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

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Abstract

We investigate the role of executive-specific attributes (or 'styles') in explaining bank business models beyond pay-per-performance incentives. We decompose the variation in business models and document that the 'style' of members of a bank's top management team is reflected in key bank policy choices. Manager styles far outrank executive compensation and other observable manager variables in terms of their ability to describe variation in bank business models. Bank manager styles also explain differences in risk and performance across banks. Finally, we combine manager styles from various bank policies to derive manager profiles that are associated with manager's personal risk preferences, board characteristics and whether or not managers will be appointed as CEO during their careers.

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1. Introduction

A growing body of evidence has produced important insights into how pay and other individual manager characteristics affect bank business models.[1] However, little is known about how much of the variation in bank business policies is actually explained by such factors. Banks differ greatly in terms of their business models. Understanding what explains bank heterogeneity is therefore an important issue. In this paper, we investigate how much of the heterogeneity in bank business models can be traced back to individual bank managers and how this affects bank performance and risk.

The policy choices made by banks (for example, their reliance on non-interest income or the exposure to short-term funding risk) are shaped by a variety of factors, including bank and manager attributes. Our paper takes a novel perspective and demonstrates that a significant proportion of banks' policies choices can be explained by bank manager attributes that go beyond the traditional paradigm of manager compensation or other managerial or bank attributes which are observable to the econometrician. We describe the role of unobservable time-invariant manager heterogeneities (i.e. manager fixed effects) in explaining banks' policy choices. In essence, we posit that two seemingly identical bank managers (that is, managers who work for the same bank at the same time, have identical compensation incentives and are identical in terms of demographics, education and career history) can have a distinct impact on a set of bank policies. We call the manager fixed effects 'styles' that capture latent manager attributes such as

[1] For the role of manager pay in the financial industry, see Bebchuk and Spamann (2010), Fahlenbrach and Stulz (2011), Bayazitova and Shivdasani (2012), and DeYoung, Peng and Yan (2013). 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), Malmendier, Tate, and Yan (2011), Benmelech and Frydman (2015) and Bernile, Bhagwat, and Rau (2016).

innate ability, preferences or personality.[2] Our key finding is that manager styles are crucial to understand bank business models.

We start our analysis by estimating regression models that relate ten bank policy choices to bank, manager, and other controls. Among others, we analyze bank dependence on non-interest income, banks' holdings of liquid assets, their exposure to off-balance sheet derivatives, lending diversification and risk, and banks' short-term liquidity risk. We then compare the adjusted R^2 produced by these regressions to show that time-invariant manager fixed effects (or 'styles') are an important factor in explaining bank policy choices. In particular, manager fixed effects far outrank executive compensation and other observable manager variables in terms of their ability to explain variation in bank business models. As an illustration, regressions models that only include compensation variables or only include other observable manager attributes (e.g. education, life and work experience) produce an average adjusted R^2 of 4%. By contrast, models that include manager fixed effects as the only variables produce an adjusted R^2 of 72% on average.[3]

However, our initial results also point to substantial overlap between firm- and manager-fixed effects. To more accurately estimate the contribution of manager fixed effects to bank business policies, we use the *connectedness sample method* of Abowd, Kramarz and Margolis (1999). This 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).

[2] 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, Li, and Qiu (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.

[3] Naturally, when regressions are based on a small group of explanatory variables, they will invariably overestimate the importance of these variables for bank business models (as the impact of omitted controls tends to be absorbed by the small number of included variables). However, our approach still serves a useful purpose, because it illustrates the potential maximum contribution of each group of variables in explaining business policies.

However, since managerial turnover is small and firms that employ moving managers are likely to differ from other firms in ways that affects firm policies (Fee, Edward, and Hadlock, 2013), the key difference between the connectedness method and other approaches is that the former does not rely on manager mobility alone to identify manager styles.

Instead, Abowd et al.'s (2003) connectedness method allows us to separate manager and firm fixed effects not only for moving managers, but also for non-moving managers as long as non-moving managers 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 can still be connected to another bank as long as at least one mover-manager has worked at that other bank. This way, the connectedness sampling method uses a small number of managers who move across banks to derive information about non-movers who work in banks that have employed at least one moving manager. Using this approach, we show that manager fixed effects usually explain well above 25% of the variation in the R^2 of bank policy regressions. For example, bank manager styles explain around 37% of the predicted values of a bank's liquidity gap or 44% of its holdings of derivatives.

To validate that we have been successful in extracting manager fixed effects that are distinct from firm fixed effects, we demonstrate significant variation in manager styles within individual banks. 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). We also control for a possible selection bias linked to our sample of connected banks by applying a two-step Heckman (1979) selection model. The correlation between our original manager styles and new estimates that control for

sample selection bias is on average above 99% thus eliminating selection bias as driver of our results.

We then demonstrate that the policy styles of bank managers have observable risk implications. We follow the previous literature by using the global financial crisis as a natural experiment similar to Fahlenbrach and Stulz (2011), Beltratti and Stulz (2012) and Fahlenbrach, Prilmeier, and Stulz (2012). We find that bank manager styles (as measured before the crisis) predict bank risk in the crisis period. For instance, bank managers with a preference for holding mortgage-backed securities are linked to higher crisis losses and higher systemic risk while managers with a preference for, for example, lending diversification before the crisis experienced lower losses and lower tail risk during the crisis.

Bank managers potentially differ along many style dimensions complicating style comparisons between individual managers. In the final part of the paper, we thus use factor analysis to collapse the various styles into two factors. We then use the loadings of individual managers with respect to these factors to assign each manager to one of six style profiles that comprehensively capture the idiosyncratic effects that bank managers have on bank polices. There are: (1) the aggressive innovator, (2) the cautious innovator, (3) the aggressive traditionalist, (4) the cautious traditionalist, (5) the prudent and (6) the extremely prudent manager.

We confirm that the style profiles are relevant and identify the groups of managers with the highest propensity for aggressive risk-taking. We relate the style profiles to manager fixed effects detectable in various measures of bank risk (we call the latter 'risk style') and show that, relative to the group of extremely prudent managers, the other groups of managers have

significantly larger risk styles, with the group of aggressive innovators having the largest risk style.

Do managers with certain manager personalities work for a particular bank? We show that 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 match with managers we profile as innovators and less so with traditionalists or prudent managers.

Finally, we examine which style profile makes it more likely that a manager is appointed as a CEO during her career. Since CEOs are the most senior managers in a firm, this test helps answer the question if style profiles are related to the career trajectory of managers. Our findings show that managers classed as aggressive traditionalists have a higher probability of being appointed CEOs. This provides additional evidence in favor of the relevance of manager styles that also appear to be related to the career trajectory of individual managers.

We provide the first study of idiosyncratic manager-specific effects on bank policy choices and bank risk. A limited number of recent studies have employed methods similar to ours but not related to bank polices or measures of bank risk. These studies focus on the impact of manager fixed effects on a range of corporate decisions (Bertrand and Shoar, 2003), executive compensation arrangements (Graham, Li, and Qiu, 2012; Coles and Li, 2014) and corporate disclosure practices (Bamber et al., 2010; Davis, Matsumoto and Zhang, 2015).[4]

[4] With the exception of Graham at al.'s (2012) study on CEO compensation, previous studies rely on moving managers for a separate identification of firm- and manager-fixed effects. However, this method can only be deployed on relatively small datasets of firms that employ moving managers. In contrast by using Abowd et al.'s (2003) connectedness method, it is possible to examine more substantial sets of firms and managers.

We expand this literature in a variety of ways. In particular, ours is the first study that examines the managerial styles of *groups* of top managers (not just of a single manager such as the CEO) and their effect on corporate outcomes. This allows us to study novel questions around the effects of diversity in manager styles, how policy styles can be used to profile managers and how these profiles relate to the career trajectories of managers.

Our paper proceeds as follows. Section 2 describes the data. Section 3 derives manager fixed effects (or styles) using traditional methods before Section 4 introduces the connectedness sample method to more accurately delineate manager fixed effects relative to observable and unobservable factors. Section 5 investigates the impact of manager style on bank risk during the global financial crisis. We derive manager specific style profiles in Section 6. Section 7 concludes.

2. Sample Construction and Variables

2.1 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.[5]

2.2 Bank Policy Choices

To describe bank business models, we use a set of ten bank policy variables that are summarized in Panel A of Table 1. The policy variables parsimoniously capture important differences across banks in terms of income sources, asset mix and funding structure.

********TABLE 1 AROUND HERE********

The first policy variable we analyze is *Non interest income* scaled by total operating income to account for sources of income other than interest. Over recent decades, banks have increased their fee-based business (e.g., investment banking, brokerage and asset management services). DeYoung and Roland (2001) show that fee-based activities require higher operating

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

leverage and increase the volatility of revenues and bank earnings. Brunneremeir, Dong and Palia (2012) show that non-interest income also increases the systemic risk of banks.

Additionally, we analyze mortgage-backed securities (*MBS*) over total assets to measure banks' investments in MBS.[6] Before the global financial crisis, substantial amounts of high-risk loans were securitized and numerous financial institutions invested in the resulting MBS securities. During the crisis, losses on MBS securities played a pivotal role in the failure of hundreds of US banks. Further, we measure *Derivatives* as the logarithm of the ratio of derivative contracts held for trading over total assets. This ratio captures a bank's exposure to off-balance sheet derivative trading activity. Elul and Yeramilli (2013) argue it is also related to the importance of risk management within a bank and the quality of risk oversight provided by a bank's boards of directors.

