THE WOLVES OF WALL STREET: MANAGERIAL ATTRIBUTES AND BANK BUSINESS MODELS

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Abstract

We show that compensation and other manager characteristics that attract public scrutiny in the banking industry only account for a small amount of heterogeneity in bank business models. Instead, idiosyncratic manager-specific effects (or ‘styles’) explain substantial differences in policy choices, risk and performance across banks. We combine manager styles and derive manager profiles that also reflect managers’ personal risk preferences, predict whether managers will be appointed as CEO, and match managers with boards based on risk appetite. Our results suggest that attempts to rein in bank risk-taking by targeting readily observable manager characteristics will be extremely challenging.

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1. Introduction

The banking industry is unusual, if not unique, in terms of the level of scrutiny that specific manager characteristics attract. For instance, the view that executive pay arrangements may encourage bank managers to take on extreme risk exposures and cause negative systemic externalities is now widely accepted. Likewise, banks are on the sharp end of official recommendations regarding the compensation arrangements and qualifications of senior managers.[1] The empirical literature has offered some support for this attention to bank manager characteristics. A growing body of evidence has produced important insights into how pay and other individual manager characteristics affect bank business models (see e.g., Fahlenbrach and Stulz, 2011; DeYoung, Peng and Yan 2013; Berger, Kick and Schaeck, 2014; Nguyen, Hagendorff and Eshraghi, 2017).[2]

In this paper, we challenge the extent to which compensation and publicly available biographical information on managers (such as age, gender, education and professional experience) explain significant variation in bank business policies and risk taking in a sample of U.S. bank holding companies. This is an important issue. Regulatory actions or investor activism targeted at manager characteristics in the banking sector can only be effective if these characteristics correlate with policies and risk in a meaningful way. Otherwise, the ability of regulators, investors and other bank stakeholders to mold bank behavior by recruiting managers

[1] In the U.S., the main regulatory agencies have issued guidance on the compensation structures of bank employees. In the European Union, the so-called 'bonus cap' restricts bonus payment to bankers since 2013. A UK banking review led by Sir David Walker in 2009 and the Dutch Banking Code both contain guidelines on the expertise and qualifications of senior bank managers. In 2016, the ECB announced plans to conduct 'fit and proper assessments' for the directors of banks it supervises directly. The assessments include experience and other manager variables to ascertain the ability of individuals 'to safeguard the safety and soundness of their own bank, but possibly also of the wider banking sector'.

[2] Outside the financial industry, examples of studies that examine the role of individual managerial heterogeneity and corporate actions and performance include Bertrand and Schoar (2003), Chava and Purnanandam (2010), Malmendier, Tate and Yan (2011), Benmelech and Frydman (2015), Dittmar and Duchin (2016), Bernile, Bhagwat, and Rau (2017) and Yonker (2017).

with certain characteristics or by offering managers certain compensation incentives is limited with possible detrimental consequences for the economy.

Further, low correlations between specific manager characteristics and bank policy choices suggest that unobservable manager characteristics such as latent managerial skills or preferences could play a key role in shaping bank behavior. If so, extreme risk-taking and other unsustainable business models in banking could ultimately be a 'people problem' that is rooted in the idiosyncratic preferences of individuals and not easily reined in by regulators or investors.

We start our analysis by estimating regression models that relate eight strategic policy choices to a range of bank, manager, and other controls. Among the policy variables we examine are asset choices such as the size and diversification of the loan portfolio and the amount of derivatives banks hold for trading. On the liabilities side, we study, among others, the importance of wholesale versus deposit funding and the extent to which loans are funded by deposits. These proxies are standard in the literature. We then compare the adjusted R^2 produced by each of these regressions to contrast the explanatory power of compensation and other managerial variables with bank characteristics.

Our first observation is straightforward, but important. Compensation and various other observable manager characteristics only describe a *small* amount of the variation in bank business models. As an illustration, detailed CEO compensation variables increase the adjusted R^2 of our eight policy regressions by less than 1% on average relative to a benchmark model with just bank controls. Similarly, when we expand the number of managers per bank in our analysis to include all managers listed on Execucomp, we find that the addition of detailed compensation data increases the adjusted R^2 of our policy variables by less than 0.5% on average. Furthermore, controlling for a host of other publicly available biographical information on managers, including education and career variables, jointly adds around 3% to the average adjusted R^2 of our policy regressions. To the best of our knowledge, our paper is the first to document this important finding.

We confirm the limited role of executive compensation and biographical manager characteristics using two plausibly exogenous industry shocks. Industry shocks force managers to make complex and non-routine decisions, and manager characteristics should be particularly salient in how managers respond to industry shocks (Yonker, 2017). Consequently, if specific manager characteristics explain bank policy variables and risk, we should observe systematic post-shock differences across firms led by managers who differ along observable characteristics. Put differently, we re-run our analysis in settings in which we expect manager effects to be particularly important in order to confirm that manager characteristics exert small effects on bank policies.

As a first industry shock, we follow Cornaggia et al. (2015) and Nguyen et al. (2017) and employ the staggered *state*-level deregulation of interstate branching. Between 1994 and 2005, the Interstate Banking and Branching Efficiency Act (IBBEA) of 1994 delegated decisions over when to open to out-of-state competition to individual states by permitting states to erect barriers to interstate branching (see Rice and Strahan 2010). Using the series of state-level competitive shocks unleashed by IBBEA, we continue to find that readily observable manager attributes exert a very small effect on bank policies. As a second shock, we use the financial crisis of 2007-2009 (see Beltratti and Stulz, 2012, Fahlenbrach, Prilmeier, and Stulz, 2012, and Fahlenbrach and Stulz, 2011). We show that most of the manager-level variables (measured before the crisis) do not predict bank risk in the crisis period and add very little explanatory power to prediction models based on bank characteristics.

Our finding that key observable manager characteristics only explain a small fraction of the heterogeneity in bank business models is consistent with either managers being of little relevance for bank policies or, alternatively, with managers affecting bank policies idiosyncratically and even then, in ways that are only loosely related to specific managerial attributes. To quantify the importance of idiosyncratic manager characteristics on banks' policy choices, we estimate the proportion that can be explained by manager fixed effects (or 'manager styles'). Manager fixed effects reflect latent manager attributes such as innate ability, preferences or personality.[3] Essentially, the question we explore is this: To what extent do seemingly identical bank managers (that is, managers who work for the same bank, who have identical compensation incentives and identical biographical characteristics such as education and career histories) have a distinct impact on a set of bank policies?

To separately identify manger fixed effects from other effects, we run a series of three-way fixed effect models (with firm, manager and time fixed effects) on a sample of banks assembled using the *connectedness sampling method* of Abowd, Kramarz and Margolis (AKM, henceforth) (1999). The AKM method builds on approaches that rely on subsets of managers who switch firms for a separate identification of firm- and manager-fixed effects (see Bertrand and Schoar, 2003). However, unlike approaches that are restricted to the small subset of managers who move across banks, the AKM approach separates manager and firm fixed effects not only for moving managers, but also for non-moving managers as long as non-moving managers work for connected banks. The premise of this approach is that banks are connected (and thus enter our sample) if they have hired at least one mover manager from another sample bank.

[3] By construction, manager fixed effects capture the time-invariant dimension of unobservable heterogeneity. Abowd, Kramarz, and Margolis (1999) interpret person fixed effects as capturing human capital. Graham et al. (2012) and Coles and Li (2014) interpret manager fixed effects as capturing latent managerial skills and talent, respectively. Manager fixed effects could equally capture traits other than ability if they are time-persistent.

The following example illustrates our sampling approach. During our sample period, JP Morgan employs seven managers who work for at least one other Execucomp-listed bank at some point. Amongst these mover-managers is James (Jamie) Dimon who moved to JP Morgan in 2005 after having served as Bank One CEO since 2000. Therefore, JPMorgan and Bank One enter our sample by virtue of being connected through Dimon's tenure at both institutions. We map out the career moves of other managers at JPMorgan and Bank One to identify any institutions that these managers are connected to. We continue to populate our connectedness sample until we have included all banks that hire at least one mover-manager from another sample bank. Under this approach, a modest amount of manager mobility generates substantial amount of connectedness. In total, our sample contains 776 managers who work for 74 U.S. bank holding companies between 1992 and 2010.[4]

Using the AKM sampling method, we show that manager fixed effects explain an average of 28% of the variation in the R^2 of bank policy regressions. For example, bank manager styles explain around 33% of the predicted values of a bank's liquidity gap or 48% of investments in derivatives. We report very similar results when we implement Bertrand and Schoar's (2003) mover-manager approach that restricts the sample only to managers who move between banks or when we correct for potential sample selection bias that results if connected banks differ from non-connected banks. Next we confirm that the AKM method has been successful in extracting

[4] Our method also partly addresses selection issues that have been raised when manager fixed effects are based on samples of moving managers only. Fee, Edward, and Hadlock (2013) show that exogenous CEO turnovers are not accompanied by significant changes in a firm's financing or investment policies. The authors argue that new managers are selected to implement policies in line with their preferences. However, the selection issues identified in Fee et al. (2013) are greatly reduced in our set-up. Our identification does not rest on manager turnover, but on managers being connected through managers who have moved between firms. The vast majority (>95%) of the manager styles our apporach identifies belong to managers who do not move across firms. Further, recent studies have shown evidence consistent with manager effects shaping outcomes. Dittmar and Duchin (2017) confirm that, while the average exogeneous CEO turnover is not associated with policy changes, variation in a CEO's professional experience within the subset of exogenous turnovers does affect corporate policy. Likewise, Yonker (2017) show that manager backgrounds shape labor policies in different geographic regions *within* individual firms.

manager fixed effects not only for moving managers but also for non-moving managers at connected banks. To do so, we show that there is substantial *within*-bank variation in manager styles, including within-bank variation in styles for the subset of non-moving managers.[5]

Furthermore, we confirm that our interpretation of the estimated manager fixed effects as capturing idiosyncratic manager preferences is valid by demonstrating that key observable manager characteristics (e.g. age, education and career variables) only explain about 5% of the variation in manager styles. At the same time, our results show that styles are not randomly distributed across managers but shaped by the early life experiences and career paths of managers (e.g., Malmendier et al., 2011; Dittmar and Duchin, 2016; Bernile et. al, 2017; Schoar and Zuo, 2017). For instance, we show that more traditional banking models are associated with younger executives and with executives who have a banking background and hold no Ivy League degree.

Since individual bank managers exhibit styles in each of the eight policy variables we analyze, it is difficult to describe commonalities in the styles that managers show across different policy choices. However, the detection of style patterns is a worthwhile undertaking, because it allows us to describe the general preferences of individual managers for certain business models and it permits us to identify something that can be described as a manager's "personality".

Therefore, we use factor analysis, a traditional approach in studies of personality traits (see for instance, Kaplan and Sorensen, 2016), to identify the main dimensions of variation in managerial styles. We find two factors are dominant in explaining patterns across the styles of individual managers. Broadly, the two factors capture managerial preferences for policies that are different from the traditional business model of deposit-taking and loan-making. The first factor

[5] Finding manager style diversity at the same bank makes it less likely that our manager fixed effects simply capture some source of heterogeneity across banks rather than latent characteristic at the manager level (in which case manager styles would be homogeneous and relatively indistinguishable from the firm fixed effects).

captures a managerial preference for non-traditional forms of bank income and assets. The factor loads positively on manager styles in non-interest income and negatively on manager styles in the loans-to-assets ratio. The second factor captures a managerial preference for non-traditional bank liabilities and loads positively on styles in non-deposit funding.

We then use the loadings of individual managers on the two factors to assign each manager to one of three profiles. The three profiles capture the idiosyncratic effects of managers on bank polices as (1) Traditionalists, (2) Innovators, or (3) Partial Innovators. For instance, Hugh McColl, the long-standing Bank of America CEO is a Traditionalist. Citigroup's Vikram Pandit is classed as an Innovator and Wachovia's John Strumpf as a Partial Innovator.

To validate our style profiles as a relevant depiction for systematic differences in how managers affect policies, we first show that the manager profiles we identify help explain manager careers. Our results show that those managers we classify as Traditionalists have a higher probability of being appointed CEOs than other groups of managers. We then show that manager profiles also affect measures of bank risk-taking, including equity volatility, tail risk systemic risk. In particular, we show that managers identify as Innovators display the highest propensity for aggressive risk-taking.

In the final section of the paper, we provide additional evidence for why certain banks exhibit a more pronounced risk culture (as documented, for example, in Fahlenbrach et al. (2012) and Ellul and Yerramilli (2013)). We show that managers with certain style profiles match with particular banks. Further, our style profiles help explain the widely documented finding that banks with shareholder-friendly boards were more exposed to risks that manifested themselves during the Great Recession (Fahlenbrach and Stulz, 2011; Beltratti and Stulz, 2012). We show that more shareholder-aligned boards are more likely to match with Innovators and less likely to match with

Traditionalists. Consequently, shareholder-aligned boards are more likely to appoint aggressive risk-takers with a preference for innovative business models.

2. Related Literature and Data

2.1 Related Literature

Our paper relates to different strands of the literature. First, our paper relates to the literature on executive compensation and risk-taking in banking. The evidence on how manager pay affects the business models and risk of banks is surprisingly mixed. While DeYoung et al. (2013) show that option-based CEO compensation is linked to non-traditional bank business models and higher risk, Fahlenbrach and Stulz (2011) find no evidence that CEO option compensation before the crisis adversely affected performance during the crisis. In contrast, Fahlenbrach and Stulz (2011) argue that bank managers responded to performance-based compensation designed to boost shareholder returns before the crisis. The latter contradicts the view that managers respond to risk-taking incentives and increase their personal wealth at the expense of shareholder wealth.

Likewise, Cheng, Hong, and Scheinkman (2015) present evidence in conflict with the notion that pay incentives cause risk-taking in the financial industry. The authors show that risk and compensation will be naturally correlated if risky firms compensate managers for the higher wealth uncertainty linked to managing riskier firms. More generally, Ellul and Yeramilli (2013) show that weak risk management rather than managerial risk-taking incentives explain the extreme risk exposures of banks. Finally, theory has long argued that the effects of contractual risk-taking incentives depend on the risk attitudes of managers (e.g., Smith and Stulz, 1985; Ross, 2004). This implies that the relationship between pay and risk includes an idiosyncratic component that is rooted in the preferences of managers.

However, the previous literature does not provide a systemic comparison between specific and unobservable managerial traits in explaining bank policies and bank risk. Our study offers such a comparison, and our findings contribute to discussions over the effectiveness of regulating pay in financial institutions (e.g., Fahlenbrach and Stulz, 2011; Cheng et al., 2015). Specifically, our findings suggest regulating managerial pay components is unlikely to be effective, because the correlations between specific manager characteristics and risk are small compared with the correlations between risk and manager characteristics that are unobservable and thus difficult to regulate.

Our paper is also related to the literature on the corporate governance of financial institutions (Beltratti and Stulz, 2012; Erkens et al., 2012; Berger et al., 2014; Minton et al., 2014). These papers investigate the impact of board characteristics and ownership structure on bank risk-taking and bank performance. We add to this literature by documenting that bank boards systematically match with managers who have preferences for specific business models. In doing so, our findings help explain persistence in the risk culture and business models of some banks documented elsewhere in the literature (see Fahlenbrach, Prilmeier, and Stulz, 2012; Ellul and Yerramilli, 2013).

