the Adrian and Brunnermeier's (2016) ΔCoVaR approach. See Adrian and Brunnermeier (2016) for details.
Delta	Following Core and Guay (2002), the change in the dollar value of the CEO's wealth for a 1% change in the bank's stock price.
Economic Index	The average value of the Philadelphia Fed's Coincident Index of State Economic Conditions facing the bank, weighted by the share of the bank's deposits across the states in which it operates.
Expected Return	The one-year predicted value from a three-factor market model estimated annually using daily data. The three factors are CRSP value-weighted stock market return, the 2-to-10 year Treasury yield spread, and the 6-month T-Bill rate.
Interest Margin	(Interest Revenue – Interest Expense) / Total Assets
LEV	Following Acharya, et al. (2010, Appendix B), the financial leverage component of *SES*.
Market-to-Book	Market value of total assets divided by book value of total assets.
MES	Following Acharya, et al. (2010, Appendix B), the marginal expected shortfall component of *SES*.
ΔMktCap/Assets	Change in market capitalization divided by total assets.
ROA	Net income divided by total assets.
ROE	Net income divided by equity capital.
SES	Following Acharya, et al. (2010, Appendix B), the systemic expected shortfall.
ε_{SES}	External systemic risk. The value of the residual term from an ordinary least squares regression of *SES* on *Std(ROE)*, *Std(ROA)*, *Std(Idio. Return)*, *Std(Return)*, *Beta*, *and Z Score*.
SRISK	The expected capital shortfall for an individual bank conditional on a systemic event. See Brownlees and Engle (2015) for details.

Std(Idio. Return)	Standard deviation of idiosyncratic returns, the residual values predicted from a three-factor market model estimated annually using daily data. The three factors are CRSP value-weighted stock market return, the 2-to-10 year Treasury yield spread, and the 6-month T-Bill rate.
Std(Return)	Standard deviation of daily stock returns over one year.
Std(ROA)	Standard deviation of ROA over 5 years.
Std(ROE)	Standard deviation of ROE over 5 years.
TLCA	Following Berger and Bouwman (2009), the liquidity creation per dollar of assets generated by the bank's on- and off-balance sheet activities.
ε_{TLCA}	External liquidity creation. The value of the residual term from an ordinary least squares regression of *TLCA* on *Market-to-Book*, *Interest Margin*, *ROA*, *ΔMktCap/Assets*, *ROE*, and *Expected Return*.
Vega	Following Core and Guay (2002), the change in the dollar value of the CEO's wealth for a 0.01 change in stock volatility from a Merton option pricing model.
Z Score	Distance to default: (ROA + (Equity Capital/Total Assets)) / Standard Deviation of ROA, where Standard Deviation of ROA is measured over 5 years.

Table 2 – Summary Statistics

1,211 bank-year observations on 1994-2016. All variables are winsorized at the 1st and 99th percentiles. Dollar variables are in 2016 U.S. dollars. See Table 1 for full set of variable definitions.