Acharya and Naqvi (2012) argue that access to abundant liquidity is linked to riskier bank business polices, while others have emphasized the fragility of the business models of banks with relatively illiquid balance sheets during the crisis (e.g., Brunnermeier, 2009). We use two measures of banks' holdings of liquid assets. *Securities* are held-to-maturity plus available for sale securities over total assets (Kashyap and Stein, 2000). *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 next12 months scaled by total assets. A greater value of this ratio indicates that bank policies expose an institution to more funding liquidity risk.

Comm/real estate loans is the logarithm of the ratio between commercial and real estate loans. *Lending Diversification* is defined as 1 minus the Herfindahl index (HHI) of the shares of real estate, C&I, consumer, and other loans as a percentage of total loans. This measure follows

[6] We sum up all private-label MBS as in Erel et al. (2014).

Acharya, Hasan and Saunders (2006) who show that there are diversification benefits within the loan portfolios of individual banks. *Lending risk* is the percentage of loans that is nonperforming (loans past due by 90 or more days or on a non-accrual basis) relative to total loans.

Finally, we analyze two measures of short term funding that expose banks to higher funding liquidity risk. Previous work emphasizes how policies that exposed banks to short-term finance from capital markets for a substantial fraction of their financing made banks fragile and vulnerable to runs during the financial crisis of 2007/08 (Brunnermeier, 2009; Beltratti and Stulz, 2012). We employ two measures of short-term funding: *Wholesale funding* from capital markets (as used in Calomiris and Nissim, 2007; Elul & Yeramilli, 2013) and a broader measure of *Other short funding* which includes large deposits (with a maturity of less than one year, as defined in Calomiris and Nissim, 2007).

2.3. Manager Attributes and Manager Fixed Effects

We employ three 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 observable manager characteristics that have received attention by researchers as a driver of risky bank polices (Fahlenbrach and Stulz, 2011; Bayazitova and Shivdasani, 2012; DeYoung, Peng and Yan, 2013).

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.[8] Panel B of Table 1 shows that in our sample, pay-risk sensitivity and pay-performance incentives of managers correspond to about 5% and 16% of cash compensation, respectively. 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 the literature on CEOs in non-financial firms. This literature demonstrates that CEO attitudes and firm policies can in part be shaped by variation in individual life and career experiences (Malmendier, Tate, and Yan, 2011; Benmelech and Frydman, 2015, Bernile, Bhagwat, and Rau, 2016, Dittmar and Duchin, 2016). For instance, there is evidence of more 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 biographical 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. In particular, our manager attributes include birth year, gender, whether or not the manager was born in the decade leading up to the Great Depression (*Depression baby*) or has completed *MilitarysService*.

[7] We obtain detailed information on outstanding equity awards at each fiscal year-end from the Execucomp database 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 indication 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.

We also control for managers with an *MBA* degree, a degree from an *Ivy League* university[9], and the age at which the manager had her first appointment as an executive on a board (*Fast track*). Further, we include a dummy equal to one if a manager has served as a non executive director outside the banking sector (*NonBank Experience (Nex*) and a dummy 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 variables takes the value of one if the manager's first appointment was not with a financial services or an accounting firm.

The observable manager characteristics described above are unlikely to comprehensively capture all manager attributes that might matter for bank business models. As a third type of manager control, we therefore include manager fixed effects in some models. Graham, Li, and Qiu (2012) and Coles and Li (2014) interpret manager fixed effects as capturing latent manager skills and talent, respectively. Bernard and Shoar (2003) understand manager fixed effects to capture manager skills that are time-invariant (or very persistent over time) and transferable to a new employer by a moving manager. Therefore, managerial ability is all but one possible explanation for a manager fixed effect. Manager fixed effects could equally capture manager traits other than ability so long as these traits are fixed or relatively time-persistent.

2.4 Bank-level and Other Controls

We control for a number of bank characteristics that can explain cross-sectional differences in bank policy choices. The set of controls is reported in Panel D of Table 1.

[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.

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 assets. 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). Table 1 shows that that the importance of core deposit funding varies widely in our sample between 53% and nearly 100% of bank assets. Further, to control for the importance of bank lending across banks, we include *Loans* as total loans (in million $) over full-time employees.

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

3. The Determinants of Bank Policy Choices: How Important Are Manager Attributes?

This section analyses how much of the variation in bank business policies can be explained by executive compensation and other manager attributes and how important these variables are compared to other explanatory factors. To specify the relevance of manager compensation and other attributes, we run a series of different regression models on the various bank policy variables. We then compare the adjusted R^2 from these regressions to ascertain how important manager and other controls are in explaining observed differences in bank policy choices.

[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.

We start with a pooled OLS regression with manager compensation variables (*Vega, Delta, Bonus*) as the only determinants of bank business models. We then estimate the adjusted R^2 of models with manager attributes related to life and career experience only before jointly including compensation variables, the other manager attributes and a set of additional firm and local controls (all as described in Section 2.3). We then derive the adjusted R^2 from models estimated with manager fixed effects and different sets of controls and, finally, the spell method (that employs a fixed effect for each combination of firm-manager in our dataset). Naturally, when regressions are based on a small group of explanatory variables, they will invariably overestimate the importance of these variables for bank business models (as the impact of omitted controls tends to be absorbed by the small number of included variables). However, our approach serves a useful purpose. It illustrates the potential *maximum* contribution of each group of variables in explaining business policies.

********FIGURE 1 AROUND HERE********

Figure 1 offers a preliminary picture of the results by showing the adjusted R^2 based on each regression model. The reported percentage is the average adjusted R^2 across the ten policy variables. We find that regressions that only include compensation variables or only include other observable manager attributes produce an average adjusted R^2 of only 4%. In contrast, models that include manager fixed effects as the only variables produce an adjusted R^2 of 72% on average. Therefore, unobservable manager characteristics (as captured by manager fixed effects) far outrank executive compensation and other observable manager variables in terms of their ability to explain variation in bank business models.

The conclusion that manager fixed effects capture substantially more variation in bank business models than other manager variables is confirmed by the full set of results in Panel A of

Table 2. We find that pay variables or other manager attributes each explain less than 10% of the adjusted R^2 in all but one policy regression. By contrast, manager fixed effects alone explain more than 60% of the total variation in bank business policies in seven out of ten specifications. Further, there is a substantial increase in the adjusted R^2 of each of the policy regressions when we move from an OLS specification with controls (reported in the third row of Table 2) to models with manager fixed effects. For instance, the adjusted R^2 increases from 54% to nearly 90% for non-interest income and from 8% to 60% for banks' investments in mortgage-backed securities.

********TABLE 2 AROUND HERE*********

However, compared to models that already control for firm fixed effects, the addition of manager fixed effects in the policy regressions only leads to a marginal increase (and for some policy regressions to no additional increase) in adjusted R^2. Evidently, there are large overlaps between firm- and manager fixed effects when our dependent variables are observed at the firm-level and repeated across multiple managers working for the same bank in a given year.[11]

Additionally, it appears our approach may well underestimate the importance of manager fixed effects. In Panel B of Table 2, we replicate our analysis only for bank CEOs only (rather than all managers disclosed in Execucomp). When we do so, manager fixed effects improve the explanatory power of the models by quite a margin. The adjusted R^2 produced by models with manager fixed only even outrank those models which combine manager fixed effects with various sets of controls. Most importantly, the analysis based on bank CEOs confirms our key

[11] By contrast, Graham et al. (2012) find a large increase in the explanatory power of their regressions following the inclusion of manager fixed effects. However, the authors use a dependent variable that is observed at the level of individual managers that may well be driven by unobservable manager characteristics to a larger extent than the firm outcomes we study in this paper.

finding that manager fixed effects far outrank other manager traits including executive compensation in terms of their ability to explain bank business models.

The results of this section highlight the important role that unobservable manager attributes play relative to observable manager and firm controls. However, our results also highlight that conventional estimation methods are imprecise when trying to isolate the exact contribution of manager fixed effects to bank business policy relative to bank fixed effects. In the face of substantial overlap between manager and bank fixed effects, attempts to estimate the exact importance of manager fixed effects are challenging. We elaborate on this issue in the next section where we employ a methodology that disentangles manager from firm fixed effects for bank business models.

4. Separating Manager Fixed Effects from Firm Fixed Effects

4.1 The Connectedness Sample Method

While conventional econometric models do not allow us to separate the contribution of manager fixed effects from the contribution of firm fixed effects to bank business models, the adoption of the *connectedness sample method* of Abowd et al. (1999) offers a suitable solution to this empirical challenge.[12]

The connectedness sampling method uses a small number of managers who move across banks to derive information about non-movers who work in banks that have employed at least one moving manager. This method allows us to separate manager and firm fixed effects not only

[12] Alternatively, the mover dummy approach uses subsamples of managers who have been employed at more than one company. The approach, as employed in Bertrand and Schoar (2003), captures manager mobility via a dummy variable for managers who have switched between firms. However, since managerial turnover is relatively small in most samples, the approach can only be applied to very small subsamples of firms with managerial turnover. This might introduce a strong selection bias if either managers who move between firms or firms who employ moving managers differ from other firms in ways that affects firm policies (Fee, Edward, and Hadlock, 2013).

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.

For a bank to be included 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. The technique of sampling connected banks permits us to isolate manager styles from bank fixed effects while obtaining a much larger sample size compared to a restricted sample that can be used under alternative methodologies.