Finally, our work is also related to previous studies that have found evidence of manager effects in a number of different contexts and for non-financial institutions (e.g. Bertrand and Shoar, 2003; Malmendier and Tate, 2008; Graham et al., 2012; Cronqvist et al., 2012; Ewens and Rhodes-Kropf, 2015; Shoar and Zuo, 2017). We complement these studies by illustrating how policy styles can be used to profile the personalities of bank managers and how these profiles relate to the career trajectories and the risk preferences of individual managers. Among other things, our findings identify some of the personality traits of managers who eventually become CEOs.

2.2 Sample

To investigate the influence of manager fixed effects and other manager attributes on bank business models, we use all banks listed on Execucomp between 1992 and 2010. Execucomp provides data on the highest paid managers working for banks currently or previously included in the S&P 500, S&P MidCap 400 and S&P SmallCap 600. We include firms with SIC codes between 6000 and 6300. In total, Execucomp lists 3,078 executives working for 305 firms with these SIC codes.

We then match the resulting firms with the Federal Reserve Y-9C database that provides financial statement data for U.S. bank holding companies. Focusing on firms that report to the Federal Reserve, our sampling strategy excludes those firms that are not engaged in traditional banking activities, such as investment advisors, online brokerages, or payment processors.

We omit foreign-owned banks and focus on U.S. banks. A small number of managers (30 manager-year observations) are listed as at more than one bank in a single fiscal year. For these cases, we consult the LEFTCO item in Execucomp and, where unavailable, perform news searches on Factiva and LexisNexis to determine when a bank executive moved. We then allocate managers to those banks where they spent most of the fiscal year. We subsequently match our sample of banks with CRSP for equity prices and lose 14 bank managers because we did not find a match.

Applying the above filter, we obtain a matched Execucomp population of 1,578 bank managers who work for 165 banks over the period 1992-2010.[6]

[6] The complete list of matched Execucomp banks is included in Appendix 1.

2.3 Bank Policy Variables

To describe bank business models, we use a set of eight bank policy variables that are summarized in Panel A of Table 1. The policy variables are based on balance sheet characteristics that parsimoniously reflect key choices that bank managers make with respect to the asset and liability side of a bank's balance sheet.

********TABLE 1 ABOUT HERE********

A key differentiator between the business models of banks is the importance of traditional lending-based activities versus other lines of business. Over recent decades, banks have steadily increased their fee-based business lines by offering investment banking, brokerage and asset management services with widely documented implications for the risk and return profile of institutions. For instance, DeYoung and Roland (2001) show that fee-based business models require higher operating leverage and increase the volatility of revenues and bank earnings. Brunnermeir, Dong and Palia (2012) show that non-interest income increases the systemic risk of banks. To capture sources of income other than interest, we analyze the ratio of *Non-interest income* to total operating income. We also include the share of loans in total assets (*Loans*) as a measure of how focused banks are on lending.

Among the indicators of non-traditional bank business polices, the proportion of assets held in banks' own trading books is an important differentiator that has been linked to risk spillovers amongst financial institutions (Adrian and Brunnermeier, 2016). To identify banks that hold more assets in the form of tradable securities, we use two ratios. First, we analyze the share of mortgage-backed securities (*MBS*) in total assets. Specifically, we follow Ellul and Yeramilli (2013) and sum up different private-label MBS in both trading and investment portfolios (not including less risky MBS that are either issued or guaranteed by government sponsored enterprises). We are interested in MBS because of the pivotal role that MBS holdings played in the financial crisis of 2007-2009 and the underperformance of some banks during the crisis (Erel et al., 2014). Second, to capture a bank's general exposure to off-balance sheet derivative trading activity, we measure *Derivatives* as the logarithm of the ratio of the notional amount of derivative contracts held for trading to total assets.

Lending diversification is measured as 1 minus the Herfindahl index (HHI) of the shares of real estate, commercial and industrial, consumer, and other loans as a percentage of total loans. This measure follows Acharya, Hasan and Saunders (2006) who show that there are diversification benefits within the loan portfolios of individual banks.

We also consider differences in bank policies as evident from the liabilities side of a bank's balance sheet by measuring the funding gap and funding structures of banks. *Gap12* captures a bank's liquidity gap over a 12 months period. As in Flannery and James (1984), Gap12 is measured as the difference between assets and liabilities maturing within the next 12 months scaled by total assets. A greater value of this ratio indicates that bank policies expose an institution to more funding liquidity risk. Acharya and Naqvi (2012) argue that access to abundant liquidity is linked to riskier bank business polices, while other studies emphasize the fragility of the business models of banks with relatively illiquid balance sheets (Adrian and Brunnermeier, 2016; Brunnermeier, 2009).

Finally, the literature emphasizes how short-term finance from capital markets made banks fragile and vulnerable to runs during the financial crisis of 2007-2009 (Beltratti and Stulz, 2012; Brunnermeier, 2009). We consider two variables that explain differences in the funding structures of banks: the share of loans that are financed by deposit funding (*Loans/Deposits*) and the proportion of bank liabilities that are not financed via deposits (*Non-deposit Funding*).

2.4 Compensation and Biographical Manager Attributes

We employ two types of variables to capture the impact of manager attributes on bank business models. We choose pay variables as our starting point because pay variables offer an example of manager characteristics that have been shown to explain risky bank polices (Fahlenbrach and Stulz, 2011; DeYoung et al., 2013; Berger et al., 2014; Nguyen et al., 2017).

As shown in Panel B of Table 1, for each manager, we compute the sensitivity of her wealth to bank risk (*Vega*) as the dollar change in wealth linked to a 0.01 increase to stock return volatility. If riskier polices increase equity volatility, mangers with higher *Vega* have incentives to engage in riskier bank policies. Further, the sensitivity of manager wealth to bank performance (*Delta*) measures dollar changes in CEO wealth to stock price performance. As *Delta* exposes managerial wealth also to falling stock prices, a higher *Delta* might discourage managers from choosing risky bank policies and to opt for a less risky business model.[7] We scale both performance measures by cash compensation and use the log transformation of the resulting variable in our analysis.[8] We also control for the log of cash bonuses (*bonus*) separately.

A second group of variables, described in Panel C of Table 1, is motivated by a literature that demonstrates that CEO attitudes and firm policies are in part shaped by variation in individual life and career experiences (Malmendier, Tate, and Yan, 2011; Benmelech and Frydman, 2015, Dittmar and Duchin, 2016; Bernile et al., 2017). For instance, there is evidence of more

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[7] We obtain detailed information on outstanding equity awards at each fiscal year-end (and other compensation data) from Execucomp and use these awards to compute the Black-Scholes value of each option as well as its sensitivity to volatility and stock price changes. Coles, Daniel and Naveen (2006) and Core and Guay (2002) provide details on the calculation of these variables.

[8] This is in line with Edmans et al. (2009) and Graham and Rogers (2002) who argue that a scaled Vega and Delta offer a clearer identification of the magnitude of economic incentives embedded in CEO compensation contracts. Both Vega and Delta are functions of bank size, i.e. CEOs at larger banks see their wealth increase faster as a result of both increases in risk and share prices. This makes meaningful comparisons of these incentive measures difficult when using the dollar value of pay incentives.

conservative firm policies if CEOs have lived through the Great Depression (Malmendier et al., 2011) or have previously served in the military (Benmelech and Frydman, 2015).

We obtain biographic data on bank managers from Boardex, Marquis Who's Who, Riskmetrics, and via Google searches and public data sources. In our sample, the variables we collect tend to be time invariant and observed before managers took on their current positions. The biographic manager data we collect include the birth year, gender and whether or not the manager was born in the decade leading up to the Great Depression (*Depression baby*)). Further, we control for education using *MBA* degree and whether the manager graduated from an *Ivy League* university[9].

Career and experience variables include whether the manager has completed *Military service*, the age of her first appointment as an executive on a board (*Fast track*). Further, we include a dummy that is equal to one if a manager has served as a non executive director outside the banking sector (*Nonbank experience (N_ex*) and a dummy that is equal to one if a manager had executive appointments outside the banking sector (*Nonbank experience (Ex)*). We also control for manager careers that started outside the finance and accounting industries by including *Generic*. This variable takes the value of one if the manager's first appointment was not with a financial services or an accounting firm.

2.5 Bank-level and Other Controls

We control for a number of bank characteristics that can explain cross-sectional differences in bank policy choices. The primary data source are the Consolidated Financial Statements for

[9] The group of Ivy League universities includes Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania and Yale University.

bank holding companies (form FR Y-9C) published quarterly by the Board of Governors of the Federal Reserve System. This set of controls is reported in Panel D of Table 1.

In particular, we control for differences in bank size using the natural logarithm of the book value of total assets in 2000 $ terms (*Size*). *Equity* is measured as equity over total assets and captures differences in bank leverage. The log of the market-to-book equity ratio (*Market to book*) accounts for differences in bank-specific investment opportunities. *Core deposits* are deposits up to $100,000 over total liabilities. Core deposits capture the extent to which banks fund their assets by retail depositors that are fully FDIC-insured (i.e., protected depositors that are not incentivized to monitor bank managers). Further, to control for difference in *Productivity* across banks, we control for the value of assets (in million $) per full-time employee.

Finally, we also control for macroeconomic conditions at state-level via the Federal Reserve Bank of Philadelphia's Coincident Index (*Economy*).[10]

3. How Much Do Compensation and Other Manager Attributes Matter for Bank Business Policies?

3.1 Main Results

This section analyses how much of the variation in bank business policies can be explained by executive compensation and other readily observable manager attributes and how important these variables are compared to other explanatory factors. To do so, we run a series of pooled OLS regressions on the various bank policy variables (P_{it}). We then compare changes in the adjusted R^2 of the policy regressions that follow the inclusion of different sets of controls relative to a

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[10] Coincident Indexes are monthly indicators of economic conditions compiled at state-level. The components are non-farm payroll employment, average hours worked in manufacturing, the unemployment rate, and wage and salary disbursements (deflated by the consumer price index). We compute the 12-month average for every year.

benchmark model that controls for bank variables and the economic condition (X) and year fixed effects (μ_t):

$$P_{it} = X_{it-1}\beta + \mu_t + \varepsilon_{it} \tag{1}$$

The vector X includes *Size, Equity, Market to book, Core deposits, Productivity, and Economy*. This simple benchmark model produces an average adjusted R^2 of around 30% across the various policy regressions.

********TABLE 2 ABOUT HERE********

We next ascertain how important certain sets of additional variables are in explaining observed differences in bank policy choices. The results are presented in Table 2. Panel A runs the policy regressions for bank CEOs. Panel B repeats the same regressions using all bank managers in our sample. We report the CEO results separately to demonstrate that there are no substantial differences in how CEO attributes affect bank policies compared to the full sample of bank managers. For the average bank in our sample, we have data on 73 managers during our sample period. Showing results for a single manager versus all managers also helps us demonstrate that the inclusion of multiple managers per bank (in Panel B) does not inflate the explanatory power of the models and, therefore, does not overstate the importance of manager attributes. Further, the approach we adopt in Section 4 to isolate the idiosyncratic effect of individual managers to a bank's business policy choices requires us to employ the full set of managers.

We start by adding manager compensation variables (*Vega*, *Delta*, *Bonus*) to the benchmark model and then estimate the resulting increase in the adjusted R^2 of the various policy regressions. The results, displayed in line (2) of Panels A and B, show that manager pay variables only fractionally improve the explanatory power of our models. Across the eight policy variables, improvements in the adjusted R^2 of the CEO regressions range from 0.4% (MBS holdings) to 1.7% (lending diversification). This does not change materially when we control for other manager attributes (e.g. age, career background; see Section 2.3) or for manager compensation and other manager attributes. Across all models, the addition of specific manager attributes leads to an average increase in adjusted R^2 of about 4.5%. Consequently, compensation and biographical variables play only a small role in explaining differences in bank policy choices across banks. We achieve similar conclusions when we employ the full sample of managers in our empirical tests.

********FIGURE 1 ABOUT HERE********

We then derive the adjusted R^2 from models estimated with firm fixed effects. Relative to the benchmark model, the results in Table 2 show that the inclusion of firm fixed effects add between 40% (for derivatives holdings) and 70% (for the proportion of loans in bank assets) to the explanatory power of our models. The results are very similar irrespective of whether we include CEO variables or variables for all bank managers. Consequently, unobservable firm characteristics far outrank executive compensation and other readily observable manager variables in terms of their ability to explain variation in bank business models. Figure 1 graphically illustrates this point. We show the average increases in the adjusted R^2 across all policy variables that follow from the inclusion of different sets of variables. Figure 1 is based on the full sample of managers.

In summary, the results in this section highlight that executive compensation and other manger attributes contribute very little to explaining variation in bank business policy choices especially when compared with the contribution offered by firm fixed effects.

3.2 Manager Characteristics Under Competitive Shocks

Establishing relationships between manager and firm variables is challenging. For instance, managers with certain policy preferences may self-select into riskier banks (see Cronqvist et al., 2012; Graham, Harvey and Puri, 2013). We therefore provide additional tests on the importance (or lack thereof) of manager characteristics for bank business policies by presenting evidence on how banks respond to an unexpected industry shock.

Industry shocks force managers to make decisions to lead a bank through a changing industry environment. These decisions are expected to be complex, non-routine and unstructured. If bank manager characteristics were indeed to shape bank policies, manager characteristics should be particularly salient in how managers respond to an industry shock (Yonker, 2017; Nguyen et al., 2017). Put simply, to confirm that manager characteristics are indeed exerting small effects on bank policies, we re-run our analysis in a setting in which we expect manager effects to be particularly important.

As industry shocks, we employ the *state*-level deregulation of interstate branching under the Interstate Banking and Branching Efficiency Act (IBBEA) of 1994. IBBEA introduced interstate branching but granted individual U.S. states powers to block out-of-state competition up to 2005 (see Cornaggia et al. 2015; Rice and Strahan 2010).[11] Therefore, IBBEA introduces substantial variation in industry competition along both geographical and temporal dimensions. We use the definition of competitive states employed by Nguyen et al. (2017).

[11] Specifically, IBBEA gives states the option to: (1) impose a minimum age of three years on the target institutions of interstate acquirers; (2) not to permit de novo interstate branching; (3) not to permit the acquisition of individual branches by an out-of-state bank; and (4) block out-of-state banks from acquiring an in-state bank that holds more than 30% of the deposits in that state. A state is defined as competitive if it chooses not to adopt either (3) or (4).

Panels C and D of Table 2 repeat the analysis for banks located in competitive states over a three-year-period following the competitive shock. We report the results for CEOs (Panel C) and the full sample of all bank managers (Panel D) separately. As both panels show, we continue to find that compensation and other manager attributes make only a limited contribution to explaining bank business policies.