	Mean	Std. Dev.	25%	50%	75%	*For selected variables:* Cross sectional means of firm-CEO specific standard deviations
Systemic risk						
SES	0.092	0.047	0.064	0.080	0.104	0.0200
ε_{SES}	0.000	0.039	-0.023	-0.007	0.015	0.0187
MES	0.0274	0.0220	0.0135	0.0205	0.0325	0.0143
ε_{MES}	0.0000	0.0126	-0.0084	-0.0006	0.0071	0.0101
LEV	2.1923	1.1278	1.5102	1.9015	2.4773	0.4713
ε_{LEV}	-0.0027	0.9690	-0.5778	-0.1949	0.3660	0.4534
SRISK	-0.125	0.066	-0.157	-0.114	-0.081	0.0336
ε_{SRISK}	0.000	0.057	-0.026	0.009	0.038	0.0304
Classic-ΔCoVaR	0.063	0.027	0.043	0.057	0.074	0.0196
$\varepsilon_{Classic\text{-}\Delta CoVaR}$	0.001	0.015	-0.009	-0.001	0.009	0.0105
Adapted-ΔCoVaR	0.057	0.025	0.038	0.050	0.076	0.0185
$\varepsilon_{Adapted\text{-}\Delta CoVaR}$	0.000	0.017	-0.011	-0.002	0.011	0.0133
Liquidity creation						
TLC ($1,000,000s)	32,777	89,539	2,358	5,763	17,914	
TLCA	0.447	0.175	0.356	0.451	0.544	0.0512
ε_{TLCA}	-0.016	0.178	-0.135	-0.010	0.096	0.0655
TLCA On-balance Sheet	0.2888	0.1437	0.2219	0.2969	0.3800	0.0373
$\varepsilon_{TLCA\ On\text{-}balance\ Sheet}$	-0.0005	0.1186	-0.0774	-0.0026	0.0821	0.0482
TLCA Off-balance Sheet	0.1571	0.1131	0.0860	0.1283	0.1889	0.0216
$\varepsilon_{TLCA\ Off\text{-}balance\ Sheet}$	-0.0167	0.1320	-0.0964	-0.0277	0.0506	0.0558
TLCA Derivatives	-0.0004	0.0013	-0.0003	0.0000	0.0000	0.0005
$\varepsilon_{TLCA\ Derivatives}$	0.0000	0.0013	0.0000	0.0003	0.0005	0.0005
TLCA Credit Commitments	0.1575	0.1136	0.0860	0.1285	0.1897	0.0217
$\varepsilon_{TLCA\ Credit\ Commitments}$	-0.0167	0.1324	-0.0968	-0.0283	0.0514	0.0558
Compensation incentives						
Delta ($) (CEO)	492,663	723,004	75,558	211,276	583,982	
lnDelta (CEO)	12.238	1.396	11.233	12.261	13.278	0.56
Vega ($) (CEO)	98,124	198,722	2,419	25,085	88,370	
lnVega (CEO)	8.562	4.305	7.792	10.130	11.390	2.08
Second-stage controls						
Assets ($1,000,000s)	76,993	230,916	6,894	14,193	47,040	
lnAssets	9.880	1.445	8.838	9.561	10.759	
CEO tenure	8.01	6.57	3	6	11	
lnCEOtenure	1.750	0.848	1.099	1.792	2.398	
Economic Index	129.59	18.91	113.07	133.28	142.79	
First-stage private returns						
Market-to-Book	1.08	0.08	1.03	1.07	1.12	
Interest Margin (%)	3.26	0.77	2.87	3.30	3.76	
ROA (%)	1.01	0.74	0.83	1.09	1.35	
ΔMktCap/Assets (%)	1.88	5.14	-0.96	1.63	4.57	
ROE (%)	10.92	9.14	7.84	12.27	15.84	
Expected Return (%)	16.93	32.97	-3.72	13.28	36.98	
First-stage private risk						
Std(ROE) (%)	4.94	7.72	1.52	2.61	4.89	
Std(ROA) (%)	0.41	0.56	0.12	0.21	0.41	
Std(Idio. Return) (%)	1.74	1.05	1.12	1.39	1.97	
Std(Return) (%)	2.20	1.34	1.38	1.75	2.50	
Beta	1.09	0.42	0.80	1.08	1.34	
Z Score	27.78	10.77	22.13	26.60	32.37	

Table 3 – First-stage TLCA regressions

Pooled ordinary least squares estimates of equation (4). Dependent variable is *TLCA*. In Panel A, right-hand side variables are added in order of highest correlation with *TLCA*. In Panel B, right-hand side variables are added in the order of highest impact on adjusted-R^2. Panel C displays Pearson correlations. Standard errors are clustered at the bank-CEO level and appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels. See Table 1 for full set of variable definitions.

Panel A: Regressors added in order of highest correlation with TLCA.

	[1]	[2]	[3]	[4]	[5]	[6]
Interest Margin	9.446***	8.251***	8.033***	8.097***	6.801**	6.900***
	(2.533)	(2.758)	(2.765)	(2.703)	(2.688)	(2.615)
Market-to-Book		0.689	0.607	0.459	0.657	0.567
		(0.831)	(0.773)	(0.691)	(0.772)	(0.687)
ROA			1.596	1.637	24.23*	23.88*
			(1.673)	(1.709)	(14.36)	(13.88)
ΔMktCap/Assets				0.478	0.344	1.166
				(0.317)	(0.246)	(0.978)
ROE					-2.104*	-1.987*
					(1.211)	(1.095)
Expected Return						-0.150
						(0.140)
Constant	0.157*	-0.550	-0.470	-0.321	-0.481	-0.386
	(0.0804)	(0.866)	(0.808)	(0.725)	(0.789)	(0.701)
Observations	1,211	1,211	1,211	1,211	1,211	1,211
Adjusted R^2	0.048	0.075	0.075	0.079	0.113	0.120

Panel B: Regressors added in order that produced the most concavity in the sequence of adjusted-R^2.