********TABLE 3 AROUND HERE*********

Panel A of Table 3 shows that 4.56% 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. In our sample, mover managers tend to move once. Only two managers in our sample have moved twice (that is, have been employed by three banks).

While the percentage of moving managers in our sample appears low, we emphasize again that the focus of this method is 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 small amount of manager mobility therefore generates a large degree of bank connectedness.

Consistent with this, Panel B of Table 4 reports that more than 45% of Execucomp banks are in our sample.[13]

Finally, Panel C of Table 3 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 3,689 manager-year observations exploiting bank connectedness.

For the sample of connected banks, we model a bank's policy choices (*P*) using a three-way fixed effect model:

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

Equation (1) explains the policy choices of a bank as the sum of bank characteristics $X_{it-1}\beta + \phi_i$ (observable and unobservable), manager characteristics $M_{j(i,t)t}\gamma + \theta_j$ (observable and unobservable), and time effects μ_t. The residual ε_{it} captures the variation in banks' policy choices that cannot be explained by either observable or unobservable factors. Since bank managers can change firms over time, the function *j(i,t)t* maps manager *j* to firm *i* at time *t*.

We are primarily interested in estimating θ_j, which is a manager fixed effect (or "style") that measures the influence of manager *j* on bank business policy *P*. By construction, θ_j is constant over time and transferrable across banks. In addition to a manager fixed-effect, θ_j,

[13] 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.

equation (1) estimates a bank fixed-effect ϕ_i and a time-fixed effect μ_t. The three-way fixed effect specification is particularly suited to deal with time-invariant omitted variables. Some of our independent variables may be correlated with manager skills or observable bank characteristics. If we do not to control for unobservable manager and bank characteristics, these unobserved characteristics are absorbed by the error term ε_{it} and might bias our point estimates.

4.2 How Important are Bank Manager Styles?

Table 4 reports the estimates of three-way fixed effect regressions on banks' policy choices for the sample of connected banks where manager mobility aids the identification of latent manager characteristics. The results of Table 4 show that our three-way fixed effect models explain between 67% and 98% of the variation in bank policy variables suggesting that models that allows to jointly use manager and firm fixed explains a large proportion of bank business policies.

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

To show the importance of manager styles in explaining bank policy choices in relation to other explanatory factors (including firm fixed effects), we report the statistical and economic significance of the manager fixed effects in Table 5. Panel A of Table 5 shows that both manager and firm fixed effects (from the estimations in Table 4) are jointly and statistically significantly different form zero for each policy variable.

********TABLE 5 AROUND HERE********

To understand the economic importance of manager fixed effects, we decompose the variation of the policy variables into the fitted components (consisting of the full set of controls including time dummies), manager fixed effects, firm fixed effects and the residuals.

Specifically, we use the estimated coefficients from each policy regression to decompose the R^2 into time-variant bank characteristics $X_{it-1}\hat{\beta}$, time-variant manager characteristics $M_{j(i,t)t}\hat{\gamma}$ as well time-invariant manager effects $\hat{\theta}_j$ and time-invariant bank effects $\hat{\phi}_i$ as follows:

$$
\begin{aligned}
R^2 &= \frac{\operatorname{cov}\left(P_{it}, \hat{P}_{it}\right)}{\operatorname{var}\left(P_{it}\right)} = \frac{\operatorname{cov}\left(P_{it}, X_{it-1}\hat{\beta} + M_{j(i,t)t}\hat{\gamma} + \hat{\phi}_j + \hat{\theta}_i + \hat{\mu}_t\right)}{\operatorname{var}\left(P_{it}\right)} \\
&= \frac{\operatorname{cov}\left(P_{it}, X_{it-1}\hat{\beta}\right)}{\operatorname{var}\left(P_{it}\right)} + \frac{\operatorname{cov}\left(P_{it}, M_{j(i,t)t}\hat{\gamma}\right)}{\operatorname{var}\left(P_{it}\right)} + \frac{\operatorname{cov}\left(P_{it}, \hat{\phi}_j\right)}{\operatorname{var}\left(P_{it}\right)} + \\
&+ \frac{\operatorname{cov}\left(P_{it}, \hat{\theta}\right)}{\operatorname{var}\left(P_{it}\right)} + \frac{\operatorname{cov}\left(P_{it}, \hat{\mu}_t\right)}{\operatorname{var}\left(P_{it}\right)}
\end{aligned}
\qquad 2)
$$

The results of this decomposition are reported in Panel B of Table 5. The economic relevance of the manager fixed effects is substantial. The importance of manager fixed effects in explaining the variation in the R^2 of the policy regressions is 25% in six out of the seven bank policy variables examined and as high as 44% in the case of banks' holdings of derivatives for trading purposes. Furthermore, jointly with firm fixed effects, manager fixed effects explain on average more than 62% of the variation in bank business models.

Taken together with the findings reported in Section 3, these results show that manager fixed effects (or 'styles') are important in explaining variation in bank policy choices and their effect is much larger than what can be ascribed to executive compensation and to more conventional observable manager traits employed in the corporate finance literature. Furthermore, time invariant (firm and manager) unobservable factors are by far the most important drivers of variation in bank business models.

Overall, these results provide an explanation for a persistent risk-taking culture within banks (see, for example, Elull and Yerramilli, 2013; Fahlenbrach, Prilmeier, and Stulz, 2012). In short, we find that much of the variation in bank business policy is explained by factors (manager and/or firm fixed effects) that are time invariant. It is, therefore, not surprising to observe similarities in bank performance across different crisis periods as shown in Fahlenbrach, Prilmeier, and Stulz (2012).

4.3 Validating the Estimated Manager Fixed Effects

As the policy variables we employ in our analysis are measured at the bank level, a possible concern is that the estimated manager fixed effects may be biased and simply still reflect a firm effect. To rule this out, we show in this section that a certain degree of heterogeneity exists amongst the styles of managers who work at the same bank. The presence of diversity in manager styles within the same bank is encouraging because it makes it unlikely that the manager fixed effects we estimated using equation (1) are effectively another type of firm fixed effect. If this were the case, manager styles at the firm level would be homogeneous.

********TABLE 6 AROUND HERE********

Panel A of Table 6 report descriptive statistics of the standard deviation of bank manager fixed effects within the top management teams of *individual* banks. On average, the standard deviation of manager fixed effects (computed yearly at the bank level) is significantly larger than zero (at the 1% level) for each business policy variable. In other words, we observe some variation in manager styles within individual banks. It seems unlikely, therefore, that our manager fixed effects simply capture some source of heterogeneity across banks rather than latent characteristic at the manager level.

Figure 2 suggests a similar conclusion. In this figure we plot the first principal component of the yearly standard deviations of manager fixed effects that we have computed for each bank and for each policy variable. We plot this dispersion measure by the number of executives per bank. Figure 2 confirms again the presence of diversity of manager styles within management teams and suggests that this diversity does not seem to be monotonically linked to the size of the team of executives. However, larger groups of managers have somewhat more dispersed styles that cannot be found in small teams.

********FIGURE 2 AROUND HERE*********

Further, in Panel B of Table 6 we show the correlation coefficients between the bank-level standard deviations of manager styles linked to different policy variables. We find that the correlation coefficients are positive and highly significant providing additional evidence that managers within banks exhibit heterogeneity simultaneously with respect to different bank policies.

A second potential concern is that our sample can only include banks that are connected by manager mobility. While our sample is substantial and represents about 45% of the population of matched Execucomp banks, our analysis could be biased if banks in our sample of connected banks were to differ from other Execucomp banks in ways that affect bank policies.

To control for a possible selection bias, we apply a two-step Heckman (1979) selection model. 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. 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 US 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 results of this approach, reported in the Appendix 5, show that while the inverse Mills ratio enters with a significant coefficient in a number of models, the correlation between our original manager fixed effects and the new estimates that control for sample selection bias is on average above 99% (Appendix 6).

Overall, the results in this section support our empirical approach to separate bank manager from bank fixed effects and provide evidence of diversity of bank manager styles in bank policies at the level of individual banks.

5. Bank Manager Styles and Bank Risk

Our tests show that manager fixed effects explain an important share of the variation in bank business models. However, they are of little help to infer any causal interpretation on how manager styles influence bank risk-taking; that is, how do bank manager styles (and, therefore, bank managers) affect bank risk?

As establishing causal relationships between manager and firm variables is challenging[14], we follow the previous literature and use the global financial crisis that erupted in the second half of 2007 as a natural experiment. More precisely, we re-estimate manager fixed effects using only the data from 1992 to 2006 and investigate whether pre-crisis manager styles can predict different measures of bank risk during the global financial crisis. In addition, we include in the model the index of style dispersion described in section 4.3 (and computed at the end of 2006) to control for the possible effect of team heterogeneity on a bank's risk exposure during the crisis. As in Fahlenbrach and Stulz (2011) and Fahlenbrach et al. (2012), we use market data to compute risk measures and the 1 July 2007 to 31 December 31 2008 period as crisis period.[15]

********TABLE 7 AROUND HERE********

As standard risk measures, we include the *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 the approach proposed by Acharya et al. (2010) 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. (2010)] 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 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.

[14] Manager characteristics are not random variables. Instead, managers may endogenously match with different types of companies (Cronqvist et al., 2012; Graham et al., 2013). For instance, managers with certain risk attitudes may self-select into riskier banks.

[15] While the crisis period did not end in December 2008, Fahlenbrach et al. (2012) explain that subsequent market movement were in part at least due to uncertainty over which banks will be nationalized.