3.3 How Important Are Compensation and Manager Attributes for Bank Risk During the Global Financial Crisis?

To provide further evidence on how much managers influence bank business policies, we follow the previous literature and use the financial crisis of 2007-2009 as a natural experiment. More precisely, we investigate whether compensation and other readily observable manager attributes at the end of 2006 explain different measures of bank risk between 1 July 2007 to 31 December 31 2008. We follow Fahlenbrach and Stulz (2011) and Fahlenbrach et al. (2012) in our choice of examination period and in focussing this analysis on CEOs only.[12]

********TABLE 3 ABOUT HERE********

As risk measures, we include the negative *Buy and Hold Return* and daily equity *volatility*. We also include tail risk measures such as value at risk (*VaR*) and expected shortfall (*ES*). As a systematic tail risk measure, we use an approach proposed by Acharya et al. (2017) and identify a bank's exposure to extreme market-wide events by its Marginal Expected Shortfall (*MES*). For each bank, *MES* captures the expected losses when the market [proxied by the value weighted CRSP index as in Acharya et al. (2017)] is under distress (defined as of the worst 5% of days in the daily return distribution between the 2 July 2007 and 31 December 2008). To ease the

[12] While the crisis period did not end in December 2008, Fahlenbrach et al. (2012) explain that subsequent market movements were in part at least due to uncertainty over the shape of government interventions to support distressed banks.

interpretation of our results, we multiply *Buy and Hold Return* and our tail risk measures by minus one. Higher values of these measures therefore correspond to higher exposure to extreme negative returns.

The prediction models control for the following bank variables (all measured at end 2006 as in Fahlenbrach and Stulz, 2011): bank size, capital, default risk (based on the Merton (1974) credit risk model; see Appendix 3 for details), bank beta, the ratio between non-performing loans to total loans, and realized equity returns in 2006.[13]

Table 3 reports the results. Out of the compensation variables, the contractual risk taking incentives (*vega*) enter the regressions with a negative and significant coefficient (in four out five models). Furthermore, in terms of other manager-level variables, male CEOs and an Ivy League education are the only other manager variables that enter some of the models significantly. Specifically, the results indicate that female CEOs and Ivy League educated CEOs are linked to higher risk.

Finally, the overall limited influence of compensation and manager attributes on bank risk during the crisis is also highlighted in the last rows of Table 3. Overall, our results suggest that manager-level variables are a marginal driver of a bank's risk exposures. The manager-level variables we control for improve our ability to predict the cross-sectional variation in bank risk during the global financial crisis only to a small degree.

[13] Variable definitions are presented in Appendix 2.

4. Separating Manager Fixed Effects from Firm Fixed Effects

4.1 The Connectedness Sampling Method

Our finding that the manager attributes we control for only explain a small fraction of the variation in bank business models suggests either that managers are not critical for bank policies or, alternatively, that the effects of managers on bank policies are idiosyncratic and, hence, loosely related to readily observable manager attributes. In this section, we estimate the importance of idiosyncratic manager effects—as captured by manager fixed effects—on bank policy variables.

To separate the contribution of manager fixed effects from the contribution of firm fixed effects to bank business models, we adopt the *connectedness sampling method* of Abowd et al. (1999). The connectedness sampling method uses managers who move across banks to derive information about non-movers who work in banks that have employed at least one moving manager. Therefore, this method allows us to separate manager and firm fixed effects not only for managers who have moved across banks, but also for non-moving executives as long as non-moving executives work for banks that have hired at least one mover (in this way, these banks and managers are connected). Crucially, managers who have never moved will still be connected to another bank as long as at least one mover-manager has worked at that other bank.

********TABLE 4 AROUND HERE********

For a bank to be included in the connected sample, it needs to have employed at least one manager who has worked for two or more banks listed on Execucomp during our sample period. Panel A of Table 4 shows that 4.5% of executives move at least once during the sample period. This is in line with Graham et al. (2012) who find that the share of executives who have moved at least once is 4.91% in their sample of non-financial firms. While manager mobility in the relevant literature is generally not very high, we emphasize again that this method relies on bank *connectedness* (and not on manager mobility). Executives who have worked at two banks will be connected to other executives at these two banks as well as to executives who have moved to these two banks from other institutions. A relatively modest amount of manager mobility therefore generates a large degree of bank connectedness.[14] Consistent with this, Panel B of Table 4 reports that more than 45% of Execucomp banks are in our sample.[15]

Finally, Panel C of Table 4 demonstrates how groups of banks are linked by executive mobility and give rise to a large degree of bank connectedness. Specifically, executive mobility connects the 74 banks in our sample by means of 17 groups (or connected clusters). The majority of the groups are connected as a result of a single mover-manager. A notable exception is Group 2 where 28 banks are connected by the move of 36 executives. Overall, we obtain a panel of 3,692 manager-year observations exploiting bank connectedness.

4.2 How Important are Bank Manager Styles?

4.2.1 Estimating manager fixed effects using the three-way fixed-effect model

Table 5 reports the estimates of three-way fixed effect policy regressions with firm, manager and time fixed effects using the sample of connected banks:

$$P_{j(it)} = X_{it-1}\beta + M_{j(it)}\gamma + \theta_j + \mu_t + \phi_i + \varepsilon_{it} \tag{2}$$

where the policy choices observed for a manager *j* in a bank *i* at time *t* are explained by bank characteristics $X_{it-1}\beta+\phi_i$ (time-variant and unobservable bank characteristics), manager

[14] Since the vast majority of styles we identify belong to non-moving managers, our identification is not directly based on executive turnovers. This greatly reduces selection issues because of differences in manager and/or banks involved in executive turnover events (as for instance identified in Fee at al. (2003)). Later parts of our analysis confirm that we have indeed been able to estimate distinct fixed effects for moving and non-moving managers and how the manager fixed effects differ between the two groups.

[15] This, too, is comparable to the 55.3% of sampled Execucomp firms reported in Graham et al. (2012) in their analysis of manager pay in non-financial firms. We confirm that the main findings in our paper are not sensitive to selection bias. The results of these tests are shown in Section 4 and in Appendix 2.

characteristics $M_{j(it)}\gamma+\theta_j$ (time-variant and unobservable manager characteristics), and time effects μ_t. The residual ε_{it} captures the variation in banks' policy choices that cannot be explained by any of the factors we control for. Since some bank managers in our sample of connected banks move across firms over time, the function *j(i,t)t* maps manager *j* to firm *i* at time *t*. The results of Table 5 show that our three-way fixed effect models explain between 76% and 98% of the variation in bank policy variables demonstrating that models that allow us to jointly estimate manager and firm fixed effects explain a large proportion of variation in bank business policies.

********TABLE 5 ABOUT HERE********

We report the statistical and economic significance of the manager fixed effects in Table 6. Panel A of Table 6 shows that both manager and firm fixed effects (from the estimations in Table 5) are jointly and statistically significantly different form zero for each policy variable.

********TABLE 6 ABOUT HERE********

In Panel B of Table 6, we decompose the variation of the policy variables into fitted values, manager fixed effects, firm fixed effects and residual values. The decomposition is based on regressions using the full set of controls including time dummies. The results show that the economic relevance of the manager fixed effects is substantial. On average, manager fixed effects explain 28% of the variance. The contribution of manager fixed effects is larger than 23% in seven out of eight policy variables and as high as 48% in the case of banks' holdings of derivatives for trading purposes.

Panel B of Table 6 also shows that time-invariant bank-level heterogeneity, as captured by the firm fixed effects, also explains a large part of the variance in bank business models. We revert to this point in subsequent analysis when demonstrate matches between firms and managers based on risk culture. Jointly, firm and manager fixed effects explain on average 62% of the variation in bank business models. This implies the scope for time-varying firm or manager characteristics to explain variation in bank policy variables is relatively limited.

4.2.2 Comparing alternative estimation techniques

In Panel C of Table 6, we contrast the estimated manager fixed effects derived from a three-way fixed effect model to alternative estimation techniques. In a first step, we show that our results are very similar if we implement Bertrand and Schoar's (2003) identification of firm- and manager-fixed effects for the subset of moving managers only.

Despite the reduction in the number of managers for which we can estimate fixed effects under the moving manager method (from 776 connected managers to 73 moving managers), the variance explained by manager fixed effects is near identical to our method (28.49% compared with 28.15%). Since our approach means we can estimate fixed effects for *all* managers (mover or otherwise), our paper allows us to present novel insights around the implications of manager fixed effects *within*-banks (e.g. matching between banks and managers based on risk preferences or the career implications of styles for managers). By contrast, the moving manager approach cannot deal with heterogeneity in manager styles within banks.

Further, our analysis could be biased if banks in our sample of connected banks were to differ from other Execucomp banks. Indeed, Table A.4.1 in the Internet Appendix shows that sample and non-sample banks differ in terms of their policy choices. To control for potential sample selection bias, we apply a two-step Heckman (1979) selection model. The model first estimates the criteria for sample selection and then reports the results of our policy regressions conditional upon sample selection.[16] The results of this approach are reported in Table A.4.2 in the Internet Appendix and show that the correlations between our manager fixed effects estimations and the estimates that control for sample selection bias is, on average, above 99%.

In additional tests, we exclude the period 2007-2010, focus on banks that are connected by two or more moving managers, and focus on Group 2 of connected banks (see Panel C of Table 4; Group 2 accounts for a large amount of connections in our sample). These tests are designed to exclude explanations according to which our estimates of manager fixed effects could be biased because of low manager mobility in some of the groups of connected banks (see Graham et al., 2012). When we restrict the sample this way, the results remain broadly similar even though the average variance explained by manager fixed effects is reduced, possibly because of the significant decline in the number of managers and banks included in the analysis.

In a final set of robustness tests, we demonstrate that the three-way fixed effect regressions on our connectedness sample have successfully identified the styles of moving managers *and* non-moving managers. Table A.4.4 shows evidence of *within*-bank variation in styles (Panel A), including within-bank variation in styles for the subset of non-moving managers (Panel B). Further, we show differences in styles between moving and non-moving bank managers across our sample (Panel C). Demonstrating style differences of managers at the same bank as well as

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[16] The first step of the Heckman procedure estimates the probability that banks are included in our sample using data on banks included as well as on banks that are not included due to lack of manager mobility. Identification rests on the exclusion restriction that requires the first stage to be estimated using a set of variables that is larger by at least one variable than the set of variables in the second stage that estimates our bank policy variables. We use the distance from a bank's headquarters to the nearest airport as an additional variable that is included in the first but not the second stage. Geographic coordinates are obtained from U.S. Census files. The rationale for this variable is that proximity to an airport facilitates bank connectedness. Banks that are located in closer proximity to an airport will find it easier to recruit managers. At the same time, a bank's proximity to an airport is not plausibly related to its policy choices other than through the effect that distance has on recruitment decisions. The inverse Mills ratio obtained from the first-stage regression is then added as a control variable in the three-way fixed effect model before estimating manager fixed effects. The estimation results of the Heckman procedure are reported in Table A.4.3 in the Online Appendix.

between moving and non-moving managers provides further confirmation that our methods have been able to separately and distinctly identify the idiosyncratic effects of non-moving managers on bank policies.

4.3 Do Manager Styles Capture Idiosyncratic Manager Effects?

If manager styles capture idiosyncratic person-specific characteristics, they should be relatively unpredictable. In other words, if our interpretation of the estimated manager fixed effects as capturing idiosyncratic manager preferences is correct, we should struggle to comprehensively describe the origins of manager styles using biographical manager characteristics (such as age and education). In this section, we provide support for the latter by regressing bank manager styles on a set of manager characteristics described in section 2.3.

********TABLE 7 ABOUT HERE********

The results, reported in Table 7, show that while biographical variables shape manager styles in some ways, their overall effect is limited. The adjusted R^2 of each regression on styles is low (5.3% on average). This confirms that, while the origins of bank manager styles are not random but capture systematic cross-sectional differences in managers' unique bank policy styles, pay and other observable manager characteristics are not key determinants of manager styles.

Nonetheless, we find a number of plausible associations between manager fixed effects and manager characteristics. Among the manager characteristics that enter significantly into the regressions on styles are age (younger managers are linked to larger albeit less diversified loan portfolios), education (Ivy League-educated managers are linked with riskier business models), and career paths (non-banking specialists have a preference for riskier banking activities). By contrast, gender does not affect a single policy style. Consequently, male and female managers do not appear to differ in terms of their policy preferences as evident in manager fixed effects. Overall, our results suggest that more traditional banking models are associated with younger teams of executives and with executives who have a banking background and hold no Ivy League degree.

In summary, the results we present in this section are broadly in line with previous studies that show that the early life experiences and career paths of managers can be linked to firm outcomes (e.g., Malmendier et al., 2011; Dittmar and Duchin, 2016; Bernile, Bhagwat, and Rau, 2017). Importantly, however, the combined effect of pay and other key observable variables on manager fixed effects is low. Therefore, bank manager styles mostly reflect time-invariant unobservable manager characteristics.

5. Extracting Manager Profiles from Manager Styles

5.1 Cluster Analysis

As bank mangers pursue a range of different business policies, they display distinct styles in various policy variables simultaneously. Consequently, bank managers differ along a potentially vast number of style dimensions. This makes style comparisons between individual managers complex. Further, the multi-dimensional nature of our style analysis makes it difficult to detect commonalities in styles that managers may display across policy choices. However, detecting commonalities in styles helps us to identify the general preferences of individual managers for certain business models and point to something akin to a manager’s personality.

Panel A of Table 8 shows that managers do indeed exhibit some degree of commonality in their preferences for certain policy choices. For instance, the correlation between the manager fixed effects extracted from non-interest income and the manager fixed effects extracted from derivative investments is above 60%. This suggests that managers with a preference for less traditional income sources also display a preference for larger investments in off-balance sheet derivatives. Likewise, Panel A shows that managers who make a larger idiosyncratic contribution to a bank's lending intensity (more loans relative to assets) also contribute more to an institution's funding decisions, for instance via a higher idiosyncratic contribution to a bank's loan-to-deposit ratio.

********TABLE 8 ABOUT HERE********

It should thus be possible to combine the different manager fixed effects into a smaller number of typologies that closely reflect managerial preference for specific business models. In this section, we first identify the dominant combinations of styles at the manager level and refer to these as 'style patterns'. We then derive manager profiles from these style patterns. In essence, we use patterns in manager styles to map manager preferences for certain business models.

We use factor analysis to identify the main dimensions of variation in managerial styles. Factor analysis, a traditional approach in studies of personality traits (see for instance, Kaplan and Sorensen, 2016), reduces the correlations amongst our eight business policy variables to a lower number of common factors. Our analysis extracts two dominant factors (with eingenvalues >1) that summarize a relevant portion of the variance of the correlation matrix of manager styles.[17]

Panel B of Table 8 reports the factor loadings of each policy style with respect to the two factors. Jointly, the two factors appear to contrast managerial preferences for policies that are different from the traditional bank business model around deposit-taking and loan-making. Factor 1 loads positively on manager styles that capture a managerial preference for non-traditional forms

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[17] The number of factors is determined by the Kaiser criterion that retains factors with eigenvalues ≥ 1. In our analysis, only two factors satisfy this criterion. More generally, we identify five factors with eigenvalues > 0 (signaling a positive contribution in explaining total variance) with the two retained factors explaining around 70% of the total variance.

of bank income and assets. Therefore, Factor 1 loads positively on manager styles in non-interest income (0.67) and negatively on manager styles in the loans-to-assets ratio (-0.79) and the loans-to-deposits ratio (-0.9). By contrast, Factor 2 loads positively on styles linked to non-traditional liability structures. In particular, Factor 2 shows an extremely high loading on manager styles in non-deposit funding (0.97).