	[1]	[2]	[3]	[4]	[5]	[6]
Interest Margin	9.446***	8.336***	7.270***	7.267***	6.801**	6.900***
	(2.533)	(2.462)	(2.328)	(2.309)	(2.688)	(2.615)
ROA		4.941	25.79	24.39	24.23*	23.88*
		(5.639)	(16.19)	(14.79)	(14.36)	(13.88)
ROE			-1.869*	-1.848*	-2.104*	-1.987*
			(0.983)	(0.957)	(1.211)	(1.095)
ΔMktCap/Assets				0.719	0.344	1.166
				(0.653)	(0.246)	(0.978)
Market-to-Book					0.657	0.567
					(0.772)	(0.687)
Expected Return						-0.150
						(0.140)
Constant	0.157*	0.145	0.180**	0.178**	-0.481	-0.386
	(0.0804)	(0.0878)	(0.0756)	(0.0755)	(0.789)	(0.701)
Observations	1,211	1,211	1,211	1,211	1,211	1,211
Adjusted R^2	0.048	0.060	0.089	0.100	0.113	0.120

Panel C: All correlations are statistically different from zero at the 5% level.

	TLCA	*Interest Margin*	*Market-to-Book*	*ROA*	*ΔMktCap/Assets*	*ROE*	*Expected Return*
Interest Margin	0.221	1.000					
Market-to-Book	0.200	0.166	1.000				
ROA	0.160	0.221	0.546	1.000			
ΔMktCap/Assets	0.149	0.058	0.476	0.248	1.000		
ROE	0.086	0.163	0.558	0.943	0.228	1.000	
Expected Return	0.065	0.063	0.352	0.283	0.821	0.279	1.000

Table 4 -- First-stage SES regressions

Pooled ordinary least squares estimates of equation (7). Dependent variable is *SES*. In Panel A, right-hand side variables are added in order of highest correlation with *SES*. In Panel B, right-hand side variables are added in the order of highest impact on adjusted-R^2. Panel C displays Pearson correlations. Standard errors are clustered at the bank-CEO level and appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels. See Table 1 for full set of variable definitions.

Panel A: Regressors added in order of highest correlation with SES.

	[1]	[2]	[3]	[4]	[5]	[6]
Std(Idio. Return)	1.701***	1.160	0.367	1.546*	1.311	1.042
	(0.253)	(1.051)	(0.930)	(0.894)	(0.862)	(0.872)
Std(Return)		0.438	0.776	-0.278	-0.0650	0.129
		(0.735)	(0.664)	(0.626)	(0.601)	(0.604)
Std(ROE)			0.112***	0.0821**	0.271*	0.268*
			(0.0387)	(0.0391)	(0.140)	(0.139)
Beta				0.0207***	0.0230***	0.0244***
				(0.00465)	(0.00493)	(0.00536)
Std(ROA)					-2.795	-3.279*
					(1.715)	(1.820)
Z score						-0.000482*
						(0.000276)
Constant	0.0623***	0.0621***	0.0629***	0.0446***	0.0434***	0.0579***
	(0.00466)	(0.00453)	(0.00437)	(0.00591)	(0.00600)	(0.00997)
Observations	1,211	1,211	1,211	1,211	1,211	1,211
Adjusted R^2	0.147	0.148	0.174	0.199	0.209	0.217

Panel B: Regressors added in order that produced the most concavity in the sequence of adjusted-R^2.