To avoid that our results are biased because of omitted variables, the prediction models include a parsimonious set of controls (all measured at end 2006 as in Fahlenbrach and Stulz, 2011).[16] Specifically, we control for realized bank returns in 2006, bank size, market leverage, bank beta and a measure of default risk (based on the Merton (1974) credit risk model; see Appendix 3 for details). Moreover, we include in the model executive compensation and the Bebchuk, Cohen and Ferrel (2009) index of managerial entrenchment (*Entrenchment*). The index is based on six governance provisions that strengthen manager control of corporations at the expense of shareholder rights.[17] Finally, we control for the economic conditions at the state level via the Federal Reserve Bank of Philadelphia's Coincident Index.

Table 7 reports the results. We find that the styles of bank managers measured before the crisis have an impact on bank risk during the crisis. For instance, banks led by executives with a preference for MBS or a larger liquidity gap experienced a larger drop in value and have higher tail risk. By contrast, banks with managers who have a preference for lending diversification realized lower losses during the crisis. Importantly, manager styles as to MBS and maturity mismatch (*Gap12*) enter significantly negative into the regression. Managerial preferences regarding exposure to mortgage-backed securities and bank liquidity management are therefore key to understanding bank risk during the global financial crisis. We do not find robust evidence of an effect of team heterogeneity on a bank's risk exposure. That is, the index of style dispersion enters with a significant (positive) coefficient in only a single specification.

[16] Variable definitions are presented in Appendix 2.

[17] 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.

Finally, the overall influence of manager styles on bank risk during the crisis is highlighted in the last rows of Table 7. The data presented indicate that the addition of manger pre-crisis styles adds around about 20 pp to the adjusted R^2 of the various risk regressions.[18] Overall, our results suggest that, next to being an important driver of a bank's business models, manager styles also have a significant impact on the risk of their banks during the global financial crisis.

6. Extracting Manager Profiles from Manager Styles

6.1 Cluster Analysis

As bank mangers pursue a range of different business policies, they display styles in multiple policy variables simultaneously. Bank managers can therefore differ along a potentially vast number of style dimensions, which makes style comparisons between individual managers complex.

********TABLE 8 AROUND HERE********

Panel A of Table 8, where we report correlations between the manager fixed effects based on our ten bank policy choices, shows however that managers exhibit some degree of commonality with respect to bank policy choices. For instance, the correlation coefficient between manager fixed effects extracted from non-interest income and from mortgage backed securities is well above 50%. This suggests that managers who opt for less traditional income sources are also characterized by larger investments in mortgage backed securities. Also, managers with a larger contribution to a bank's non-performing loans (more "lending risk") also

[18] Interestingly, when we run the same regressions while controlling for bank polices such as non-interest income relative to total income instead of manager fixed effects related to this, we find that our results are substantially different. We include the results of this analysis in Appendix 4 of this paper. These results again support our methodological approach.

contribute more to an institution's exposure to short-term wholesale funding and less to the diversification of its loan portfolio.

It should thus be possible to combine the different manager fixed effects we have extracted into a smaller number of typologies closely related to managerial preference for specific business models. In this section, we refer to the combinations of styles at the manager level as style patterns. We then derive a manager profile from these style patterns that comprehensively captures the preference of bank managers on bank business models. In essence, we use these patterns to describe manager preferences for business models.

We use factor analysis to identify patterns in policy styles. Factor analysis reduces the correlations amongst our ten business policy variables to a lower number of common factors. This analysis extracts two factors (with eingenvalues >1) that summarize a relevant portion of the variance of the correlation matrix of manager styles.[19] Therefore, the two factors summarize manager styles in various bank policies along two dimensions.

Panel B of Table 8 describes the two dimensions that depict manager patterns in styles. We show the correlation coefficients (r) between the two factors and each policy style. We highlight cases where r>50% as key inputs into a manager's style pattern. We show that Factor 1 is mainly explained by manager styles in more innovative sources of bank income. Factor 1 correlates highly with manager styles in derivatives (r=0.86) and non-interest income (r=0.81). By contrast, Factor 2 correlates highly with manager styles in traditional banking activities, that is higher lending risk (r=0.93), less lending diversification (r=-0.55) and more short-term funding (r=0.54). Therefore, the factor analysis allows us to distinguish between style patterns

[19] 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.

along two dimensions that indicate how aggressive manager styles are with regards to innovative or traditional bank polices.

In a next step, we use the two factors to cluster bank managers into groups that differ in terms of manager preference for specific business models. We adopt a k-means 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 six clusters for managers. We refer to the clusters as manager style profiles.

The clear distinction among the six groups is highlighted in Figure 3 where we present the distribution of managers within the six clusters. For each manager, we present her value for Factor 1 (style patterns in more innovative bank policies) and Factor 2 (style patterns in polices that that rely on traditional bank policies). The figure shows that the cluster analysis has been effective in identifying six very distinct profiles in our sample of managers.

********FIGURE 3 AROUND HERE********

Panel C of Table 8 shows the average values for Factor 1 and Factor 2 for each profile. Based on these loadings, we profile managers with a highly positive loading on Factor 1 and a highly (slightly) positive loading on Factor 2 as *aggressive* (*cautious*) *innovators*. Managers with a negative Factor 1 loading and an average (high) Factor 2 loading are *cautious* (*aggressive*) *traditionalists*. Finally, managers with a low and negative Factor 1 loading and a low (high) and negative Factor 2 loading are (*extremely*) *prudent*.

In summary, we collapse the various policy styles into two factors that simultaneously explain manager preferences across a range of bank policy choices. We then use these two factors and cluster analysis to classify managers into one of six distinct style profiles. To recap, the profiles we identify are as follows: (1) the aggressive innovator, (2) the cautious innovator, (3) the aggressive traditionalist, (4) the cautious traditionalist, (5) the prudent and (6) the extremely prudent manager.

The next two sections analyze the implications associated with these manager style profiles, in particular how these profiles are related to manager risk styles and to how managers match with certain banks based on their profiles.

6.2 Manager Profiles and Manager Risk Style

Our aggregation method allows us to identify six profiles that reflect key differences in the business models each manager prefers. To understand whether these profiles are related to the individual contribution that each manager makes to bank risk, we conduct an additional analysis that relates these profiles to the manager fixed effects detectable in measures of bank risk ('risk-style' henceforth). A manager's risk-style expresses the unique contribution of each manager to bank risk in addition to well-known determinants of bank risk-taking as previously identified in the literature. We can therefore interpret risk styles as the idiosyncratic risk-preferences that characterizes bank managers. By extension, the style profile with the largest positive impact on manager risk-styles helps us identify which types of managers have the highest propensity for aggressive risk-taking.

To estimate manager risk styles we apply a modified version of equation (1) described in section 4.1. Next to the controls we have used in our previous tests, the modified version also includes lagged values of the bank policy variables. The latter are critical to avoid an omitted

variable bias in the estimation of the manger risk-fixed effects and to extract the effect of managers on risk that is not already reflected in the bank policy variables. As measures of bank risk we employ the 5% Value at Risk, the Expected Shortfall, Equity Volatility and the Marginal Expected Shortfall computed annually using daily stock returns.

As shown in Panel A of Table 9, the manager fixed effects obtained from the risk-regressions are jointly significantly different from zero. Furthermore, they explain on average around 4.2% of the variation in bank risk. While the manager style contributions to bank risk appear lower than the manager style contributions to bank policy choices previously reported, they are still economically meaningful. Additionally, it is important to point out that the manager style contributions to risk express the direct contribution of managers to bank risk in addition to what managers contribute via policy choices (which, as indicated above, are included in lagged form as controls in the risk regressions)

********TABLE 9 AROUND HERE*********

We then regress the risk styles on a set of dummy variables that each stand for one of the manager profiles identified in the previous section (with extremely prudent managers used as the omitted group). The results, reported in Panel B of Table 9, have two key implications. First, relative to the omitted group of extremely prudent managers, the other groups of managers show a significantly larger risk-style in three out of four specifications. The exception is the MES model where most of the groups have a similar impact on risk. Second, in all specifications, the group of aggressive innovators has the largest risk-style: in three out four specifications the positive coefficient associated with this group is significantly larger than those of the remaining groups included in the regression models. In general, managers classified as aggressive

innovators are the managers with the largest person-specific contribution to increases in a bank's total tail risk and systemic risk.

6.3 Manager Profiles and Bank Boards

It is well known that managers and shareholders differ in terms risk preferences (Jensen and Meckling, 1976). One implication of divergent risk preferences between shareholders and managers is that shareholder-dominated governance should facilitate riskier outcomes than insider-dominated governance. Previous studies have found evidence consistent with this view 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 study, this implies that managers with certain profiles are more likely to match with banks with certain governance structures and this matching reflects the bank risk-appetite.

********TABLE 10 AROUND HERE********

To understand if there is a correlation between boards and manager profiles, 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*). Second, we include the proportion of independent directors on the board (*Board independence*). RiskMetrics defines board members as independent if they have no business or family ties to the board or its senior management.

Table 10 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 only relate the manager profile with the bank governance structure in the year of the managerial appointment. When a manager jointed the bank before the start of our sample period, we use the governance structure in the first year a bank appears in our dataset.