In a next step, we use the two factors to cluster bank managers into groups that differ in terms of their preferences for specific business models. We adopt a k-medians clustering algorithm with the optimal number of groups determined by the Calinski and Harabasz (1974) index. This technique, which is designed to detect unknown structure in data, minimizes the variance within clusters (in terms of the Euclidian distance of factor values from the center of its own cluster) and maximizes the variance between clusters (in terms of the Euclidian distance of factor values from the center of other clusters). This approach yields three clusters of managers. We refer to the clusters as 'manager style profiles'.

********FIGURE 2 ABOUT HERE********

Figure 2 plots each manager as belonging to one of three clusters. For each manager, we present her value for Factor 1 (style patterns linked to non-traditional bank assets) and Factor 2 (style patterns linked to non-traditional bank liability structures). The figure shows that the cluster analysis has been effective in identifying three distinct profiles in our sample of managers.

Panel C of Table 8 shows the average values for Factor 1 and Factor 2 for each manager profile. Based on the reported factor scores, we refer to managers with a negative loading on both factors as Traditionalists and to managers with a positive loading on both factors as Innovators. Finally, we refer to managers with a positive Factor 1 loading and a negative Factor 2 loading as Partial Innovators because these managers combine innovation on the asset side with traditional means of bank funding. Our method assigns one profile to each bank manager. For instance, Hugh McColl, the long-standing Bank of America CEO is a Traditionalist. Vikram Pandit (Citigroup) is classed as an Innovator and Wachovia's John Strumpf as a Partial Innovator.

********TABLE 9 ABOUT HERE********

To validate our style profiles as a relevant depiction for systematic differences in how managers impact policies, we show that the style profiles we identify are related to manager careers. Kaplan and Sorensen (2016) study executive assessment data and show that CEOs differ from other executives in terms of their skill sets. Inspired by this, we run probit regressions on a variable that is one if a manager has been CEO at some point during our sample period (and zero otherwise). The results are reported in Table 9. We find that managers classified as traditionalists have a higher probability of being appointed CEOs. Further, relatively few other manager characteristics enter the model significantly. Overall, our results suggest that manager styles explain CEO appointments vis-à-vis other manager characteristics.

The next two subsections analyze the implications associated with manager style profiles. In particular, we investigate how these profiles are related to the idiosyncratic effects that managers have on bank risk and how managers match with certain banks based on their profiles,.

5.2 Manager Profiles and Manager Risk Styles

In this subsection, we analyze whether the manager profiles we identify above explain the contribution that individual managers make to measures of bank risk. This analysis serves two purposes. First, we demonstrate that the manager profiles we constructed are relevant for bank risk, a key by-product of a bank's business model decisions. Second, our analysis allows us to identify if managers with particular profiles are inherently more risk-taking.

In a first step, we compute manager fixed effects (η_j) in measures of bank risk as follows:

$$Risk_{j(it)} = X_{it-1}\beta + M_{j(it)}\gamma + P_{j(it-1)}\delta + \eta_j + \mu_t + \phi_i + \varepsilon_{it} \tag{3}$$

Risk includes the 5% Value at Risk (*VaR*), 5% Expected Shortfall (*ES*), Equity Volatility (*Equity Vol*), and 5% Marginal Expected Shortfall (*MES*) which are all measured annually using daily stock returns. As previously, we control for bank characteristics ($X_{it-1}\beta$) and manager characteristics ($M_{j(it)}\gamma + \eta_j$) and year fixed effects (μ_t). We now also control for lagged values of the bank policy variables *P*. The latter are critical to extract the effects that managers have on risk in addition to the effects that bank policies have on risk.

********TABLE 10 ABOUT HERE********

We call the estimated manager fixed effect ($\hat{\eta}$) in the risk measures of banks 'risk style'. By definition, a manager's risk style expresses her or his unique contribution to risk after controlling for various other determinants of bank risk-taking. As shown in Panel A of Table 10, the estimated risk styles are jointly and significantly different from zero. Furthermore, risk styles explain on average around 4.2% of the variation in bank risk measures.

While our findings suggest that the idiosyncratic manager contributions to bank risk are smaller than the idiosyncratic manager contributions to the individual policy choices we report above, it is important to point out that the risk styles capture the risk contribution that managers make to measures of bank risk, including measures of systemic risk, that are not completely under manager control. Further, the effects of risk styles we identify are in addition to any idiosyncratic contributions that managers make to risk via policy choices (which, as indicated above, are included in lagged form as controls in the risk regressions). The documented risk effects are therefore economically large.

In a second step, we test if the manager profiles identified in the previous section link to the risk styles of individual managers. A manager profile with a positive impact on risk indicates a manager with a propensity for aggressive risk-taking. We use binary variables to indicate a manager's *Profile* (Traditionalist or Innovator, with Partial Innovators as the benchmark) and report the results in Panels B and C of Table 10.

$$\hat{\eta}_j = Profile_j\ \omega + \varepsilon_{\mathrm{it}} \tag{4}$$

The results show that Innovators make a larger idiosyncratic contribution to every measure of risk (Panel B) and Traditionalists make a lower idiosyncratic contribution to most measures of bank risk (Panel C). This confirms that the manager profiles we identify can indeed predict the risk preferences of individual managers. Specifically, Innovators make the largest person-specific contribution to increases in a bank's tail risk and systemic risk.

5.3 Manager Profiles and Bank Boards

In the previous sections, we demonstrate that much of the variation in bank business policy is explained by manager factors that are time-invariant. This finding helps explain the persistent risk-taking culture in some banks (as documented, for example, in Fahlenbrach, Prilmeier, and Stulz (2012) and Ellul and Yerramilli (2013)). In this final section, we provide additional evidence for the existence of a risk culture in certain banks by showing evidence consistent with matching between manager profiles and banks based on risk-appetite.

Managers and shareholders differ in terms of risk preferences (Jensen and Meckling, 1976). One implication of this is that shareholder-dominated governance should facilitate riskier outcomes than insider-dominated governance. Previous studies have found evidence consistent with this view and show that bank boards with more shareholder-oriented governance take more risk (Laeven and Levine, 2009) and were more exposed to risks that manifested themselves during the Great Recession (Fahlenbrach and Stulz, 2011; Beltratti and Stulz, 2012). In our set-up, this literature motivates us to test whether managers with certain profiles might be more likely to match with banks with certain governance structures and whether this matching reflects differences in bank risk-appetite.

********TABLE 11 AROUND HERE********

We use RiskMetrics to assemble two commonly employed indicators of the power balance between managers and shareholders. First, we include the Bebchuk, Cohen and Ferrel (2009) index of managerial entrenchment (*Entrenchment*).[18] Higher values of *Entrenchment* indicate more powerful managers (and weaker shareholder influence). Second, we include the proportion of independent directors on the board (*Board independence*). Independent directors have no business or family ties to the board or its senior management and we expect more independent boards to represent shareholder interests more effectively.

Table 11 links board governance variables to the manager profiles that we have derived in the previous section. We estimate a set of probit regressions where the dependent variables are dummies equal to one if a manager belongs to a certain group of profiles. In effect, we examine if certain boards are more likely to select managers with certain profiles as evident in her idiosyncratic shaping of bank policies.

To aid identification of which boards select which manager profiles, we relate the manager profiles to a bank's governance structure in the appointment year only. Where managers join before the start of our sample period, we use the governance structure in the first year a bank

[18] The entrenchment index is the composite of the following six inputs (yes = 1; no = 0): staggered boards, limits to shareholders' by-law amendment, super-majority requirements for mergers, super-majority requirements for charter amendment, poison pills and golden parachutes. Consequently, higher values of this index indicate that mangers are more entrenched.

appears in our dataset. Our models include the share of female board members (*Female*) since a board's gender-balance could be linked the type of manager profiles that match with banks. We also control for the time period following the Gramm-Leach-Bliley Financial Modernization Act (GLBA) of 1999. GLBA extended the ability of banks to compete in non-traditional business policies (such as investment banking, insurance, brokerage and other non-interest activities) may have changed the type of manager profiles that match with boards compared to the earlier sample period.[19]

The results in Table 11 show that more entrenched boards (measured by higher *entrenchment*) are less likely to appoint Innovators and more likely to appoint Traditionalists. This implies that more shareholder-oriented boards are more likely to appoint managers who are aggressive risk-takers with preferences for innovative assets and non-traditional funding sources. Entrenched boards, by contrast, are more likely to appoint managers with a preference for a traditional asset and liability structures.

Consequently, the bank-profile matching we document in this section offers an explanation for a risk culture in some banks as well as a new explanation for why shareholder-dominated governance leads to riskier outcomes. Our results suggest that a potential reason why shareholder-controlled boards have been associated with riskier outcomes is because these banks are more likely to appoint managers with more aggressive styles in bank policies.

[19] For instance, DeYoung et al. (2013) show that bank boards offered permanently more risk-sensitive compensation deals to bank managers following GLBA. We control for this via *Post GLBA* which is equal to one during the 2000 to 2010 period.

6. Conclusions

We analyze the contribution that different types of managerial characteristics provide in explaining variation in bank business models. Even though a large part of the literature and current academic and regulatory debates highlight executive compensation, qualifications and other readily observable manager characteristics, we document that a much more important role in explaining bank business models is played by unobservable manager specific effects (or styles), measured by manager fixed effects. Bank manager styles have substantial impact on key bank policy choices such as the sources of bank income, funding and the structure of bank assets. Bank manager styles allow managers to be classified into distinct profiles that explain some of their risk preferences and help explain which managers match with certain bank boards.

Our findings have two key implications for bank regulators. First, they imply that regulatory interventions targeted towards executive compensation (or indeed other readily observable manager characteristics) are likely to have only a minor impact on bank business models and, hence, on bank risk-taking. That is because these manager characteristics only shape bank business models to a small degree compared with the extent to which managers idiosyncratically shape policies.

Second, by showing that managerial profiles significantly contribute to both tail risk and systemic risk, our results imply that factors that can produce negative systemic externalities are shaped by manager attributes that are difficult to identify and, as such, difficult to regulate. If key drivers of bank risk-taking and systemic risk are ultimately idiosyncratic and rooted in manager styles, regulatory attempts to reign in most aspects of bank risk-taking in a meaningful way will be extremely challenging. Regulators in the U.S. have recognized this important fact. The management factor (M) in the "CAMEL" rating – which is for instance used for regulatory purposes, for setting deposit insurance premia or in the stress test (CCAR) methodology – now has the same weighting as capital adequacy in calculating this rating (i.e. 25%). More quantitative approaches to assess the management factor are therefore needed and we hope that our paper inspires more research in this direction.

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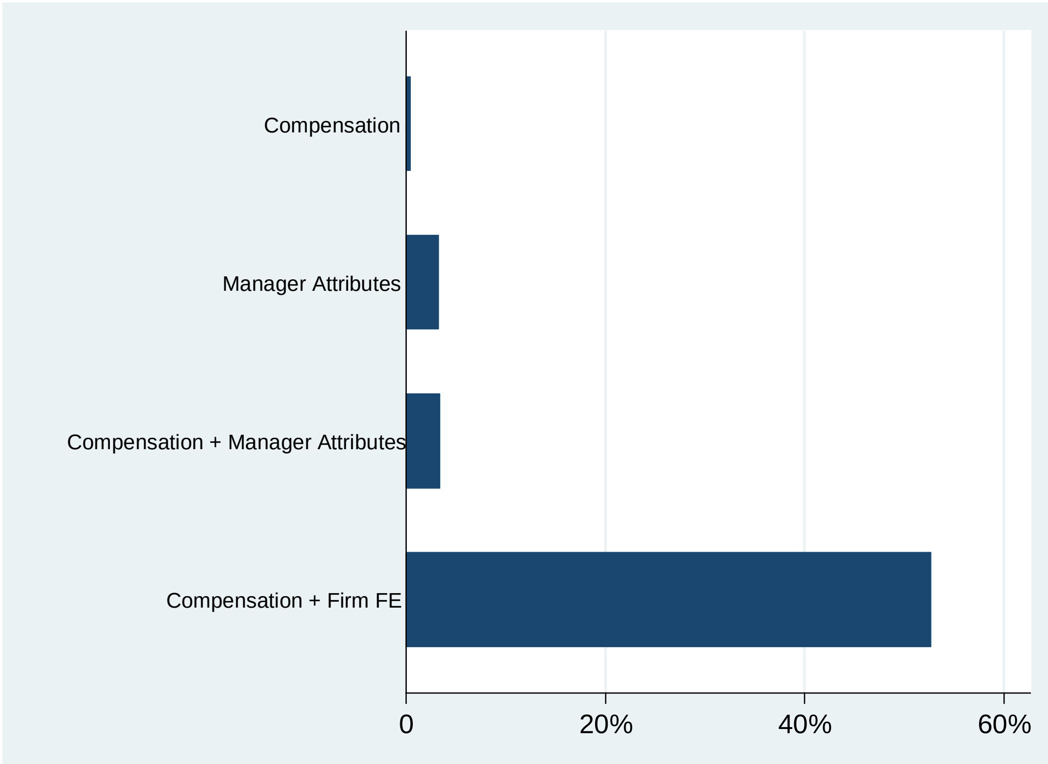

Figure 1: **The determinants of bank business policies: average increase in adjusted R^2 under different model specifications**

The figure plots the additional adjusted R^2 of pooled OLS regressions relative to benchmark model. The regressions are based on all banks and bank managers contained in Execucomp. Increases in R^2 are the averages across eight bank policy regressions (non-interest income over operating income, loans to total assets, mortgage backed securities over total assets, derivatives over total assets, lending diversification, the 12-month liquidity gap by total assets, loans over deposits, and non-deposit funding over total liabilities). The benchmark model controls for *Size, Equity, Market to book*, *Core deposits*, *Loans*, *Economy* and year dummies. We then add compensation variables (*Vega*, *Delta*, *Bonus*), other manager attributes (*Birth year*, *Male*, *Depression baby*, *Military service*, *MBA*, *Ivy league*, *Fast track*, *Nonbank experience (N_Ex)*, *Nonbank experience (Ex)*, *Generic*), both compensation and other manager attributes. The next models add firm fixed effects.