	[1]	[2]	[3]	[4]	[5]	[6]
Std(Idio. Return)	1.701***	1.458***	1.202***	1.231***	1.202***	1.042
	(0.253)	(0.252)	(0.226)	(0.226)	(0.225)	(0.872)
Beta		0.0224***	0.0198***	0.0228***	0.0248***	0.0244***
		(0.00473)	(0.00499)	(0.00518)	(0.00572)	(0.00536)
Std(ROE)			0.0850**	0.273*	0.265*	0.268*
			(0.0398)	(0.140)	(0.138)	(0.139)
Std(ROA)				-2.809	-3.245*	-3.279*
				(1.713)	(1.805)	(1.820)
Z score					-0.000476*	-0.000482*
					(0.000273)	(0.000276)
Std(Return)						0.129
						(0.604)
Constant	0.0623***	0.0422***	0.0453***	0.0436***	0.0574***	0.0579***
	(0.00466)	(0.00565)	(0.00571)	(0.00582)	(0.00965)	(0.00997)
Observations	1,211	1,211	1,211	1,211	1,211	1,211
Adjusted R^2	0.147	0.185	0.200	0.210	0.217	0.217

Panel C: All correlations are statistically different from zero at the 5% level, except for ρ(*Std(ROA), Std(Idio)*).

	SES	*Std(Idio)*	*Std(Return)*	*Std(ROE)*	*Beta*	*Std(ROA)*	*Z Score*
Std(Idio.	0.385	1.000					
Std(Return)	0.381	0.280	1.000				
Std(ROE)	0.315	0.349	0.412	1.000			
Beta	0.293	0.343	0.948	0.434	1.000		
Std(ROA)	0.289	-0.055	-0.558	-0.236	-0.566	1.000	
Z Score	-0.224	0.270	0.457	0.970	0.461	0.292	1.000

Table 5 – Baseline *TLCA* and *SES* results

Estimated impact of executive compensation incentives (*lnDelta* and *lnVega*) on external liquidity creation (ε_{TLCA}) in Panel A and external systemic risk (ε_{SES}) in Panel B. All estimates use OLS. *lnDelta*, *lnVega*, *lnAssets* and *lnCEOtenure* are lagged one year. The first two columns in each panel display the results of the baseline two-stage models. The third column in each panel displays the results of a naïve single equation model. The fourth column in each panel displays the results of an alternative second-stage specification. Standard errors are clustered at the bank-CEO level and appear in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels. See Table 1 for all variable definitions.

	Panel A: Liquidity creation models				Panel B: Systemic risk models			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Baseline first stage	Baseline second stage	Naïve one-stage model	Alternative second stage	Baseline first stage	Baseline second stage	Naïve one-stage model	Alternative second stage
Dependent variable:	*TLCA*	ε_{TLCA}	TLCA	ε_{TLCA}	*SES*	ε_{SES}	*SES*	ε_{SES}
ε_{SES}				0.3110*				
				(0.163)				
ε_{TLCA}								0.0255*
								(0.0143)
lnDelta		-0.0221***	0.00488	-0.0178**		-0.0141***	-0.0207***	-0.0136***
		(0.00762)	(0.00821)	(0.00732)		(0.00352)	(0.00434)	(0.00347)
lnVega		0.00436***	0.00214	0.00428**		0.000388***	0.000451***	0.000318**
		(0.00166)	(0.00140)	(0.00166)		(0.000147)	(0.000169)	(0.000147)
lnAssets		0.0132	0.0113	0.00879		0.0147***	0.0218***	0.0144***
		(0.0211)	(0.0209)	(0.0210)		(0.00426)	(0.00442)	(0.00419)
lnCEOtenure		-0.00993	-0.0252**	-0.0138		0.0127***	0.0155***	0.0129***
		(0.0103)	(0.0116)	(0.0102)		(0.00398)	(0.00464)	(0.00397)
Econ Index		0.000529	0.00127	0.000608		-0.000244	-0.000469	-0.000259
		(0.00101)	(0.000829)	(0.000990)		(0.000280)	(0.000306)	(0.000277)
Constant	-0.386	-0.206	0.105	-0.193	0.0579***	-0.0141***	0.0266	-0.0382
	(0.701)	(0.217)	(0.221)	(0.218)	(0.00997)	(0.00352)	(0.0488)	(0.0486)
Market-to-Book	0.567							
	(0.687)							
Interest Margin	6.900***							
	(2.615)							
ROA	23.88*							
	(13.88)							
ΔMktCap/Assets	1.166							
	(0.978)							
ROE	-1.987*							
	(1.095)							
Expected Return	-0.150							
	(0.140)							
Std(ROE)					0.268*			
					(0.139)			
Std(ROA)					-3.279*			
					(1.820)			
Std(Idio. Return)					1.042			
					(0.872)			
Std(Return)					0.129			
					(0.604)			
Beta					0.0244***			
					(0.00536)			
Z Score					-0.000482*			
					(0.000276)			
Observations	1,211	1,211	1,211	1,211	1,211	1,211	1,211	1,211
Year & Firm-CEO FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Adjusted R^2	0.120				0.217			
Within R^2		0.361	0.250	0.366		0.318	0.425	0.323