Table 10 shows that more entrenched boards (measured by higher *entrenchment*) are less likely to appoint innovators and more likely to appoint managers with traditionalist or prudent style profiles. Consistent with this, entrenched boards are least likely to appoint aggressive innovators and most likely to appoint extremely prudent managers. By contrast, more shareholder-aligned boards (higher *board independence*) are associated with managers that we refer to as cautious innovators. Shareholder-aligned boards are less likely to appoint managers we refer to as traditionalists or prudent managers.[20]

Therefore, the bank-style matching in this section offers a new explanation for existing findings that 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 have appointed managers that exhibit more aggressive styles.[21]

6.4 Manager Profiles and CEO Appointments

While the previous section demonstrates that manager profiles can to some extent explain which bank boards appoint managers of a certain style profile, this final section investigates

[20] While not the focus of this study, it is still interesting to note that a larger presence of female directors on bank boards is linked to manager appointments which are less likely profiled as innovators and most likely to fall into the extremely prudent style profile.

[21] We also demonstrate the implications for risk of our manager profiles. Appendix 7 uses the style profiles to explain risk indicators during the crisis. Since the number of managers in some of the profiles is low, Appendix 7 controls for Innovator (=1 for Cautious or Aggressive Innovators) and Traditionalist (=1 for Cautious or Aggressive Traditionalists). The results show that Innovators display a higher risk effect in three out of our five risk measures.

whether there is an association between manager profiles and their appointment as CEO. Since CEOs are the most senior managers in a firm, this test helps answer the question if style profiles are related to the career trajectory of managers. Schoar and Zuo (2011) examine how difficult economic conditions shape CEO styles and career outcomes. In a departure from this and other research on CEO careers (e.g., Dittmar and Duchin, 2016), we examine which style profile makes it more likely that a manager is appointed as a CEO during his/her career. If we were to find that certain style profiles are more prevalent amongst CEOs compared to other managers, this would provide additional evidence consistent with the view that manager styles matter.

To test this, we run probit regressions where the dependent variable is a binary variable that is one if a manager has been CEO at some point during our sample period (and zero otherwise). We include a variety of observable manager characteristics including age, education and experience to control for factors that determine which managers hold a CEO position at some stage during their career. We then include binary variables for five of our six style profiles to test whether certain style profiles affect the probability that a manager is appointed CEO. The results are reported in Table 11.

We find that managers classified as aggressive traditionalists have a higher probability of being appointed CEOs. No other style profile explains CEO appointments. Further, relatively few other observable manager characteristics enter significantly in the model. Out of those that enter significantly, most are age- and experience-related. For example, younger managers are less likely to be appointed CEOs. Managers, however, who have gained experience outside the banking sector are more likely to be appointed CEOs. While it is not straightforward to gauge the explanatory power from our models due their non-linearity, our results suggest that manager styles substantially explain CEO appointments vis-à-vis observable manager characteristics.

7. Conclusions

We analyze the contribution that different types of managerial characteristics provide in explaining variation in bank business models. Despite a large part of the literature and current academic and regulatory debates focusing on executive compensation, 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 style has substantial impact on key bank policy choices such as the sources of bank income, funding and asset mix. Moreover, style has a significant impact on bank risk during the 2007-08 financial crisis. Bank manager style allows managers to be classified into distinct style profiles that explain some of their risk preferences, help explain which managers match with certain bank boards, and also help predict whether or not a manager is appointed as a CEO.

Our results imply that any attempt to understand differences in bank policies and risk has necessarily to account for idiosyncratic manager-specific effects. However, they also highlight that our understating of what constitutes the idiosyncratic manager-specific effects, and consequently what drives its influence on bank business models, is limited.

Our findings have two key implications for bank regulators. First, our findings imply that regulatory interventions targeted towards executive compensation are only likely to have a small impact on bank business models, and hence on bank risk-taking. Second, by showing that managerial profiles significantly contribute to the tail risk and the systemic risk generated by banks, our findings also imply that manager attributes that are difficult to identify, and as such hard to regulate, significantly contribute to producing negative systemic externalities. Therefore, if key drivers of bank risk-taking and systemic risk are ultimately idiosyncratic and rooted in manager styles, systematic approaches to regulating bank risk-taking are challenging.

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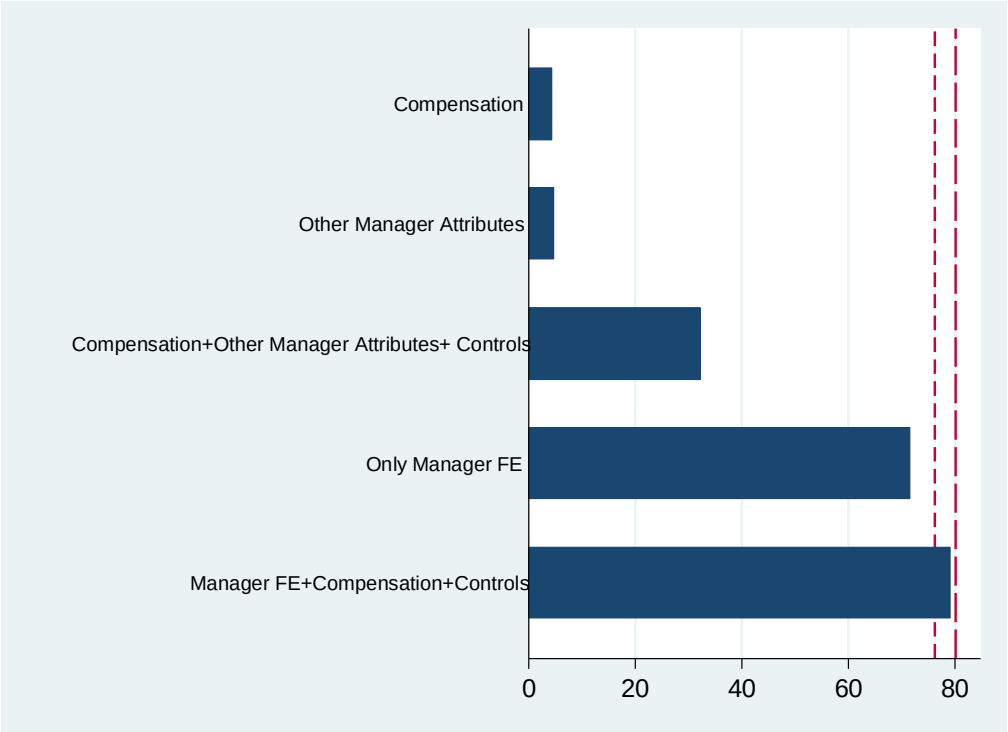

Figure 1: **Determinants of Bank Business Policies: Average Adjusted R^2 under different model specifications**

The figure plots the adjusted R^2 of various regressions with different sets of controls using all banks and bank managers contained in Execucomp. The R^2 are the averages across ten bank policy regressions. The sets of controls in the bank policy regressions are as follows. OLS regressions with compensation variables only (*Vega*, *Delta*, *Bonus*), OLS regressions with other manager attributes (*Birth year*, *Male*, *Depression baby*, *Military service*, *MBA*, *Ivy league*, *Fast track*, *Nonbank Experience (N_Ex)*, *Nonbank Experience (Ex)*, *Generic*), OLS regressions with compensation, other manager attributes and other controls (*Size*, *Equity*, *Market to book*, *Core deposits*, *Loans*, *Economy*). As a reference point, the dashed lines show the average adjusted R^2 of other fixed effect regressions. The line with shorter dashes relates a model with firm fixed effects and other controls and the line with longer dashes refers to a model with a fixed effect for every unique manager-bank combination (the Spell Method).

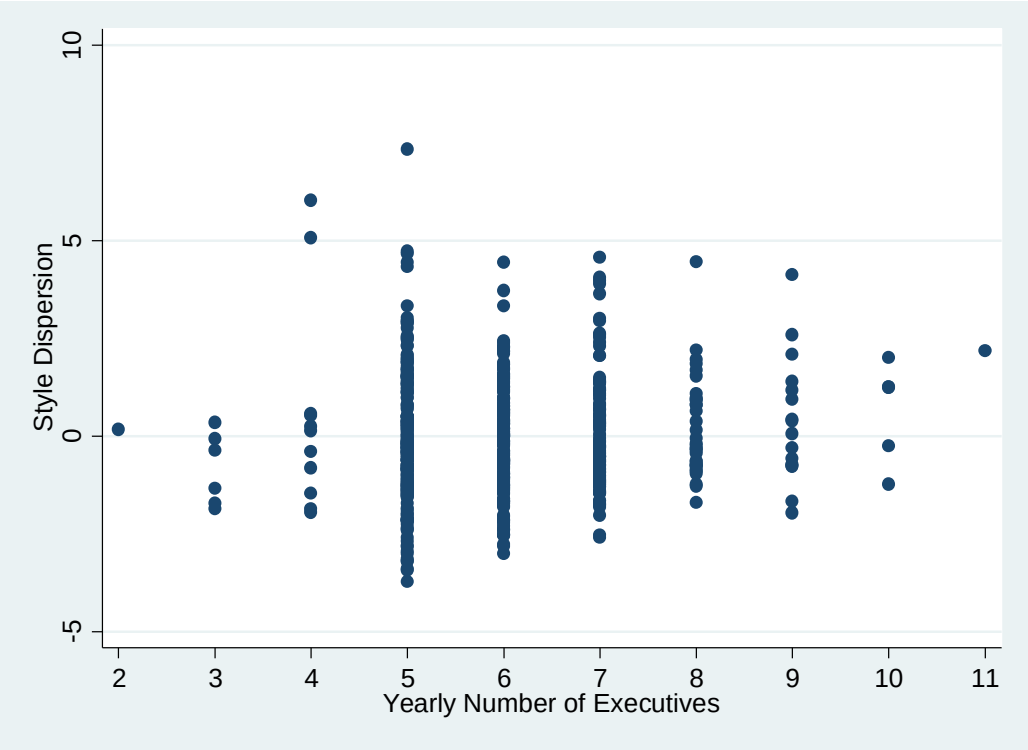

Figure 2: Within-firm Dispersion of Managerial Styles, by Number of Managers

The figure plots the first principal component of the standard deviation of all manager fixed effects (styles) related to various bank policy variables. Manager styles are estimated using 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. This dispersion measure is plotted by the number of executives per bank.