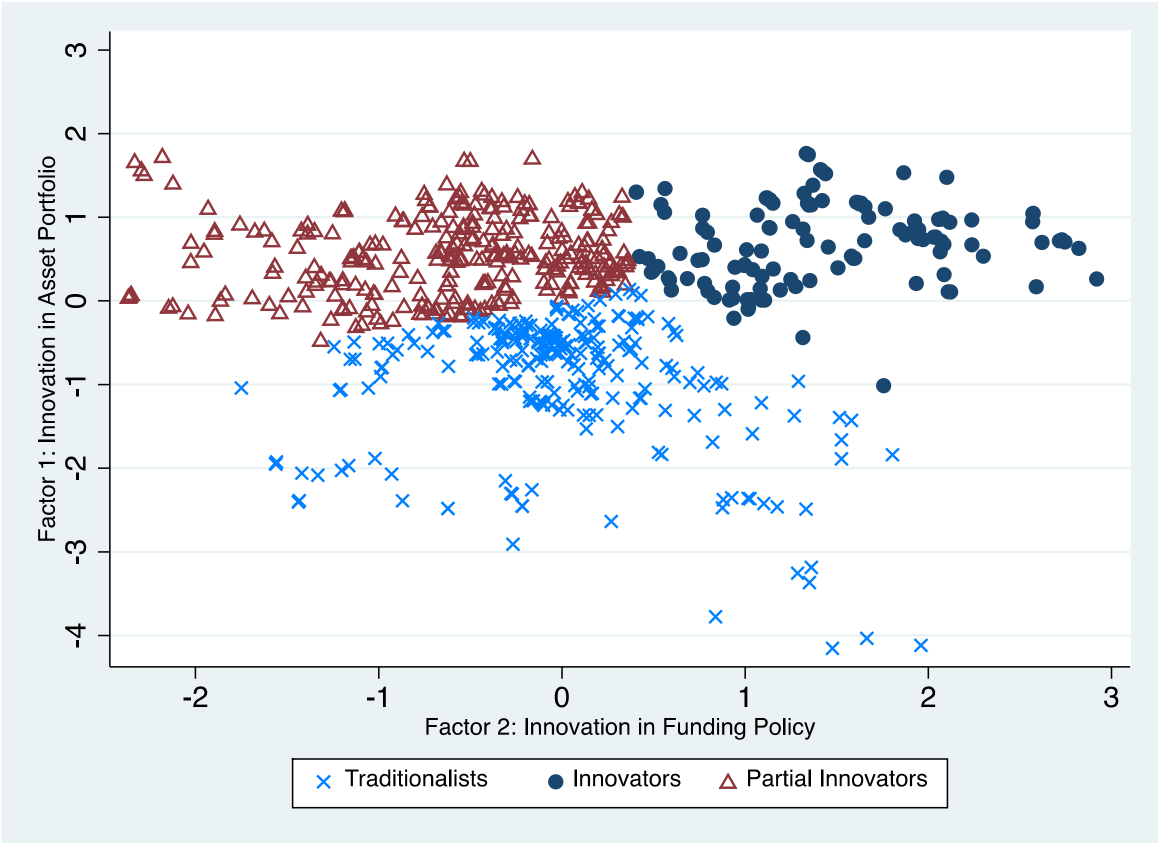

Figure 2: Clustering of manager styles

The figure presents the graphical clustering of managerial patterns in styles. Using factor analysis, we extract two factors (with eingenvalues >1) that summarize a relevant portion of the correlation matrix of managerial styles. For each manager, we present her average value for *Factor 1* (style patterns in non-traditional bank asset and income choices) and *Factor 2* (style patterns in non-traditional bank funding choices). We use the two factors to cluster bank managers into six groups. The number of groups is determined by a k-means clustering algorithm and the Calinski and Harabasz (1974) index. We refer to the clusters as manager style profiles. There are: (1) Innovators, (2) Partial Innovators, and (3) Traditionalists.

Table 1 Variable definitions and descriptive statistics

Bank-level data are from form FR Y-9C of the Consolidated Financial Statements published by the Board of Governors of the Federal Reserve System with references to data mnemonics displayed. Compensation data are from Execucomp. Managerial attributes are from Boardex, Marquis Who's Who and Riskmetrics, State-level coincident indices are from the Federal Reserve Bank of Philadelphia.

Variable Name	Definition	N	Mean	Median	St.Dev.
Panel A: Bank Business Policy Variables					
Non-interest income	Non-interest income (bhck4079) over to the sum of interest income (bhck4107) and non-interest income (bhck4079)(%)	1,480	23.53	20.97	13.10
Loans	Total loans (bhck2122) over total assets (bhck2170) (%)	1,480	63.20	66.22	13.41
MBS	Private-label mortgage backed securities (bhck1709 + bhck1733 + bhck1713 + bhck1736 + bhck3536) over total assets (%)	1,330	1.45	0.07	3.23
Derivatives	Gross notional amount of derivative contracts held for trading (log of 1 + gross notional amounts on contracts on interest rate (bhcka126), foreign exchange (bhcka127), equity derivatives (bhck8723), and others (bhck8724)) over total assets (%)	1,253	26.41	0.00	67.93
Lending diversification	1–Herfindahl index of the shares of real estate (bhck1410), commercial and industrial (bhck1763 + bhck1764), consumer (bhck1975) and other loans out of total loans	1,480	0.51	0.55	0.16
Gap12	Liabilities repricing or maturing within 12 months (bhck3197) minus assets repricing or maturing within 12 months (bhck3296 + bhck3298) divided by total asset (%)	1,480	-17.68	-17.96	16.18
Loans/Deposits	Total loans over total deposits (bhdm6631 + bhdm6636 + bhfn6631 + bhfn6636) (%)	1,480	90.98	91.05	30.09
Non-deposit funding	1 – (deposits over total liabilities (bhck2948)) (%)	1,480	21.79	20.48	12.09
Panel B: Compensation					
Vega $_t$	Log ($ value of pay-risk sensitivity / cash compensation)	7,205	0.05	0.02	0.16
Delta $_t$	Log ($ value of the pay-performance sensitivity / cash compensation)	7,205	0.17	0.10	0.27
Bonus $_t$	Log (1 + the $ value of cash bonuses)	8,495	4.13	4.86	2.61
Panel C: Biographic Manager Attributes					
Birth year	Year a manager was born	1,282	1948.38	1948.00	8.62
Male	1 for male managers	1,431	0.94	1.00	0.25
Depression baby	Born between 1920 and 1929	1,234	0.13	0.00	0.34
MBA	Holds an MBA degree	1,026	0.40	0.00	0.49
Ivy league	Graduated from an Ivy League university (Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania and Yale University)	1,026	0.19	0.00	0.40
Military service	Indicator for managers with prior military service	1,135	0.11	0.00	0.32
Fast track	Log of age of first executive director appointment	1,175	3.77	3.78	0.18
Nonbank experience (N_Ex)	A dummy equal to one if a manager has served as non executive in non banking firms	1,200	0.23	0.00	0.42
Nonbank experience (Ex)	A dummy equal to one if the manager has served as executive in non banking firms	1,200	0.03	0.00	0.18
Generic	Generic career track. First appointment is not with a financial services or accounting industry firm.	1.201	0.78	1.00	0.41
Panel D: Other Controls					
Size $_{t-1}$	Log of total assets (in 2000 $)	1,480	16.49	16.25	1.52
Equity $_{t-1}$	Total equity (bhck3210) over total assets (%)	1,480	8.63	8.25	2.32
Market to book $_{t-1}$	Log of the ratio of the market to book value of equity	1,474	0.63	0.66	0.51
Core deposits $_{t-1}$	1 – (total time deposits of $100,000 or more (bhcb2604) over total deposits (%)	1,480	86.83	89.42	9.32
Productivity $_{t-1}$	Total assets over full-time employees (bhck4150) ($ millions)	1,480	3.66	3.22	1.98
Economy $_t$	12 month average of the monthly coincident index at the state level	1,480	130.89	133.62	18.53

Table 2. Compensation, manager attributes, controls and adjusted R^2

The panels display the additional adjusted R^2 of various pooled OLS regressions on eight different bank policy choices *P* (Non-interest income, Loans, MBS, Derivatives, Lending diversification, Gap12, Loans/Deposits Non-deposit funding). The benchmark model is given by:

$$P_{it} = X_{it-1}\beta + \mu_t + \varepsilon_{it}$$

The adjusted R^2 of models with various sets of controls are compared to the benchmark model that controls for bank variables contained in X_{it-1} (*Size, Equity, Market to book, Core deposits, Loans, Economy* and year dummies). All panels then sequentially add compensation variables (*Vega, Delta, Bonus*), other manager attributes (*Birth year, Male, Depression baby, Military service, MBA, Ivy league, Fast track, Nonbank experience (N_Ex), Nonbank experience (Ex), Generic*), both compensation and biographical manager attributes, and both firm fixed effects and compensation variables. The results are shown for bank CEOs (Panels A & C) and for all bank managers listed in Execucomp (Panels B & D). Panels C & D estimate the models in the three years following the deregulation of interstate branching in the state where a bank is headquartered. State-level deregulation is based on the Interstate Banking and Branching Efficiency Act (IBBEA) and the data are from Cornaggia et al. (2015). Each regression model is estimated with robust standard errors clustered at the level of every unique firm-manager combination. Variable definitions are reported in Table 1.

Panel A: Bank CEOs

Dependent Variable:	(1) Non-interest income	(2) Loans	(3) MBS	(4) Derivatives	(5) Lending diversification	(6) Gap12	(7) Loans/Deposits	(8) Non-Deposit Funding	(9) Average
1 Adj. R-squared benchmark model	0.426	0.135	0.061	0.533	0.382	0.165	0.085	0.400	0.273
2 + Compensation	0.005	0.005	0.004	0.020	0.017	0.010	-0.002	0.006	0.008
3 + Manager Attributes	0.068	0.057	0.026	0.046	0.029	0.027	0.037	0.069	0.045
4 + Compensation + Manager Attributes	0.068	0.056	0.030	0.062	0.048	0.033	0.036	0.076	0.051
5 + Firm FE +Compensation	0.449	0.697	0.517	0.417	0.539	0.494	0.677	0.440	0.529

Panel B: Full Sample of Bank Managers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1 Adj. R-squared benchmark model	0.436	0.149	0.066	0.540	0.385	0.166	0.115	0.434	0.286
2 + Compensation	0.001	0.001	0.010	0.015	0.004	0.011	-0.002	-0.003	0.005
3 + Manager Attributes	0.033	0.064	0.009	0.043	0.012	0.033	0.005	0.059	0.032
4 + Compensation + Manager Attributes	0.026	0.064	0.019	0.052	0.018	0.039	0.005	0.053	0.035
5 + Firm FE +Compensation	0.437	0.697	0.530	0.416	0.537	0.512	0.669	0.418	0.527

Panel C: Bank CEOs & Competitive States (3 Years After a Competitive Shock)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1 Adj. R-squared benchmark model	0.404	0.372	0.041	0.582	0.565	0.226	0.175	0.615	0.373
2 + Compensation	0.052	0.025	-0.008	-0.001	-0.007	0.079	0.052	0.015	0.026
3 + Manager Attributes	0.185	0.024	0.096	0.022	0.003	0.104	-0.019	0.059	0.059
4 + Compensation + Manager Attributes	0.212	0.044	0.102	0.02	0.004	0.153	0.023	0.06	0.077
5 + Firm FE +Compensation	0.561	0.572	0.898	0.38	0.403	0.639	0.736	0.315	0.563

Panel D: Full Sample of Bank Managers & Competitive States (3 Years After a Competitive Shock)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1 Adj. R-squared benchmark model	0.440	0.397	0.112	0.584	0.573	0.277	0.262	0.645	0.411
2 + Compensation	0.038	0.041	0.017	0.025	0.015	0.008	0.017	0.003	0.021
3 + Manager Attributes	0.004	0.037	0.002	0.039	-0.008	0.054	0.021	0.075	0.028
4 + Compensation + Manager Attributes	0.040	0.081	0.020	0.067	0.014	0.067	0.041	0.078	0.051
5 + Firm FE +Compensation	0.538	0.569	0.819	0.396	0.410	0.640	0.689	0.313	0.547

Table 3. Compensation, manager attributes and the global financial crisis

The table shows OLS regressions on bank buy and hold returns (*BHR*), the *Volatility* of daily returns, the 5% value at risk *(VaR)*, the 5% expected shortfall (*ES*) and 5% marginal expected shortfall (*MES*). MES captures a bank's return on the worst 5% days in terms of market returns. All dependent variables are observed between 07/ 2007 and 12/2008. The regressions control for compensation variables (*Vega, Delta, Bonus*), manager attributes (*Birth year, Male, Depression baby, Military service, MBA, Ivy league, Fast track, Nonbank experience (N_Ex), Nonbank experience (Ex), Generic*) are employed to explain cross-sectional variation in bank risk during the global financial crisis. Controls are measured at the end of 2006. Huber White robust standard errors are reported in parentheses. significant at 10%; ** significant at 5%; *** significant at 1%.

	(1) Negative BHR	(2) Volatility	(3) VaR	(4) ES	(5) MES
Compensation					
Vega	-0.702***	-0.031**	-0.037**	-0.062**	-0.027
	(0.255)	(0.013)	(0.015)	(0.027)	(0.018)
Delta	0.045	0.008	0.012	0.013	-0.004
	(0.171)	(0.009)	(0.011)	(0.017)	(0.009)
Bonus	-0.020	-0.001	-0.001	-0.002	-0.001
	(0.014)	(0.001)	(0.001)	(0.002)	(0.001)
Demographics					
Birth year	-0.006	0.000	0.000	0.000	0.001
	(0.009)	(0.000)	(0.001)	(0.001)	(0.001)
Male	-0.532***	-0.021***	-0.022***	-0.057***	-0.041***
	(0.141)	(0.005)	(0.006)	(0.011)	(0.008)
Depression baby	0.046	0.001	-0.001	-0.004	-0.003
	(0.185)	(0.008)	(0.010)	(0.025)	(0.020)
Education					
MBA	0.055	0.003	-0.003	-0.000	-0.001
	(0.088)	(0.005)	(0.006)	(0.011)	(0.007)
Ivy league	0.265**	0.006	0.013**	0.021**	0.010
	(0.121)	(0.004)	(0.005)	(0.009)	(0.006)
Career and Experience					
Military service	-0.011	-0.000	0.001	0.002	0.001
	(0.129)	(0.007)	(0.008)	(0.016)	(0.010)
Fast Track	-0.012	0.005	0.013	0.011	0.019
	(0.225)	(0.011)	(0.014)	(0.024)	(0.014)
Nonbank experience (Non ex)	0.052	0.000	0.002	-0.004	0.002
	(0.087)	(0.005)	(0.006)	(0.011)	(0.006)
Nonbank experience (Ex)	-0.160	-0.000	-0.002	-0.007	-0.002
	(0.109)	(0.005)	(0.007)	(0.012)	(0.009)
Generic	-0.182*	0.003	0.002	-0.001	0.001
	(0.099)	(0.005)	(0.006)	(0.010)	(0.007)
Other control variables					
Size	0.126***	0.006*	0.005*	0.014**	0.013***
	(0.047)	(0.003)	(0.003)	(0.006)	(0.004)
Equity	3.499**	0.066	0.157*	0.199	0.129
	(1.508)	(0.066)	(0.079)	(0.146)	(0.116)
Beta	-0.068	0.010	0.011	0.013	0.003
	(0.130)	(0.007)	(0.008)	(0.015)	(0.010)
Probability of Default	0.009	0.000	0.001	0.002	0.003*
	(0.015)	(0.001)	(0.001)	(0.002)	(0.001)
Non-Performing Loans	21.155**	0.882*	1.489***	1.707	0.133
	(10.363)	(0.500)	(0.555)	(1.126)	(0.769)
Stock return 2006	0.252	-0.003	0.010	0.003	-0.008
	(0.326)	(0.015)	(0.021)	(0.035)	(0.022)
Constant	11.323	-0.365	-0.859	-0.863	-1.252
	(17.983)	(0.783)	(1.029)	(1.681)	(1.035)
Observations	77	77	77	77	77
Adj. R2	0.319	0.056	0.093	0.088	0.214
Adj. R2 – only firm controls	0.216	0.088	0.092	0.095	0.227

Table 4. Managerial mobility and bank connectedness (1992 – 2010)

Panel A shows how many bank managers have worked for more than a single bank listed on Execucomp between 1992 and 2010. We apply a technique employed by Abowd, Kramarz, and Margolis (1999) to sample Execucomp banks which have employed at least one manager who has worked for two or more banks listed on Execucomp during our sample period. Panel B shows that the resulting sample, which is connected via mover-managers, contains about 45% of Execucomp banks. Panel C demonstrates that banks that have employed at least one mover-manager in our sample are widely connected to groups of other banks.