Table 6 – Components of liquidity creation

Estimating the impact of executive compensation incentives (*lnDelta* and *lnVega*) on components of external liquidity creation (ε_{TLCA}). *On-balance sheet* is liquidity creation per asset dollar from balance sheet assets and liabilities only. *Off-balance sheet* equals *TLCA* minus *on-balance sheet*. *Derivatives* measures the portion of *off-balance sheet* generated by derivatives positions. *Credit Commitments* measures the portion of *off-balance sheet* generated by credit commitments. The variables *lnDelta*, *lnVega*, *lnAssets* and *lnCEOtenure* are lagged one year. All estimations use OLS. Standard errors are clustered at the bank-CEO level and appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels. See Table 1 for full set of variable definitions.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	On-balance Sheet		*Assets*		*Liabilities and Equity*		*Off-balance Sheet*		*Derivatives*		*Credit Commitments*	
	TLCA	ε_{TLCA}	*TLCA*	ε_{TLCA}	*TLCA*	ε_{TLCA}	*TLCA*	ε_{TLCA}	*TLCA*	ε_{TLCA}	*TLCA*	ε_{TLCA}
lnDelta		0.0112*		0.00390		0.00288		-0.0349***		3.40e-05		-0.0350***
		(0.00590)		(0.00625)		(0.00334)		(0.00672)		(5.58e-05)		(0.00672)
lnVega		0.000206		0.00118		-0.000240		0.00441***		-1.13e-05		0.00442***
		(0.00121)		(0.00111)		(0.000722)		(0.00107)		(1.12e-05)		(0.00107)
lnAssets		-0.0474***		-0.0410**		-0.0119		0.0595***		0.000105		0.0594***
		(0.0152)		(0.0168)		(0.00837)		(0.0132)		(0.000164)		(0.0132)
lnCEOtenure		-0.0287***		-0.0216**		-0.00590		0.0216**		-0.000184		0.0218**
		(0.00844)		(0.00900)		(0.00482)		(0.00896)		(0.000118)		(0.00896)
Econ Index		0.00120*		0.00114		-7.02e-05		-0.000580		-1.24e-05		-0.000566
		(0.000657)		(0.000728)		(0.000431)		(0.000657)		(8.63e-06)		(0.000657)
Constant	0.408***	0.130	0.155	0.0910	0.147*	0.152*	-0.794	-0.331**	-0.00153	0.00108	-0.793	-0.333**
	(0.110)	(0.148)	(0.133)	(0.171)	(0.0774)	(0.0888)	(0.743)	(0.143)	(0.00165)	(0.00180)	(0.743)	(0.144)
Market-to-Book	-0.374***		-0.268**		-0.0675		0.940		0.000745		0.940	
	(0.0964)		(0.127)		(0.0785)		(0.726)		(0.00143)		(0.726)	
Interest Margin	9.259***		8.049***		4.994***		-2.359		0.0112		-2.370	
	(1.771)		(1.826)		(0.621)		(1.591)		(0.0158)		(1.599)	
ROA	9.798***		9.335***		-4.625***		14.09		-0.00251		14.09	
	(2.897)		(3.557)		(1.731)		(14.30)		(0.0207)		(14.30)	
ΔMktCap/Assets	0.248		0.232		0.0695		0.917		0.00139		0.916	
	(0.167)		(0.202)		(0.104)		(1.017)		(0.00181)		(1.017)	
ROE	-1.059***		-1.083***		0.500***		-0.928		-3.07e-06		-0.928	
	(0.242)		(0.304)		(0.140)		(1.123)		(0.00185)		(1.123)	
Expected Return	-0.00944		-0.0489*		0.0351**		-0.141		-7.42e-05		-0.141	
	(0.0223)		(0.0268)		(0.0148)		(0.146)		(0.000196)		(0.146)	
Observations	1,211	1,211	1,211	1,211	1,211	1,211	1,211	1,211	1,211	1,211	1,211	1,211
Year and Firm-CEO fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.339		0.248		0.271		0.100		0.003		0.100	
Within R^2		0.438		0.374		0.327		0.440		0.120		0.440