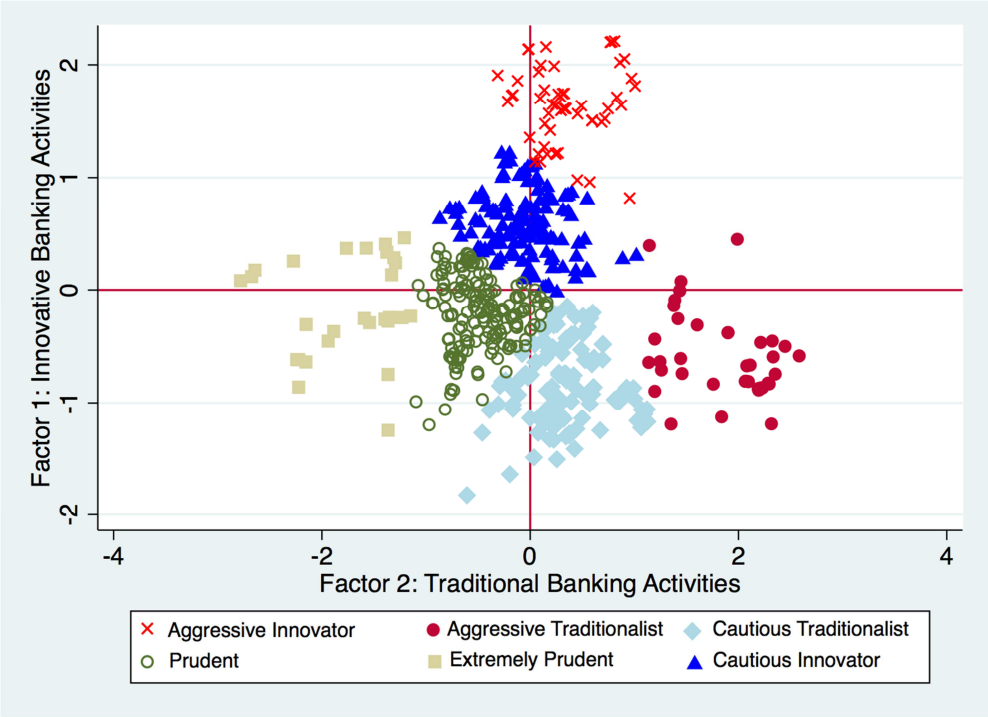

Figure 3: Clustering of Manager Styles

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 variance of the correlation matrix of managerial styles. For each manager, we present her average value for *Factor 1* (style patterns in more innovative bank policies) and *Factor 2* (style patterns in polices that that rely on traditional bank policies). 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) the aggressive innovator, (2) the cautious innovator, (3) the aggressive traditionalist, (4) the cautious traditionalist, (5) the prudent and (6) the extremely prudent manager.

Table 1 Variable definitions and descriptive statistics

		N	Mean	Median	St.Dev.
Panel A: Bank Business Policy Variables					
Non interest income	Non interest income over operating income (percent)	1480	23.53	20.97	13.10
MBS	Private-label mortgage backed securities (bhck1709 + bhck1733 + bhck1713 + bhck1736 + bhck3536) over total assets (percent)	1330	1.45	0.07	3.23
Derivatives	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 (percent)	1253	26.41	0.00	67.93
Securities	Held-to-maturity plus available for sale securities (at fair value) (bhck0390 + bhck2146 [-1993], bhck1754 + bhck1773 [1994-]) over total assets (percent).	1480	21.74	20.72	10.03
Gap12	Liabilities repricing or maturing within 12 months (bhck3197) minus assets repricing or maturing within 12 months (bhck3296 + bhck3298) divided total asset (percent)	1480	-17.68	-17.96	16.18
Comm/real estate loans	Log of the ratio between commercial and real estate loans	1480	0.41	0.31	0.42
Lending Diversification	Loan diversification, measured as 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans	1480	0.51	0.55	0.16
Lending risk	Loans that are past due ≥90 days or are on nonaccrual basis (bhck5525-bhck3506+bhck5526-bhck3507+bhck2744) over total loans (percent)	1480	1.48	0.93	2.19
Wholesale funding	Commercial paper and other borrowed funds with a remaining maturity of ≤1 year (percent) (=bhck2309 + bhck2332)	1480	4.39	3.27	4.39
Other short funding	Federal funds purchased and securities sold under agreements to repurchase (BHDMB993 + BHCKB995)[before 2002: bhck2800] + domestic time deposits ≥ $100k with a remaining maturity ≤1 year (BHDMA242) + long-term debt that reprices within one year (BHCK3298+ BHCK3409) + interest-bearing foreign deposits (BHFN6636) over total liabilities (percent)	1480	17.91	16.97	13.03
Panel B: Compensation					
$Vega_t$	Log ($ value of pay-risk sensitivity / cash compensation)	7205	0.05	0.02	0.16
$Delta_t$	Log ($ value of the pay-performance sensitivity / cash compensation)	7205	0.17	0.10	0.27
$Bonus_t$	Log (1 + the $ value of cash bonuses)	8495	4.13	4.86	2.61
Panel C: Managerial Attributes related to Life and Career Experience					
Birth year	Year a manager was born	1282	1948.38	1948.00	8.62
Male	1 for male managers	1431	0.94	1.00	0.25
Depression baby	Born between 1920 and 1929	1234	0.13	0.00	0.34
Military service	Indicator for managers with prior military service	1135	0.11	0.00	0.32
MBA	Holds an MBA degree	1026	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)	1026	0.19	0.00	0.40
Fast track	Log of age of first executive director appointment	1175	3.77	3.78	0.18
Nonbank Experience (N_Ex)	A dummy equal to one if the managers has served as non executive in non banking firms	1200	0.23	0.00	0.42
Nonbank Experience (Ex)	A dummy equal to one if the managers has served as executive in non banking firms	1200	0.03	0.00	0.18
Generic	Generic career track. First appointment outside finance or accounting				
Panel D: Other Controls					
$Size_{t-1}$	Log of total assets (in 2000 $)	1465	16.50	16.25	1.51
$Equity_{t-1}$	Total equity over total assets (percent)	1465	8.61	8.25	2.25
$Market\ to\ book_{t-1}$	Log of the Market to book ratio	1465	0.62	0.66	0.51
$Core\ deposits_{t-1}$	Total core deposits over total assets (percent)	1465	86.85	89.42	9.28
$Loans_{t-1}$	Total loans over full-time employees	1465	2.29	2.02	1.27
$Economy_t$	12 month average of the monthly coincident index at the state level	1480	130.89	133.62	18.53

Table 2. Manager attributes, controls and the adjusted R^2

The panels display the adjusted R^2 of various regressions on banks' policy choices for all of managers of Execucomp banks (Panel A) and for CEOs only (Panel B). The models are OLS regressions with compensation variables only (*Vega, Delta, Bonus*), OLS regressions with other manager attributes (*Birth year, Male, Depression baby, Military service, MBA, Ivy league, Fast track, Nonbank Experience (N_Ex), Nonbank Experience (Ex), Generic*), OLS regressions with compensation, other manager attributes and other controls (*Size, Equity, Market to book, Core deposits, Loans, Economy*), Manager fixed effects only, manager fixed effects with compensation and other controls, and a fixed effect for every unique manager-bank combination (the spell method). Each regression model is estimated with robust standard errors clustered at the level of *firm-manager* combination. Variable definitions are reported in Table 1. significant at 10%; ** significant at 5%; *** significant at 1%

Panel A: Execucomp – all Managers

Dependent Variable:	**(1) Non interest income**	**(2) MBS**	**(3) Derivatives**	**(4) Securities**	**(5) Gap12**	**(6) Commercial/Real Estate Loans**	**(7) Lending Diversification**	**(8) Lending Risk**	**(9) Wholesale Funding**	**(10) Other short funding**
OLS (Compensation)	0.073	0.020	0.113	0.004	0.028	0.069	0.050	0.032	0.024	0.031
OLS (Manager Attributes)	0.056	0.003	0.108	0.024	0.056	0.047	0.090	0.009	0.024	0.062
OLS (Compensation + Manager Attributes + Controls)	0.567	0.088	0.556	0.207	0.188	0.195	0.376	0.406	0.160	0.476
Only Manager FE	0.809	0.535	0.936	0.718	0.663	0.873	0.918	0.499	0.469	0.731
Manager FE (Compensation + Controls)	0.894	0.604	0.952	0.786	0.700	0.865	0.939	0.721	0.562	0.891
Firm FE (Compensation + Controls)	0.882	0.614	0.956	0.752	0.682	0.819	0.922	0.571	0.542	0.888
Spell method	0.901	0.610	0.975	0.801	0.714	0.876	0.944	0.722	0.572	0.896