Panel A. Mover-managers in the sample

Mover-manager	# banks in which managers have been employed	# managers	%
No	1	1,505	95.37
Yes	2	71	4.50
	3	2	0.06
Subtotal (Mover = 'Yes')		73	4.56
Total		1,578	100

Panel B. Execucomp banks, by # of mover-managers

# movers per bank	frequency	%	cumulative
0	91	55.15	55.15
1 – 5	32	19.39	74.55
6 – 10	24	14.55	89.09
11 – 20	16	9.7	98.79
21 – 30	2	1.21	100
Subtotal (# movers>0)	74	44.85	-
Total	165	100	-

Panel C. Sample banks connected by mover-managers

Group	manager-years	# managers	# movers	# banks
1	169	33	1	2
2	1,346	306	36	28
3	429	79	10	8
4	80	16	1	2
5	150	24	1	2
6	107	22	1	2
7	32	11	1	2
8	153	31	2	3
9	546	107	11	9
10	89	21	1	2
11	39	15	1	2
12	180	32	1	2
13	131	24	2	2
14	77	15	1	2
15	66	11	1	2
16	55	15	1	2
17	43	14	1	2
Total	3,692	776	73	74

Table 5. Managerial fixed effects and bank policy choices: three way fixed effects model

This table reports three-way fixed effect regressions (manager, bank, and year effects) on banks' policy choices for our connectedness sample. The connectedness sample is based on Abowd, Kramarz, and Margolis (1999) and includes all banks that have employed at least one manager who has worked for two or more banks during the sampling period.

$$P_{j(jt)} = X_{it-1}\beta + M_{j(it)}\gamma + \theta_j + \mu_t + \phi_i + \varepsilon_{it}$$

where $P_{j(it)}$ is a policy choice variable observed for manager *j* in bank *i* at time *t* and explained by bank characteristics $X_{it-1}\beta+ \phi_i$, manager characteristics $M_{j(it)}\gamma+\theta_j$, and time effects μ_t. Since some bank managers in our sample of connected banks move across firms over time, the function *j(i,t)t* maps manager *j* to firm *i* at time *t*. *Non-interest income* is divided by operating income, *Loans* are total loans divided by total assets, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans, *Gap12* is the 12-month liquidity gap by total assets, *Loans/Deposits* is the ratio between total loans and total customer deposits, *Non-deposit funding* is the ratio between non-deposit funding in total liabilities. *Vega* denotes pay-based risk-taking incentives as the log of ($ value of pay-risk sensitivity/cash compensation), *Delta* is the Log ($ value of the pay-performance sensitivity/cash compensation), *Bonus* is the log (1 + the $ value of cash bonuses), *Size* is the Log of total assets (in 2000$), *Equity* is equity/total assets, *Market to book* is the Log of the ratio of the market to book value of equity, *Core deposits* is 1 – ($100,000+ deposits/total deposits, *Productivity* is assets/full-time employees, and *Economy* is the 12-month average of the monthly coincident index at the state level. Each regression model is estimated with robust standard errors clustered at the level of every unique firm-manager combination. Variable definitions are reported in Table 2. significant at 10%; ** significant at 5%; *** significant at 1%.

Dependent Variable:	(1) Non-interest income	(2) Loans	(3) MBS	(4) Derivatives	(5) Lending diversification	(6) Gap12	(7) Loans/Deposits	(8) Non-Deposit Funding
Compensation variables								
Vega $_t$	0.016	0.019	-0.005	0.146***	-0.045	0.038	0.002	0.015
	(0.014)	(0.017)	(0.004)	(0.051)	(0.030)	(0.024)	(0.012)	(0.014)
Delta$_t$	-0.007	-0.022	0.005	-0.084**	0.049*	-0.039	-0.000	-0.009
	(0.013)	(0.017)	(0.004)	(0.039)	(0.029)	(0.024)	(0.012)	(0.012)
Bonus $_t$	0.000	-0.001	0.001***	-0.003	0.001	-0.000	-0.001*	0.001**
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)
Bank characteristics								
Size $_{t-1}$	-0.019**	0.014	0.042	-0.870**	0.017	0.063***	0.001	0.031***
	(0.009)	(0.018)	(0.031)	(0.363)	(0.013)	(0.023)	(0.006)	(0.008)
Equity $_{t-1}$	0.012	0.107	-0.007*	-0.015	0.108	-0.192	0.180	-0.707***
	(0.101)	(0.119)	(0.004)	(0.035)	(0.200)	(0.190)	(0.119)	(0.102)
Market to book$_{t-1}$	0.009	-0.021**	0.001	0.001	0.006	-0.002	0.007*	0.017***
	(0.006)	(0.009)	(0.001)	(0.020)	(0.008)	(0.012)	(0.004)	(0.005)
Core deposits $_{t-1}$	-0.035	-0.053	0.033**	0.051	-0.298***	0.020	0.089**	0.077*
	(0.051)	(0.041)	(0.013)	(0.121)	(0.061)	(0.070)	(0.036)	(0.040)
Productivity $_{t-1}$	-0.020***	-0.005	-0.003***	0.020*	-0.007	0.008	-0.001	0.014***
	(0.005)	(0.004)	(0.001)	(0.012)	(0.005)	(0.008)	(0.002)	(0.003)
Other control variables								
Economy $_t$	-0.000	0.001**	0.000	0.002	-0.001*	0.003***	-0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Observations	3,692	3,692	3,201	2,801	3,692	3,692	3,692	3,692
R^2 (%)	92.54	89.10	75.95	98.10	95.04	78.80	84.63	91.32
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Manager FE	776	776	773	653	776	776	776	776

Table 6. How important are bank manager styles?

Panel A shows F-statistics (p-values in parenthesis) to test if the fixed effects (FE) estimated with three-way fixed effect models in Table 4 are jointly significantly differently from zero. The three-way fixed effect regressions (manager, bank, and year effects) on banks' policy choices are run on a connectedness sample based on Abowd, Kramarz, and Margolis (1999) that includes all banks that have employed at least one manager who has worked for two or more banks during the sampling period. *Non-interest income* is divided by operating income, *Loans* are total loans divided by total assets, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans, *Gap12* is the 12-month liquidity gap by total assets. *Loans/Deposits* is the ratio between total loans and total customer deposits, *Non-deposit funding* is the ratio between non-deposit funding in total liabilities. Panel B compares the relative importance of unobservable manager characteristics by decomposing the variation in the adjusted R^2 of the policy variables into the fitted components, manager FE, firm FE and residuals. Panel C compares the results to alternative methods of estimating manager FE. *significant at 10%; ** significant at 5%; *** significant at 1%.

Panel A. Statistical significance. F-test that fixed effects = 0

	(1) Non-interest income	(2) Loans	(3) MBS	(4) Derivatives	(5) Lending diversification	(6) Gap12	(7) Loans/Deposits	(8) Non-Deposit Funding
Firm and manager FE	20.57***	19.73***	80.75***	15.47***	39.27***	11.94***	15.77***	14.34**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Manager FE	3.14***	4.16***	5.47***	3.02***	3.02***	2.01***	3.37***	2.54***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	12.03***	16.57***	66.06***	12.22***	20.73**	10.30***	12.59***	14.92***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B. Economic significance. % of adjusted R^2 attributable to

	(1) Non-interest income	(2) Loans	(3) MBS	(4) Derivatives	(5) Lending diversification	(6) Gap12	(7) Loans/Deposits	(8) Non-Deposit Funding
Fitted values	11.83	0.09	4.39	1.54	13.44	7.40	17.47	41.66
Manager FE	**25.83**	**29.53**	**24.20**	**48.04**	**24.76**	**32.73**	**23.69**	**16.40**
Firm FE	53.45	59.50	47.36	48.82	56.84	38.77	43.47	33.27
Residuals	8.89	10.87	24.05	1.59	4.95	21.10	15.36	8.67

Panel C: How important are manager styles? Comparing alternative estimation techniques

	Maximum number of estimated managers FE	Average correlation with (1)	Average % variance explained by manager FE	Are manager FE statistically significant?
(1) Three-way FE on connectedness sample (as above)	776	–	28.15	Yes
(2) Mover-manager approach (Bertrand and Schoar, 2003)	73	0.761	28.49	Yes
(3) Heckman correction for sampling bias	776	0.998	28.37	Yes
(4) Excluding the period 2007-2010	661	0.917	28.65	Yes
(5) At least two movers per firm	547	0.975	16.41	Yes
(6) Only the largest connected group	306	0.815	13.58	Yes

Table 7: Do manager styles reflect idiosyncratic manager effects?

The table reports OLS regressions on the estimated bank manager fixed effects ($\hat{\theta}$) linked to different bank policy variables on a vector of biographical manager characteristics (M).

$$\hat{\theta}_j = M_j \gamma + \varepsilon_j$$

The fixed effect for manager *j* is estimated in Table 5 using three-way fixed effect regressions (manager, bank, and year effects) on banks' policy choices in a connectedness sample. The connectedness sample is based on Abowd, Kramarz, and Margolis (1999) and includes all banks that have employed at least one manager who has worked for two or more banks during the sampling period. Vector M contains the manager characteristics *Birth Year*, *Male* (via a binary variable), and *Depression baby* which indicates if a manager was born in the decade leading up to the Great Depression. We also control for managers with an *MBA* degree and a degree from an *Ivy League* university. *Military service* indicates if a manager has served in the military. *Fast track* is the age at which the manager held her first appointment as an executive on a board. We also include the number of board level appointments outside the banking sector (*NonBank experience*) and board-level appointments as an executive only (*NonBank Experience (Ex)*) during a manager's career. *Generic* takes the value of one if the manager's fist appointment was not with a financial or an accounting firm. Huber White robust standard errors are reported in parentheses. *significant at 10%; ** significant at 5%; *** significant at 1%

	(1) Non-interest income	(2) Loans	(3) MBS	(4) Derivatives	(5) Lending diversification	(6) Gap12	(7) Loans/Deposits	(8) Non-Deposit Funding
Demographics								
Birth year	**-0.002****	**0.002*****	**-0.000*****	**-0.013****	**-0.002*****	**0.004*****	**0.003*****	0.000
	(0.001)	**(0.001)**	**(0.000)**	**(0.006)**	**(0.000)**	**(0.001)**	**(0.001)**	(0.001)
Male	-0.008	0.012	-0.000	-0.117	-0.009	0.017	0.013	-0.001
	(0.023)	(0.019)	(0.004)	(0.148)	(0.014)	(0.022)	(0.028)	(0.013)
Depression baby	0.010	0.007	-0.003	0.131	**-0.014***	0.022	0.029	0.014
	(0.016)	(0.014)	(0.003)	(0.134)	**(0.008)**	(0.017)	(0.018)	(0.012)
Education								
MBA	0.013	0.006	-0.000	0.045	-0.002	**-0.026*****	0.010	-0.003
	(0.009)	(0.009)	(0.002)	(0.069)	(0.005)	**(0.010)**	(0.012)	(0.007)
Ivy league	**0.021****	**-0.041*****	**0.004***	**0.387*****	0.001	0.005	**-0.027****	**0.032*****
	(0.010)	**(0.010)**	**(0.002)**	**(0.093)**	(0.005)	(0.011)	**(0.014)**	**(0.008)**
Career and Experience								
Military service	-0.012	0.010	-0.001	-0.001	-0.004	0.020	0.007	-0.005
	(0.011)	(0.013)	(0.003)	(0.110)	(0.007)	(0.016)	(0.016)	(0.010)
Fast Track	-0.011	0.011	**-0.010***	-0.234	0.005	0.048	0.023	0.003
	(0.028)	(0.026)	**(0.005)**	(0.224)	(0.016)	(0.036)	(0.040)	(0.020)
Nonbank experience (Non ex)	**0.033*****	**-0.026****	0.003	**0.234*****	**0.011***	-0.012	-0.015	**0.020****
	(0.010)	**(0.010)**	(0.002)	**(0.081)**	**(0.006)**	(0.011)	(0.014)	**(0.008)**
Nonbank experience (Ex)	**0.050****	-0.029	-0.000	**0.428****	0.015	0.011	-0.002	0.026
	(0.025)	(0.024)	(0.005)	**(0.187)**	(0.011)	(0.024)	(0.030)	(0.019)
Generic	0.017	-0.005	-0.002	0.112	0.009	**-0.032****	0.010	0.011
	(0.012)	(0.012)	(0.003)	(0.090)	(0.007)	**(0.013)**	(0.017)	(0.009)
Constant	3.620**	-3.626***	0.821***	26.164**	3.462***	-7.248***	-6.751***	-0.736
	(1.455)	(1.333)	(0.290)	(11.220)	(0.907)	(1.777)	(2.128)	(1.104)
Adjusted R^2	0.069	0.059	0.010	0.117	0.047	0.061	0.021	0.046
Adjusted R^2 Demographics	0.029	0.016	0.002	0.039	0.044	0.037	0.020	-0.001
Adjusted R^2 Education	0.021	0.039	0.005	0.072	-0.001	0.006	0.009	0.036
Adjusted R^2 Career	0.037	0.017	-0.000	0.053	0.023	0.018	-0.002	0.017
Observations	530	530	518	471	530	530	530	530

Table 8. Profiling bank managers based on styles - factor and cluster analysis

Panel A shows the correlations between manager fixed effects (styles) in eight bank business policy variables. The manager styles are estimated with three-way fixed effects as in Table 5 on a sample of connected banks. The connectedness sample is based on Abowd, Kramarz, and Margolis (1999) and includes all banks that have employed at least one manager who has worked for two or more banks during the sample period. *Non-interest income* is divided by operating income, *Loans* are total loans divided by total assets, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans, *Gap12* is the 12-month liquidity gap by total assets, while *Loans/Deposits* is the ratio between total loans and total customer deposits, *Non-deposit funding* is the ratio between non-deposit funding in total liabilities. Panel B extracts *Factor 1* and *Factor 2* using factor analysis with eingenvalues >1 that summarize the correlation matrix of managerial styles. Factor loadings >60% are highlighted as key inputs into a factor. Panel C shows three profiles and loadings on Factor 1 and Factor 2. The profiles are derived from a k-median clustering algorithm with the optimal number of groups determined by the Calinski and Harabasz (1974) index. *significant at 10%; ** significant at 5%; *** significant at 1%.