Table 7 – Components of systemic risk

Estimating the impact of executive compensation incentives (*Delta* and *Vega*) on the components of external systemic risk (ε_{SES}). Marginal expected shortfall (*MES*) is the (negative of) bank i's average daily stock returns on the 12 worst trading days of each year for the broad stock market index. Financial leverage (*LEV*) is the market value of bank i's assets divided by the market value of its equity. The variables *lnDelta*, *lnVega*, *lnAssets* and *lnCEOtenure* are lagged one year. All estimations use OLS. Standard errors are clustered at the bank-CEO level and appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels. See Table 1 for full set of variable definitions.

	MES		*LEV*	
	[1]	[2]	[3]	[4]
Dependent variable:	*MES*	ε_{MES}	*LEV*	ε_{LEV}
lnDelta		-0.000595		-0.350***
		(0.000541)		(0.0880)
lnVega		0.0000674*		0.00938**
		(3.50e-05)		(0.00366)
lnAssets		0.000894		0.363***
		(0.000853)		(0.106)
lnCEOtenure		0.000776		0.313***
		(0.000790)		(0.0989)
Econ Index		0.000117**		-0.00639
		(5.88e-05)		(0.00693)
Constant	-0.0131***	-0.0204*	1.491***	-1.054
	(0.00183)	(0.0113)	(0.245)	(1.205)
Std(ROE)	-0.0543***		6.762**	
	(0.0192)		(3.398)	
Std(ROA)	1.141***		-84.73*	
	(0.277)		(44.54)	
Std(Idio. Return)	-1.402***		31.06	
	(0.154)		(21.64)	
Std(Return)	1.661***		-2.777	
	(0.119)		(15.02)	
Beta	0.0250***		0.515***	
	(0.00156)		(0.132)	
Z Score	-3.27e-05		-0.0118*	
	(4.51e-05)		(0.00676)	
Observations	1,211	1,211	1,211	1,211
Year and Firm-CEO fixed effects	No	Yes	No	Yes
Adjusted R^2	0.654		0.188	
Within R^2		0.786		0.291

Table 8 – Alternative measures of systemic risk

Estimating the impact of executive compensation incentives (*Delta* and *Vega*) on external systemic risk creation. Columns 1-2: *SES* for 879 bank-year observations on the shorter 2000-2016 sample window. Columns 3-4: *SRISK* adapted from Brownless and Engle (2015). Columns 5-6: *ΔCoVaR* estimated as in Adrian and Brunnermeier (2016). Columns 7-8: *ΔCoVaR* estimated using five-year rolling windows as in Sedunov (2014). The variables *lnDelta*, *lnVega*, *lnAssets* and *lnCEOtenure* are lagged one year. All estimations use OLS. Standard errors are clustered at the bank-CEO level and appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels. See Table 1 for full set of variable definitions.

	SES (2000-2016)		*SRISK*		*Classic-ΔCoVaR*		*Adapted-ΔCoVaR*	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	SES	ε_{SES}	*SRISK*	ε_{SRISK}	Δ*CoVaR*	$\varepsilon_{\Delta CoVaR}$	Δ*CoVaR*	$\varepsilon_{\Delta CoVaR}$
lnDelta		-0.0161***		-0.0171***		0.000438		0.00173
		(0.00438)		(0.00435)		(0.000912)		(0.00112)
lnVega		0.000468***		0.00128***		0.000175		-4.41e-06
		(0.000142)		(0.000423)		(0.000160)		(0.000143)
lnAssets		0.0163***		0.0113		-0.00351**		-0.00595*
		(0.00491)		(0.00727)		(0.00163)		(0.00340)
lnCEOtenure		0.0161***		0.0202***		-0.00139		-0.000155
		(0.00500)		(0.00484)		(0.00121)		(0.00173)
Econ Index		-4.91e-05		-0.000527		9.35e-05		0.000268*
		(0.000303)		(0.000384)		(0.000114)		(0.000158)
Constant	0.0450***	-0.0851	-0.236***	0.0618	0.0431***	0.0204	0.0181***	0.0217
	(0.00823)	(0.0687)	(0.0155)	(0.0731)	(0.00320)	(0.0199)	(0.00325)	(0.0406)
Std(ROE)	0.261*		-0.0144		0.0129		0.0160	
	(0.139)		(0.117)		(0.0308)		(0.0218)	
Std(ROA)	-2.759		4.687***		-1.524***		-0.135	
	(1.721)		(1.775)		(0.440)		(0.348)	
Std(Idio. Return)	0.940		0.447		-1.722***		-2.481***	
	(1.009)		(0.993)		(0.322)		(0.318)	
Std(Return)	0.400		0.187		3.057***		2.979***	
	(0.719)		(0.722)		(0.242)		(0.251)	
Beta	0.0221***		0.0278***		-0.00548***		0.00792***	
	(0.00529)		(0.00796)		(0.00187)		(0.00186)	
Z Score	-0.000247		0.00181***		-0.000222***		0.000190**	
	(0.000199)		(0.000428)		(7.59e-05)		(7.89e-05)	
Observations	879	879	1,160	1,160	1,137	1,137	943	943
Year and Firm-CEO fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.311		0.220		0.635		0.518	
Within R^2		0.299		0.439		0.469		0.384