Panel B Execucomp – CEOs only

Dependent Variable:	**(1) Non interest income**	**(2) MBS**	**(3) Derivatives**	**(4) Securities**	**(5) Gap12**	**(6) Commercial/Real Estate Loans**	**(7) Lending Diversification**	**(8) Lending Risk**	**(9) Wholesale Funding**	**(10) Other short funding**
OLS (Compensation)	0.055	0.019	0.102	0.001	0.027	0.060	0.074	0.038	0.015	0.029
OLS (Manager Attributes)	0.137	0.030	0.196	0.042	0.102	0.081	0.190	0.018	0.067	0.038
OLS (Compensation + Manager Attributes + Controls)	0.590	0.090	0.570	0.189	0.189	0.204	0.410	0.252	0.177	0.455
Only Manager FE	0.828	0.581	0.948	0.717	0.709	0.883	0.938	0.356	0.501	0.736
Manager FE (Compensation + Controls)	0.904	0.638	0.954	0.777	0.736	0.890	0.954	0.528	0.576	0.884
Firm FE (Compensation + Controls)	0.883	0.608	0.950	0.707	0.666	0.791	0.922	0.519	0.482	0.866
Spell method	0.905	0.639	0.976	0.781	0.738	0.892	0.954	0.527	0.580	0.888

Table 3. 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	1,341	305	36	28
3	429	79	10	8
4	80	16	1	2
5	155	24	1	2
6	107	22	1	2
7	32	11	1	2
8	153	31	2	3
9	546	107	11	9
10	85	20	1	2
11	39	15	1	2
12	180	32	1	2
13	131	24	2	2
14	77	15	1	2
15	71	11	1	2
16	55	15	1	2
17	39	14	1	2
Total	3,689	774	73	74

Table 4. 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. *Non interest income* is divided by operating income, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Securities* are held-to-maturity plus available for sale securities over total assets, *Gap12* is the 12-month liquidity gap by total assets. *Comm/real estate loans* is the Log of the ratio between commercial and real estate loans. *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans. *Lending risk* are loans that are past due ≥90 days or are on a nonaccrual basis over total loans. *Wholesale funding* is commercial paper and other borrowed funds with a remaining maturity of ≤1 year while *Other short funding* includes large deposits. Panel B runs policy regressions on all Execucomp banks between 1992 and 2010 and displays the resulting R^2 for: OLS regressions with compensation variables only (Vega, Delta, Bonus), OLS regressions without manager or firm fixed effects, regressions with firm fixed effects, with bank fixed effects, and with a fixed effect for every unique manager-bank combination (the spell method). Each regression model is estimated with robust standard errors clustered at the level of *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) MBS**	**(3) Derivatives**	**(4) Securities**	**(5) Gap12**	**(6) Commercial/Real Estate Loans**	**(7) Lending Diversification**	**(8) Lending Risk**	**(9) Wholesale Funding**	**(10) Other short funding**
Compensation variables										
$Vega_t$	0.022*	-0.004	0.145***	-0.025**	-0.042	-0.073	0.002	0.010*	0.004	0.001
	(0.013)	(0.004)	(0.047)	(0.011)	(0.031)	(0.063)	(0.012)	(0.006)	(0.005)	(0.011)
$Delta_t$	-0.017	0.004	-0.089**	0.026**	0.047	0.055	-0.002	-0.006	-0.005	0.005
	(0.012)	(0.004)	(0.039)	(0.011)	(0.029)	(0.057)	(0.011)	(0.005)	(0.005)	(0.011)
$Bonus_t$	0.000	0.001***	-0.003	0.000	0.001	0.003	-0.001**	0.000	-0.000**	0.001**
Bank characteristics										
$Size_{t-1}$	-0.017***	-0.008***	0.028	-0.015	0.015	0.024	0.003	0.013***	0.008***	0.037***
	(0.006)	(0.003)	(0.033)	(0.010)	(0.013)	(0.021)	(0.006)	(0.004)	(0.001)	(0.006)
$Equity_{t-1}$	0.032	0.045	-1.494***	-0.153	0.182	5.491***	0.120	-0.085	-0.193***	-0.400***
	(0.108)	(0.032)	(0.402)	(0.115)	(0.203)	(1.665)	(0.113)	(0.080)	(0.032)	(0.120)
$Market\ to\ book_{t-1}$	0.004	0.000	-0.019	0.025***	0.007	-0.010	0.005	0.008**	-0.013***	0.006
	(0.005)	(0.001)	(0.022)	(0.006)	(0.008)	(0.020)	(0.004)	(0.004)	(0.001)	(0.004)
$Core\ deposits_{t-1}$	-0.042	0.028**	0.027	0.060	-0.346***	0.025	0.024	0.013	-0.006	-0.119***
	(0.050)	(0.013)	(0.141)	(0.042)	(0.065)	(0.083)	(0.025)	(0.020)	(0.007)	(0.030)
$Loans_{t-1}$	-0.061***	-0.009***	-0.072***	-0.022***	-0.006	-0.027	-0.023***	-0.005	-0.004**	0.006
	(0.008)	(0.002)	(0.019)	(0.008)	(0.010)	(0.020)	(0.003)	(0.004)	(0.001)	(0.006)
Other control variables										
$Economy_t$	-0.000	0.000**	0.002	-0.000	-0.001*	0.004***	-0.000	0.001***	0.000	-0.001**
	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,689	3,193	2,793	3,689	3,689	3,689	3,689	3,689	3,689	3,689
R^2	0.921	0.738	0.981	0.827	0.79	0.863	0.953	0.829	0.671	0.921
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. How important are bank manager styles?

Panel A shows F-statistics (and p-values in parenthesis) to test if the fixed effects estimated with three-way fixed effects models in Panel A of Table 3 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. 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. *Non interest income* is divided by operating income, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Securities* are held-to-maturity plus available for sale securities over total assets, *Gap12* is the 12-month liquidity gap by total assets. *Comm/real estate loans* is the Log of the ratio between commercial and real estate loans. *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans. *Lending risk* are loans that are past due ≥90 days or are on a nonaccrual basis over total loans. *Wholesale funding* is commercial paper and other borrowed funds with a remaining maturity of ≤1 year while *Other short funding* includes large deposits. Panel B compares the relative importance of unobservable manager characteristics by decomposing the variation in the R^2 of the dependent variables into the fitted components, manager fixed effects, firm fixed effects and the residuals. *significant at 10%; ** significant at 5%; *** significant at 1%

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

	(1) Non-interest income	(2) MBS	(3) Derivatives	(4) Securities	(5) Gap12	(6) Commercial/Real Estate Loans	(7) Lending Diversification	(8) Lending Risk	(9) Wholesale Funding	(10) Other short funding
Firm and manager FE	17.20***	9.69***	80.75***	15.47***	11.15***	20.06***	41.83***	5.90***	6.06***	16.67***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Manager FE	2.81***	1.21***	5.47***	3.02***	1.95***	1.48***	2.90***	2.26***	1.76***	1.69***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	10.03***	7.80***	66.06***	12.22***	9.66***	11.68***	21.58***	4.91***	5.32***	8.32***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B. Economic significance. % of R^2 attributable to manager fixed effects

	(1) Non-interest income	(2) MBS	(3) Derivatives	(4) Securities	(5) Gap12	(6) Commercial/Real Estate Loans	(7) Lending Diversification	(8) Lending Risk	(9) Wholesale Funding	(10) Other short funding
Fitted values	24.61	6.84	6.26	17.19	9.90	9.96	12.67	66.01	25.74	50.19
Manager FE	**23.20**	**23.70**	**44.29**	**28.64**	**37.11**	**23.56**	**23.35**	**14.01**	**22.78**	**20.06**
Firm FE	44.26	43.22	47.87	36.91	31.94	52.82	59.30	2.85	18.59	21.73
Residuals	7.93	26.24	1.57	17.27	21.05	13.65	4.67	17.11	32.89	7.91

Table 6. Are we separating bank manager styles from firm fixed effects?

The table reports correlations between the bank manager fixed effects (styles) linked to different bank policy variables. The bank manager fixed effects are estimated in Panel A of Table 3 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. *Non interest income* is divided by operating income, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Securities* are held-to-maturity plus available for sale securities over total assets, *Gap12* is the 12-month liquidity gap by total assets. *Comm/real estate loans* is the Log of the ratio between commercial and real estate loans. *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans. *Lending risk* are loans that are past due ≥90 days or are on a nonaccrual basis over total loans. *Wholesale funding* is commercial paper and other borrowed funds with a remaining maturity of ≤1 year while *Other short funding* includes large deposits. Panel A reports correlations in manager fixed effects *across banks*. Panel B reports correlations between bank manager fixed effects *within banks*. Manager fixed effects are normalized to have a mean equal to zero as in Graham et al. (2012). *significant at 10%; ** significant at 5%; *** significant at 1%

Panel A: *Within*-bank standard deviations of manager fixed effects linked to:

	N	Mean	Median	St. Dev.	1 Pctile	99 Pctile
1. Non interest income	721	0.014***	0.010	0.013	0.000	0.070
2. Mortgage-backed Securities	614	0.003***	0.002	0.003	0.000	0.016
3. Derivatives	538	0.057***	0.038	0.061	0.005	0.338
4. Securities	721	0.016***	0.013	0.014	0.001	0.059
5. Gap12	721	0.026***	0.022	0.019	0.001	0.093
6. Commercial over real estate loans	721	0.039***	0.031	0.040	0.002	0.136
7. Lending diversification	721	0.011***	0.009	0.009	0.000	0.049
8. Lending risk	721	0.003***	0.002	0.003	0.000	0.011
9. Wholesale funding	721	0.008***	0.006	0.007	0.000	0.033
10. Other short term funding	721	0.013***	0.011	0.009	0.001	0.044