Panel A. Manager fixed effects correlation matrix

	(1) **Non-interest income**	(2) **Loans**	(3) **MBS**	(4) **Derivatives**	(5) **Lending diversification**	(6) **Gap12**	(7) **Loans/Deposits**
2. Loans	-0.630***						
3. Mortgage-backed Securities	0.368***	-0.518***					
4. Derivatives	0.635***	-0.632***	0.332***				
5. Lending diversification	0.469***	-0.260***	0.211***	0.287***			
6. Gap12	-0.366***	-0.050	-0.020	-0.263***	-0.379***		
7. Loans/Deposits	-0.441***	0.771***	-0.473***	-0.381***	-0.317***	-0.028	
8. Non-deposit funding	0.392***	-0.566***	0.161***	0.521***	-0.005	0.096**	0.054

Panel B. Factor loadings on manager fixed effects

	Factor 1	**Factor 2**
Eigenvalue	**3.31934**	**1.13326**
% of variance explained	**65.0**	**22.2**
1. Non-interest income	**0.6737**	0.3664
2. Loans	**-0.7897**	-0.5174
3. Mortgage-backed Securities	0.5319	0.1525
4. Derivatives	0.5453	0.5092
5. Lending diversification	0.5227	0.1084
6. Gap12	-0.2552	0.0801
7. Loans/Deposits	**-0.8997**	0.1084
8. Non-deposit funding	0.0429	**0.9705**

Panel C. Average factor loadings, by manager profile

	Factor 1	**Factor 2**
Profile 1: Traditionalist (249)	-0.974	-0.002
Profile 2: Innovator (124)	0.689	1.439
Profile 3: Partial innovator (300)	0.524	-0.593

Table 9. Manager profiles and bank CEOs

The table shows the results of probit regressions where the dependent variable is a dummy equal to one if a manager has been a CEO over the sample period and the set of explanatory variables are managerial characteristics. *Birth year* is the log transformation of the year of birth of a bank manager, *Male* is a dummy equal to one for male managers and zero otherwise, *Depression baby* indicates if a manager was born in the decade leading up to the Great Depression, *Military service* indicates if a manager has served in the military. We also control for managers with an *MBA* degree, a degree from an *Ivy League* university, and the age at which the manager held her first appointment as an executive on a board (*Fast track*). Further, we include the number of board level appointments outside the banking sector (*NonBank experience*) and board-level appointments as an executive only (*NonBank Experience (Ex)*). *Generic* takes the value of one if the manager's fist appointment was not with a financial or an accounting firm. *Traditionalist* and *Innovator* are binary variables indicating the profile a manager is allocated to based on the factor and cluster analysis performed in Table 8. Huber White standard errors are reported in parentheses. *significant at 10%; ** significant at 5%; *** significant at 1%

	(1)	(2)	(3)	(4)
Dependent Variable		**Prob (Manager = CEO)**		
Birth year	-0.038***	-0.043***	-0.037***	-0.043***
	(0.012)	(0.013)	(0.012)	(0.013)
Male	0.379	0.359	0.402	0.371
	(0.391)	(0.379)	(0.389)	(0.378)
Depression baby	0.333	0.357	0.400*	0.390
	(0.230)	(0.237)	(0.234)	(0.240)
Military service	-0.077	-0.089	-0.102	-0.102
	(0.204)	(0.204)	(0.203)	(0.203)
MBA	0.049	0.032	0.017	0.018
	(0.138)	(0.142)	(0.141)	(0.143)
Ivy league	0.091	0.112	0.145	0.139
	(0.164)	(0.169)	(0.166)	(0.170)
Fast Track	-1.107***	-1.225***	-1.094***	-1.206***
	(0.416)	(0.429)	(0.422)	(0.431)
Nonbank experience (Non ex)	0.460***	0.545***	0.502***	0.557***
	(0.158)	(0.158)	(0.159)	(0.160)
Nonbank experience (Ex)	-0.050	0.010	0.001	0.031
	(0.307)	(0.309)	(0.303)	(0.308)
Generic	0.601***	0.657***	0.623***	0.662***
	(0.212)	(0.213)	(0.213)	(0.213)
Traditionalist		**0.500*** **		**0.441*** **
		(0.151)		**(0.157)**
Innovator			**-0.390** **	-0.209
			(0.195)	(0.209)
Constant	75.524***	86.575***	75.272***	85.307***
	(24.663)	(26.019)	(24.941)	(26.135)
Pseudo- R^2	0.122	0.144	0.138	0.146
Observations	471	471	471	471

Table 10. Manager fixed effects in risk and manager profiles

Panel A estimates three-way fixed effect regressions (manager, bank, and year effects) on bank risk for our connectedness sample. The connectedness sample is based on Abowd, Kramarz, and Margolis (1999) and includes all banks that have employed at least one manager who has worked for two or more banks during the sampling period.

$$Risk_{j(it)} = X_{it-1}\beta + M_{j(it)}\gamma + P_{j(it-1)}\delta + \eta_j + \mu_t + \phi_i + \varepsilon_{it}$$

where $Risk_{j(it)}$ is observed for manager j in bank i at time t and explained by bank characteristics. The function $j(i,t)t$ maps manager j to firm i at time. *Risk* includes 5% Value at risk (*VaR*), 5% Expected Shortfall (*ES*), equity volatility (*Equity Vol*), 5% marginal expected shortfall (*MES*). We control for the characteristics of banks $X_{it-1}\beta + \phi_i$, managers $M_{j(it)}\gamma + \eta_j$, lagged values of the bank policy variables $P_{j(it-1)}$ (Non-interest income, Loans, Mortgage-backed Securities, Derivatives, Lending diversification, Gap12, Loans/Deposits, and Non-deposit funding), and time effects μ_t. Panel A tests if the manager fixed effects in risk are jointly and significantly different from zero and shows the % contribution of manager risk fixed effects to the adjusted R^2 of the regressions on risk. Panels B and C report OLS regressions that regress binary variables that identify a manager's *Profile* (Innovators and Traditionalists) on the estimated manager fixed effects in risk ($\hat{\eta}_j$).

$$\hat{\eta}_j = Profile_j\ \omega + \varepsilon_{it}$$

Each manager is allocated to one profile based on the factor and cluster analysis performed in Table 8. Huber White standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Panel A: Statistical and economic significance of manager fixed effects in risk measures

	(1) VaR	(2) ES	(3) Equity Vol	(4) MES
F-test that all manager risk fixed effects = 0	1.35	1.20	1.19	1.33
	(0.00)	(0.002)	(0.003)	(0.00)
% of adjusted R^2 due to manager risk fixed effects	4.00	5.60	2.60	5.40

Panel B: Regressions of manager profiles on manager risk fixed effects: innovators

	(1) VaR	(2) ES	(3) Equity Vol	(4) MES
Innovators	**0.003*** **	**0.004*** **	**0.031*** **	**0.008*** **
	(0.001)	**(0.001)**	**(0.010)**	**(0.001)**
Constant	-0.000	-0.001	-0.002	-0.001***
	(0.000)	(0.001)	(0.004)	(0.000)
Observations	603	603	603	603
Adjusted R^2	0.014	0.016	0.016	0.087

Panel C: Regression of manager profiles on manager risk fixed effects: innovators and traditionalist

	(1) VaR	(2) ES	(3) Equity Vol	(4) MES
Traditionalists	**-0.004*** **	**-0.002** **	**-0.038*** **	-0.000
	(0.001)	**(0.001)**	**(0.008)**	(0.001)
Innovators	0.001	**0.003** **	0.014	**0.008*** **
	(0.001)	**(0.002)**	(0.011)	**(0.001)**
Constant	0.002***	0.000	0.015***	-0.001*
	(0.000)	(0.009)	(0.006)	(0.001)
Observations	603	603	603	603
Adjusted R^2	0.049	0.020	0.049	0.087

Table 11: Bank-manager style matching: bank governance and bank manager profiles

The table shows the results of probit regressions on manager profiles with robust standard errors. Manager profiles (*Innovators, Traditionalists, Partial innovators*) are binary variables and each manager is allocated to one manager profile based on factor and cluster analysis performed in Table 8. The profiles are derived from a k-median clustering algorithm with the optimal number of groups determined by the Calinski and Harabasz (1974) index. The control variables are measured in the year the manager was appointed. *Entrenchment* is the Bebchuk et al. (2009) entrenchment index of six governance provisions which strengthen managers at the expense of shareholders, *board independence* is the % of board Members classified as independent, *Board size* is the number of board members, *Female* is the % of female directors on a board, *Post GBLA* is a dummy equal to one from 2000 to 2010. * significant at 10%; ** significant at 5%; *** significant at 1%.

Manager Profile:	**(1) Innovators**	**(2) Traditionalists**	**(3) Partial innovators**
Entrenchment	**-0.154** **	**0.247** ***	-0.087
	(0.068)	**(0.072)**	(0.065)
Board size	0.000	0.136***	-0.114***
	(0.027)	(0.033)	(0.036)
Board independence	-0.464	1.538	-0.703
	(0.823)	(0.939)	(0.809)
Female	-1.648	-0.252	1.907
	(1.633)	(1.888)	(1.726)
Post GBLA	0.210	0.055	-0.191
	(0.242)	(0.239)	(0.240)
Constant	0.044	-4.272***	2.139**
	(0.824)	(0.929)	(0.938)
Pseudo R^2	0.026	0.116	0.073
Observations	216	216	216

Appendix to

The Wolves of Wall Street: Managerial Attributes and Bank Business Models

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Appendix 1: List of Matched Execucomp Banks

The table contains the list of Execucomp banks between 1992 and 2010 that match with CRSP and Compustat data. Names and PERMCO identifiers are from Execucomp.

Name	PERMC	Name	PERMC	Name	PERMC	Name	PERMC
AMEGY BANCORP INC	15289	CORUS BANKSHARES INC	2343	INDEPENDENT BANK CORP/MI	7720	RIGGS NATL. CORP	3849
AMSOUTH BANCORP	25	COUNTRYWIDE FIN. CORP	796	INTL BANCSHARES CORP	31854	S & T BANCORP INC	11480
ASSOCIATED BANC-CORP	362	CRESTAR FIN. CORP	4752	IRWIN FIN. CORP	7502	SHAWMUT NATL. CORP	2171
BANCORPSOUTH INC	7784	CULLEN/FROST BANKERS INC	840	JPMORGAN CHASE & CO	20436	SIMMONS FIRST NATL CP -CL	7460
BANCWEST CORP	1718	DAUPHIN DEPOSIT CORP	1248	KEYCORP	2535	SOUTH FIN. GROUP INC	8711
BANK OF AMERICA CORP	3151	DEPOSIT GUARANTY CORP	1292	KEYSTONE FIN. INC	7366	SOUTHTRUST CORP	3987
BANK OF HAWAI CORP	589	EAST WEST BANCORP INC	16402	LIBERTY BANCORP INC/OK	2655	STATE STREET CORP	4260
BANK OF NY MELLON CORP	20265	FIFTH THIRD BANCORP	1741	LIBERTY NATL. BANCORP/KY	2687	STERLING BANCORP/NY	21670
BANK OF THE OZARKS INC	15596	FIRST AMERICAN CORP/TN	1636	M & T BANK CORP	1689	STERLING BANCSHRS/TX	11767
BANK ONE CORP	606	FIRST CHICAGO CORP	20712	MAGNA GROUP INC	5841	STIFEL FIN. CORP	6185
BANKAMERICA CORP-OLD	437	FIRST CHICAGO NBD CORP	3134	MARK TWAIN BANCSHARES	3086	SUMMIT BANCORP	21822
BANKBOSTON CORP	20264	FIRST COMMERCIAL CORP	1021	MARSHALL & ILSLEY CORP	3042	SUMMIT BANCORP	4307
BANKNORTH GROUP INC-OLD	10396	FIRST COMMONWLTH FINL	29505	MBNA CORP	28976	SUNTRUST BANKS INC	21691
BARNETT BANKS INC	586	FIRST FIDELITY BANCORP	20717	MELLON FIN. CORP	2968	SUSQUEHANNA BANCSHARES	7050
BB&T CORP	4163	FIRST FINL BANCORP INC/OH	6736	MERCANTILE BANCORP	3079	SVB FIN. GROUP	9588
BOATMENS BANCSHARES INC	594	FIRST FINL BANKSHARES INC	12525	MERCANTILE BANKSHARES	3029	SYNOVUS FIN. CORP	781
BOSTON PRIVATE FIN.	12848	FIRST HORIZON NATL. CORP	1856	MERIDIAN BANCORP INC	302	TCF FIN. CORP	8292
CAPITAL ONE FIN. CORP	30513	FIRST INDIANA CORP	6246	MORGAN (J P) & CO	21222	TEXAS CAPITAL BANCSHARES	44292
CASCADE BANCORP	12784	FIRST INTERSTATE BNCP	20720	N B T BANCORP INC	11403	TEXAS REGL BCSHS INC -CL A	12923
CATHAY GENERAL BANCORP	10805	FIRST MICHIGAN BANK CORP	6217	NARA BANCORP INC	15933	TOMPKINS FIN. CORP	8228
CCB FIN. CORP	786	FIRST MIDWEST BANCORP INC	5908	NATL. CITY CORP	3157	TRUSTCO BANK CORP/NY	5926
CENTRAL FIDELITY BANKS INC	842	FIRST OF AMERICA BANK	1621	NATL. COMMERCE FIN.	3143	TRUSTMARK CORP	1658
CENTRAL PACIFIC FIN. CP	9449	FIRST SECURITY CORP/DE	1846	NATL. PENN BANCSHARES INC	6523	U S BANCORP-OLD	4717
CENTURA BANKS INC	28913	FIRST VIRGINIA BANKS INC	20724	NY CMNTY BANCORP INC	12608	U S BANCORP/DE-OLD	1645
CHARTER ONE FIN. INC	9662	FIRSTAR CORP-OLD	20726	NORTH FORK BANCORP	5627	U S TRUST CORP	13949
CHASE MANHATTAN CORP -OLD	20432	FIRSTMERIT CORP	5259	NORTHERN TRUST CORP	3275	UCBH HOLDINGS INC	16308
CHITTENDEN CORP	991	FLEETBOSTON FIN. CORP	20734	OLD KENT FIN. CORP	3359	UMB FIN. CORP	4673
CITICORP	20456	FRONTIER FIN. CORP/WA	16053	OLD NATL. BANCORP	7067	UNION PLANTERS CORP	4703
CITIGROUP INC	20483	FULTON FIN. CORP	5440	ONBANCORP INC	9381	UNITED BANKSHARES INC/WV	9213
CITY HOLDING CO	9280	GBC BANCORP/CA	9615	PACWEST BANCORP	37718	UNITED COMMUNITY BANKS	42912
CITY NATL. CORP	1194	GLACIER BANCORP INC	6944	PINNACLE FINL PARTNERS INC	43147	UST CORP	5303
COLONIAL BANCGROUP	4128	GOLD BANC CORP INC	15150	PNC FIN. SVCS GROUP INC	3685	VALLEY NATL. BANCORP	4818
COLUMBIA BANKING SYSTEM	11576	GREATER BAY BANCORP	14946	PREMIER BANCORP	7373	WACHOVIA CORP	1869
COMERICA INC	1261	GREENPOINT FIN. CORP	12807	PREMIER BANCSHARES INC	13535	WACHOVIA CORP-OLD	25115
COMMERCE BANCORP INC/NJ	7263	HANMI FIN. CORP	41159	PRIVATEBANCORP INC	16624	WEBSTER FIN. CORP	8810
COMMERCE BANCSHARES INC	779	HIBERNIA CORP -CL A	2141	PROSPERITY BANCSHARES INC	16313	WELLS FARGO & CO	21305
COMMUNITY BANK SYSTEM	7871	HUDSON CITY BANCORP INC	16646	PROVIDENT BANKSHARES CORP	9630	WELLS FARGO & CO -OLD	21902
COMMUNITY FIRST	11087	HUDSON UNITED BANCORP	2231	PROVIDENT FIN. GRP INC	3658	WEST ONE BANCORP	2887
COMPASS BANCSHARES INC	780	HUNTINGTON BANCSHARES	2093	PROVIDENT FIN. SVCS INC	43857	WESTAMERICA BANCORP	2253
CONTINENTAL BANK CORP	20511	IMPERIAL BANCORP	2252	REGIONS FIN. CORP	1620	WILSHIRE BANCORP INC	16321
CORESTATES FIN. CORP	3552	INDEPENDENT BANK	8179	REPUBLIC BANCORP INC	9454	WINTRUST FIN. CORP	15385
						ZIONS BANCORP	5057