Table 9 – Excess Liquidity Creation and Large Bank Coordination

Estimating the impact of executive compensation incentives (*Delta* and *Vega*) on external liquidity creation per bank asset dollar (ε_{TLCA}). Results shown for second-stage externality equation; first-stage orthogonalization equations are estimated but not shown. In column 1, θ = *Credit Bubble* is a dummy equal to 1 in the years 2006 and 2007, during which aggregate increases in U.S. commercial bank lending far exceeded expected lending, as indicated by a standard Hodrick-Prescott filter. In column 2, θ = *Herding* is a dummy variable equal to one if the correlation of the bank's daily returns with the industry daily returns is greater than 0.8351, which is the 90th percentile of the sample distribution. In column 3, θ = *Over250* is a dummy variable equal to one for banks with assets greater than $250 billion (2016 dollars). The variables *lnDelta*, *lnVega*, *lnAssets* and *lnCEOtenure* are lagged one year. All estimations use OLS. Standard errors are clustered at the bank-CEO level and appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels. See Table 1 for full set of variable definitions.

Definition of θ:	*Credit Bubble*	*Herding*	*Over250*
	[1]	[2]	[3]
Dependent variable:	ε_{TLCA}	ε_{SES}	ε_{SES}
θ	0.122**	-0.0159	0.104
	(0.0610)	(0.0112)	(0.0690)
lnDelta	-0.0237***	-0.0143***	-0.0136***
	(0.00762)	(0.00357)	(0.00351)
lnDelta * θ	0.0132*	0.00300	-0.0159
	(0.00686)	(0.00220)	(0.0107)
lnVega	0.00485***	0.000400***	0.000401***
	(0.00163)	(0.000144)	(0.000142)
lnVega * θ	-0.00646*	-8.21e-05	-0.000214
	(0.00350)	(0.00108)	(0.00153)
lnAssets	0.0136	0.0149***	0.0153***
	(0.0209)	(0.00429)	(0.00434)
lnCEOtenure	-0.00938	0.0130***	0.0126***
	(0.0103)	(0.00401)	(0.00395)
Econ Index	0.000470	-0.000247	-0.000221
	(0.000994)	(0.000277)	(0.000279)
Constant	-0.193	-0.0442	-0.0549
	(0.213)	(0.0477)	(0.0499)
$\partial\varepsilon_{TLCA}/\partial lnDelta$ (θ=1)	-0.0104		
$\partial\varepsilon_{TLCA}/\partial lnVega$ (θ=1)	-0.0016		
$\partial\varepsilon_{TLCA}/\partial\theta$	0.1757***		
$\partial\varepsilon_{SES}/\partial lnDelta$ (θ=1)		-0.0114***	-0.0295***
$\partial\varepsilon_{SES}/\partial lnVega$ (θ=1)		0.000318	0.000399
$\partial\varepsilon_{SES}/\partial\theta$		-0.000886	-0.00759
Observations	1,211	1,211	1,211
Year and Firm-CEO fixed effects	Yes	Yes	Yes
Within R^2	0.364	0.320	0.328

Table 10 – Effects of CEO incentives on aggregate liquidity creation externality and systemic risk externality

Calculating the estimated impact of changes in executive compensation incentives on external total liquidity creation (*TLC*) in the economy (Panel A) and external systemic risk (*SR*) in the economy (Panel B). Calculations in Panel A are based on the regression parameters shown in Table 5, column 2. Calculations in Panel B are based on the regression parameters shown in Table 5, column 6. *lnDelta* and *lnVega* are demeaned by subtracting the average value within a firm-CEO pair, and the distributional statistics for the demeaned variables are based on the cross-sectional averages of the distributional statistics for each firm-CEO pair. The top row of each panel uses delta statistics, and the bottom row uses vega statistics. All dollar amounts are in millions.

	[1]	[2]	[3] = [1]*[2]	[4]	[5] = [3]*[4]	[6]	[7] = [5]÷[6]
Panel A: Effects of CEO incentives on aggregate liquidity creation externality							
	$\Delta lnDelta$ or $\Delta lnVega$	$\hat{\beta}_{lnDelta}$ or $\hat{\beta}_{lnVega}$	Δ external TLC per $ assets at average bank	$ of assets in system	Δ external $ of TLC in system	$ of annual TLC in system	%Δ in aggregate external TLC
Increase ***lnDelta*** by one standard deviation:	0.56	-0.0221	-0.0124	4,092,191	-50,743	1,816,112	-2.79%
Increase ***lnVega*** by one standard deviation:	2.08	0.00436	0.0091	4,092,191	37,239	1,816,112	2.05%
Panel B: Effects of CEO incentives on aggregate systemic risk externality							
	$\Delta lnDelta$ or $\Delta lnVega$	$\hat{\beta}_{lnDelta}$ or $\hat{\beta}_{lnVega}$	Δ external SR per $ equity at average bank	$ of equity in system	Δ external $ of SR in system	$ of annual SES in system	%Δ in aggregate external SR
Increase ***lnDelta*** by one standard deviation:	0.56	-0.0141	-0.0079	564,534	-4,460	62,956	-7.08%
Increase ***lnVega*** by one standard deviation:	2.08	0.000388	0.00081	564,534	457	62,956	0.73%

Figure 1

Increase in the statistical fit of first-stage regressions when adding regressors.

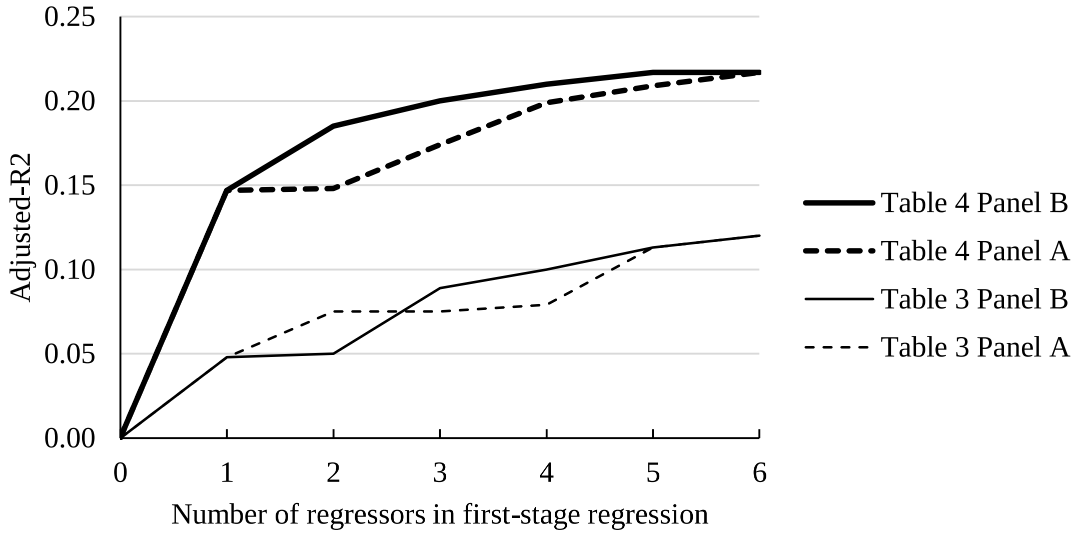

Figure 2
Annual averages for the raw values of TLCA and SES (left-hand panel) and the estimated values of the TLCA and SES externalities (right-hand panel).