Appendix 2: Additional data and definitions

		N	Mean	Median	St.Dev.	1 Pctile	99 Pctile
Measures of risk employed to compute manager risk-fixed effects							
Equity volatility	Volatility of daily returns measured at annual intervals for connected banks	722	0.323	0.266	0.209	0.129	1.255
Value at risk	5% Value at Risk measured on daily stock returns at annual intervals for connected banks	722	0.031	0.026	0.019	0.012	0.116
Expected shortfall	5% Expected Shortfall measured on daily stock returns at annual intervals for connected banks	722	0.044	0.035	0.029	0.016	0.175
MES	5% Marginal Expected Shortfall for connected banks	722	0.022	0.016	0.022	-0.016	0.118
Variable employed in the crisis test							
Buy and Hold Return	Negative buy and hold Returns between 07/ 2007 – 12/2008	77	0.364	0.358	0.366	-0.456	0.947
Volatility	Volatility of daily returns between 07/ 2007 – 12/2008	77	0.046	0.043	0.016	0.010	0.101
Value at risk	5% Value at Risk between 07/ 2007 – 12/2008	77	0.063	0.061	0.020	0.006	0.125
Expected shortfall	5% Expected Shortfall between 07/ 2007 – 12/2008	77	0.099	0.096	0.036	0.008	0.197
MES	5% Marginal Expected Shortfall between 07/ 2007 – 12/2008	77	0.068	0.066	0.025	0.003	0.151
Beta	Market beta derived from a linear regression of bank daily stock return to market daily stock return from the equally weighted CRSP index	77	1.055	1.066	0.393	0.415	2.225
Probability of default	Bank probability of default computed as described in Appendix 3 and multiplied by 1,000	77	0.382	0.000	1.869	0.000	14.359
Stock return 2006	Buy and hold return in year 2006	77	0.037	0.052	0.157	-0.591	0.339
Non-Performing Loans	Non-performing loans divided by total loans	77	0.007	0.005	0.005	0.000	0.028
Board governance variables							
Entrenchment	Bebchuk et al. (2009) entrenchment index consists of six shareholder rights provisions in a bank's charter. Varies between 0 and 6 with higher values indicating more entrenched managers.	696	1.954	2.000	1.239	0.000	5.000
Board size	Board size	350	14.443	14.000	3.809	7.000	24.000
Board independence	% of independent directors on the board	350	0.720	0.750	0.146	0.286	0.933
Female	% of female directors on the board	287	0.132	0.118	0.065	0.042	0.357

Appendix 3: Estimation of the probability of default

The estimation of a bank's probability of default for year 2006 is based on the distance to default (DD) computed via the Merton credit risk model as follows:

$$DD_t = \left[\ln\left(V_{A,t} / X_t\right) + \left(r_f - 0.5\sigma_{A,t}^2\right)T\right] / \sigma_{A,t}\sqrt{T} \tag{1A}$$

where $V_{A,t}$ is the market value of assets, X_t is the book value of total liabilities, r_f is the risk-free rate (proxied by the 1-year U.S. treasury bill rate), $\sigma_{A,t}$ is the annualized asset return volatility at t, and T is the time to maturity (conventionally set to 1 year). The computation of DD_t requires estimates of $V_{A,t}$ and $\sigma_{A,t}$ (neither of which are directly observable) that we infer through an iterative process based on the Black-Scholes-Merton pricing model (Akhigbe et al., 2007; Vassalou and Xing, 2004). Thus, the market value of a firm's equity ($V_{E,t}$) is expressed as a function of the asset value by solving the following system of nonlinear equations:

$$V_{E,t} = V_{A,t}N(d_{1,t}) - X_t e^{-r_f T} N(d_{2,t}) \tag{2A}$$

$$\sigma_{E,t} = \left(\frac{V_{A,t}}{V_{E,t}}\right) N\left(d_{1,t}\right)\sigma_{A,t} \tag{3A}$$

Equation (2A) defines $V_{E,t}$ as a call option on the market value of the bank's total assets, with $d_{1,t} = \left[\ln\left(V_{A,t} / X_t\right) + \left(r_{f_t} + 0.5\sigma_{A,t}^2\right)T\right] / \sigma_{A,t}\sqrt{T}$ and $d_{2,t} = d_{1,t} - \sigma_{A,t}\sqrt{T}$. Equation (3A) is the optimal hedge equation that relates the volatility of a bank's equity value to the volatility of the value of total assets (both on an annualized basis). We solve this system by employing as starting values for $\sigma_{A,t}$ the values of $\sigma_{E,t}$ (computed at yearly intervals) multiplied by the ratio between $V_{E,t}$ and the sum of $V_{E,t}$ and X_t. A Newton search algorithm identifies the yearly values for $V_{A,t}$ and $\sigma_{A,t}$ in an iterative process which we then employ to compute DD as in (1A).

As in Vassalou and Xing (2004) we finally covert DD in a probability measure via the following transformation based on the normal distribution:

$$\text{PD} = N(\text{-DD}) \tag{4A}$$

Appendix 4: Sample Selection Bias –comparing non-connected and connected banks

A.4.1: Are connected banks different?

This table reports summary statistics for the group of non-connected and connected banks. *Size* is the log transformation of bank total assets, *Non-interest income* is divided by operating income, *Loans* are total loans divided by total assets, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans, *Gap12* is the 12-month liquidity gap by total assets. *Loans/Deposits* is the ratio between total loans and total customer deposits, *Non-deposit funding* is the ratio between non-deposit funding in total liabilities. *significant at 10%; ** significant at 5%; *** significant at 1%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Non Connected Banks			Connected Banks		Mean Test	Ranksum Test
	N	Mean	Median	N	Mean	Median	p-value	p-value
Size	701	15.834	15.659	722	17.198	17.193	0.000***	0.000***
Non interest income	701	23.167	19.595	722	24.546	22.548	0.048**	0.000***
Loans	701	61.566	64.725	722	64.706	67.148	0.000***	0.000***
Mortgage-backed Securities	658	1.753	0.004	616	1.130	0.185	0.000***	0.000***
Derivatives	636	0.120	0.000	561	0.453	0.041	0.000***	0.000***
Lending diversification	701	0.450	0.468	722	0.576	0.600	0.000***	0.000***
Gap12	701	-14.834	-15.342	722	-20.776	-21.386	0.000***	0.000***
Loans/Deposits	701	87.579	86.564	722	94.802	94.928	0.000***	0.000***
Non-Deposit Funding	701	19.594	18.383	722	24.470	23.713	0.000***	0.000***

A.4.2: Modelling the probability of being in the connected group

The table reports estimates of the first step in a Heckman (1979) two-step framework. The results are from a Probit equation where the dependent variable is a dummy equal to one if a manager is employed by a bank in the connectedness sample (and zero otherwise). Therefore, the first step of the Heckman procedure estimates the probability that banks are included in our sample using data on banks included as well as on banks that are not included due to lack of manager mobility. Identification rests on the exclusion restriction that requires the first stage to be estimated using a set of variables that is larger by at least one variable than the set of variables used in the second stage (our main analysis of bank policy choices). We use the distance from a bank's headquarters to the nearest airport as an additional variable that is included in the first but not the second stage. Geographic coordinates are obtained from U.S. Census files. Distance from the airport is the log transformation of the distance between a bank's headquarters and the closest airport. Definitions of the other variables are reported in Table 2. *significant at 10%; ** significant at 5%; *** significant at 1%.

	(1)
Dependent Variable:	**Connectedness Sample? (1/0)**
Compensation variables	
Vega $_t$	0.126
	(0.508)
Delta$_t$	0.136
	(0.225)
Bonus $_t$	0.027*
Bank characteristics	
Size $_{t-1}$	0.529***
	(0.036)
Equity $_{t-1}$	6.690***
	(1.493)
Market to book$_{t-1}$	-0.426***
	(0.097)
Core deposits $_{t-1}$	-3.259***
	(0.473)
Productivity $_{t-1}$	-0.065***
	(0.021)
Other control variables	
Economy $_t$	-0.015***
	(0.004)
Distance from the airport	**-0.183*** **
	(0.051)
Constant	-4.184***
	(0.847)
Observations	7,192
Pseudo R^2 (%)	27,52
Time fixed effects	Yes

A.4.3 Three way fixed effect regressions on the connectedness sample after correcting for sample selection bias

The table estimates three-way fixed effect regressions (manager, bank, and year effects) on banks' policy choices for our connectedness sample. The connectedness sample is based on Abowd, Kramarz, and Margolis (1999) and includes all banks that have employed at least one manager who has worked for two or more banks during the sampling period. The table represents the second step in a Heckman (1979) two-step framework. The *Inverse Mills ratio* controls for sample selection bias and contains information from the first step to control for unobservable factors which make sample inclusion more likely. It is derived in a first step in which a probit model is fitted on banks being included in the connectedness sample based on the variables included in this table plus the distance of a bank to the nearest airport as an additional variable that is included in the first step but not included in the second step. The results of the first step are shown in Table A.4.2. Definitions of all variables are reported in Table 2. *significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable:	(1) Non-interest income	(2) Loans	(3) MBS	(4) Derivatives	(5) Lending diversification	(6) Gap12	(7) Loans/Deposits	(8) Non-Deposit Funding
Compensation variables								
Vega $_t$	0.017	0.017	-0.004	0.159***	0.001	-0.041	0.039	0.018
	(0.014)	(0.017)	(0.004)	(0.044)	(0.012)	(0.031)	(0.024)	(0.013)
Delta$_t$	-0.008	-0.018	0.004	-0.111***	0.002	0.042	-0.040*	-0.014
	(0.014)	(0.017)	(0.004)	(0.038)	(0.012)	(0.030)	(0.024)	(0.012)
Bonus $_t$	0.000	-0.000	0.001***	-0.007**	-0.000	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Bank characteristics								
Size $_{t-1}$	-0.024*	0.030	-0.013**	-0.149***	0.011	-0.019	0.054	0.006
	(0.013)	(0.027)	(0.005)	(0.053)	(0.009)	(0.015)	(0.036)	(0.010)
Equity $_{t-1}$	-0.050	0.316*	-0.030	-2.295***	0.312**	-0.353	-0.298	-1.018***
	(0.124)	(0.185)	(0.034)	(0.512)	(0.149)	(0.228)	(0.299)	(0.141)
Market to book$_{t-1}$	0.012	-0.032**	0.005**	0.076**	0.000	0.031***	0.003	0.034***
	(0.008)	(0.014)	(0.003)	(0.032)	(0.006)	(0.012)	(0.020)	(0.006)
Core deposits $_{t-1}$	-0.007	-0.149**	0.070***	0.873***	0.028	-0.085	0.069	0.220***
	(0.061)	(0.068)	(0.024)	(0.276)	(0.053)	(0.093)	(0.119)	(0.058)
Productivity $_{t-1}$	-0.019***	-0.006*	-0.002***	0.039***	-0.002	-0.003	0.009	0.017***
	(0.005)	(0.004)	(0.001)	(0.013)	(0.002)	(0.005)	(0.007)	(0.003)
Other control variables								
Economy $_t$	-0.000	0.001	0.000*	0.006**	-0.001**	0.000	0.003***	0.001**
	(0.000)	(0.001)	(0.000)	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)
Inverse Mills Ratio	-0.017	0.058	-0.020**	-0.448***	0.036*	-0.127**	-0.029	-0.086***
	(0.025)	(0.038)	(0.008)	(0.114)	(0.022)	(0.054)	(0.057)	(0.023)
Observations	3,692	3,692	3,201	2,801	3,692	3,692	3,692	3,692
R^2 (%)	91.11	89.16	76.06	98.44	95.06	79.02	84.64	91.40
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Manager FE	776	776	773	653	776	776	776	776

A 4.4 Do we identify bank manager styles for non-mover managers?

The table reports correlations between the manager fixed effects (styles) linked to different bank policy variables. The bank manager fixed effects are estimated in Table 5 using three-way fixed effect regressions (manager, bank, and year effects) in a connectedness sample. The connectedness sample is based on Abowd, Kramarz, and Margolis (1999) and includes all banks that have employed at least one manager who has worked for two or more banks during the sampling period. Manager fixed effects are normalized to have a mean equal to zero as in Graham et al. (2012). *Non-interest income* is divided by operating income, *Loans* are total loans divided by total assets, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans, *Gap12* is the 12-month liquidity gap by total assets, while *Loans/Deposits* is the ratio between total loans and total customer deposits, *Non-deposit funding* is the ratio between non-deposit funding in total liabilities. Panel A (B) reports the mean and median values of within-bank standard deviation of manager fixed effects computed at yearly intervals for all (non-mover) managers. Panel C tests for style differences between moving and non-moving managers. *significant at 10%; ** significant at 5%; *** significant at 1%.

Panel A: *Within*-bank standard deviations of manager fixed effects – the full manager sample

	(1) Non-interest income	(2) Loans	(3) MBS	(4) Derivatives	(5) Lending diversification	(6) Gap12	(7) Loans/Deposits	(8) Non-Deposit Funding
# yearly within-bank std dev	722	722	616	540	722	722	722	722
Mean	0.014***	0.018***	0.003***	0.056***	0.011***	0.027***	0.030***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median	0.010***	0.014***	0.002***	0.036***	0.009***	0.022***	0.022***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B: *Within*-bank standard deviations of manager fixed effects – excluding mover managers

	(1) Non-interest income	(2) Loans	(3) MBS	(4) Derivatives	(5) Lending diversification	(6) Gap12	(7) Loans/Deposits	(8) Non-Deposit Funding
# yearly within-bank std dev	710	710	608	533	710	710	710	710
Mean	0.014***	0.018***	0.003***	0.053***	0.011***	0.026***	0.029***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median	0.010***	0.014***	0.002***	0.034***	0.009***	0.022***	0.021	0.013
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel C: Styles in Non-Movers and Movers Managers

	(1) Non-interest income	(2) Loans	(3) MBS	(4) Derivatives	(5) Lending diversification	(6) Gap12	(7) Loans/Deposits	(8) Non-Deposit Funding
Mean styles:								
Non Movers	-0.003	-0.002	0.000	0.046	0.001	0.008	-0.003	0.001
Movers	0.024	-0.018	0.002	0.291	0.000	-0.016	-0.015	0.010
P-value (t-test)	**0.03****	0.20	0.51	**0.01****	0.93	0.11	0.47	0.33
Median styles:								
Non Movers	0.017	0.007	0.001	-0.305	0.006	0.015	-0.015	-0.005
Movers	0.036	-0.010	0.000	0.412	0.002	-0.008	-0.028	0.001
P-value (z-test)	**0.00*****	0.34	0.73	**0.02****	0.76	**0.07***	0.54	0.44