Panel B. *Within* bank correlation matrix

	(1) Non-interest income	(2) MBS	(3) Derivatives	(4) Securities	(5) Gap12	(6) Commercial/Real Estate Loans	(7) Lending Diversification	(8) Lending Risk	(9) Wholesale Funding
MBS	0.239***								
Derivatives	0.004	0.154***							
Securities	0.182***	0.249***	0.144***						
Gap12	0.147***	0.082*	-0.024	0.180***					
Commercial/Real Estate Loans	0.128***	0.027	0.188***	0.286***	0.141***				
Lending Diversification	0.115**	0.097*	0.008	0.077*	0.151***	0.385***			
Lending Risk	0.117**	0.107**	0.047	0.145***	0.282***	0.197***	0.200***		
Wholesale Funding	-0.019	0.046	0.090*	0.226***	0.171***	0.176***	0.249***	0.160***	
Other short funding	0.292***	0.217***	0.0841	0.267***	0.255***	0.270***	0.247***	0.129***	0.063

Table 7. The global crisis and bank manager styles

The table shows OLS regressions with robust standard error clustered at bank level. Pre-Crisis Styles are the bank manager fixed effects that are estimated in Panel A of Table 3 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. The dependent variables are observed from 07/ 2007 – 12/2008 and include negative 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. *Style Dispersion* the first principal component of the SD of all manager styles at a bank. Robust standard errors clustered at the firm level are reported in parentheses.

	(1) Negative BHR	(2) Volatility	(3) VaR	(4) ES	(5) MES
Pre-crisis manager styles					
Non-Interest income	0.272	0.089	0.041	0.291**	0.234***
	(0.494)	(0.066)	(0.039)	(0.126)	(0.070)
Mortgage-backed securities	5.539***	0.403***	0.251**	0.760***	0.359**
	(1.482)	(0.125)	(0.096)	(0.265)	(0.145)
Derivatives	-0.124	-0.009	-0.001	-0.019	-0.012
	(0.079)	(0.007)	(0.005)	(0.015)	(0.009)
Securities	-0.629*	-0.047*	-0.023	-0.004	0.017
	(0.347)	(0.027)	(0.022)	(0.054)	(0.032)
Gap12	1.904***	0.119***	0.132***	0.295***	0.162***
	(0.575)	(0.040)	(0.037)	(0.079)	(0.042)
Commercial/real estate	-0.062	0.009	-0.001	0.021	0.001
	(0.192)	(0.015)	(0.012)	(0.032)	(0.019)
Lending diversification	-1.808***	-0.107*	-0.136***	-0.194**	0.007
	(0.546)	(0.055)	(0.037)	(0.092)	(0.073)
Lending risk	10.378*	0.990**	1.109***	1.623*	0.023
	(5.535)	(0.374)	(0.343)	(0.793)	(0.535)
Wholesale funding	1.846	0.022	-0.022	0.170	0.139
	(1.112)	(0.098)	(0.066)	(0.222)	(0.098)
Other short term funding	-1.112**	-0.086*	-0.127***	-0.215**	-0.053
	(0.523)	(0.046)	(0.036)	(0.100)	(0.050)
Style Dispersion	0.083*	0.001	0.001	-0.000	-0.000
	(0.045)	(0.004)	(0.003)	(0.009)	(0.005)
Other control variables					
Size	0.157***	0.005	0.002	0.004	0.005
	(0.044)	(0.003)	(0.002)	(0.006)	(0.004)
Market leverage	4.309***	0.372***	0.380***	0.741***	0.304***
	(0.988)	(0.076)	(0.058)	(0.196)	(0.097)
Probability of default	17.104***	0.807***	1.176***	1.416***	-0.027
	(2.672)	(0.191)	(0.161)	(0.348)	(0.281)
Beta	-0.649***	-0.022	-0.036***	-0.050	0.015
	(0.170)	(0.018)	(0.011)	(0.033)	(0.021)
Stock return 2006	0.096	-0.006	-0.003	-0.023	-0.015
	(0.205)	(0.015)	(0.011)	(0.033)	(0.021)
Entrenchment	0.141***	0.007**	0.006***	0.008	0.005
	(0.026)	(0.003)	(0.002)	(0.006)	(0.003)
Vega	-0.419***	-0.003	0.001	-0.011	-0.019
	(0.131)	(0.013)	(0.008)	(0.023)	(0.014)
Delta	0.100*	0.003	0.001	0.006	0.010*
	(0.058)	(0.004)	(0.002)	(0.009)	(0.006)
Bonus	0.015**	0.000	0.001	0.002	0.000
	(0.007)	(0.001)	(0.000)	(0.002)	(0.001)
Economy	0.002	0.000	0.000*	0.001**	0.001**
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)
Constant	-4.863***	-0.354***	-0.307***	-0.689***	-0.348***
	(0.665)	(0.080)	(0.051)	(0.158)	(0.095)
Observations	133	133	133	133	133
Adj. R^2	0.847	0.661	0.787	0.665	0.775
Adj. R^2 - excl. style variables	0.591	0.521	0.608	0.475	0.616

Table 8. Profiling bank managers based on styles - Factor and Cluster Analysis

Panel A shows the correlations between manager fixed effects (styles) in ten bank business policy variables and Factor 1 and 2. The manager styles are estimated with three-way fixed effects in Panel A of Table 3 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. *Factor 1* and *Factor 2* are extracted by factor analysis with (eingenvalues >1) to summarize a relevant portion of the variance of the correlation matrix of managerial styles. *Non interest income* is divided by operating income, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Securities* are held-to-maturity plus available for sale securities over total assets, *Gap12* is the 12-month liquidity gap by total assets. *Comm/real estate loans* is the Log of the ratio between commercial and real estate loans. *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans. *Lending risk* are loans that are past due ≥90 days or are on a nonaccrual basis over total loans. *Wholesale funding* is commercial paper and other borrowed funds with a remaining maturity of ≤1 year while *Other short funding* includes large deposits. Correlations >50% are highlighted as key inputs into a factor. Panel B shows six profiles and their values for Factor 1 and Factor 2. The profiles are derived from a k-means 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

	Non-interest income	**MBS**	**Derivatives**	**Securities**	**Gap12**	**Commercial/ Real Estate Loans**	**Lending Diversification**	**Lending Risk**	**Wholesale Funding**
MBS	0.312***								
Derivatives	0.512***	0.252***							
Securities	0.020	0.423***	0.073						
Gap12	-0.407***	-0.057	-0.236***	0.063					
Commercial/Real Estate Loans	0.270***	0.036	0.339***	0.164***	-0.108**				
Lending Diversification	0.427***	0.219***	0.239***	0.068	-0.435***	0.247***			
Lending Risk	-0.284***	-0.045	-0.067	-0.015	-0.042	-0.266***	-0.319***		
Wholesale Funding	-0.040	-0.052	0.163***	-0.025	0.230***	0.081*	-0.307***	0.231***	
Other short funding	-0.341***	0.067	0.040	0.226***	0.362***	0.096**	-0.354***	0.293***	0.239***

Panel B. Correlations between Factor Scores and Manager Styles

	(1) **Factor 1**	**(2)** **Factor 2**
1. Non-interest income	**0.805*** **	-0.363***
2. Mortgage-backed Securities	0.320***	-0.041
3. Derivatives	**0.858*** **	0.036
4. Securities	0.022	-0.04
5. Gap12	-0.334***	0.029
6. Commercial over real estate loans	0.478***	-0.338***
7. Lending diversification	0.329***	**-0.549*** **
8. Lending risk	-0.145***	**0.932*** **
9. Wholesale funding	0.275***	0.482***
10. Other short term funding	-0.132***	**0.537*** **

Panel C. Average Factor Scores, by Managerial Profile

	(1) Factor 1	(2) Factor 2
Profile 1: The Cautious Innovator (152)	0.562	-0.068
Profile 2: The Aggressive Innovator (57)	1.628	0.345
Profile 3: The Cautious Traditionalist (133)	-0.856	0.334
Profile 4: The Aggressive Traditionalist (41)	-0.579	1.847
Profile 5: Prudent (174)	-0.209	-0.465
Profile 6: Extremely Prudent (28)	-0.159	-1.742

Table 9. Manager Risk Fixed Effects and Manager Profiles

This table reports the regression results on manger fixed effects in bank risk measures. Manager fixed effects are estimated with three-way fixed effects in Panel A of Table 3 on a sample of connected banks plus lagged values of the bank policy variables. 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. Manager risk fixed effects are computed for the 5% Value at risk (VaR), the 5% Expected Shortfall (ES) and equity volatility (*Equity Vol*), and 5% marginal expected shortfall (*MES*). Panel A shows the manager fixed effects in risk measures are jointly significantly different from zero. We also show what the % contribution of the manager risk fixed effects to explaining measures of bank risk. Panel B regresses manager profiles in the form of binary variables (*Cautious Innovators, Aggressive Innovators, Cautious Traditionalist, Aggressive Traditionalist, Prudent Risk-Takers*) on bank risk measures. Each manager is allocated to one manager profile based on factor and cluster analysis performed in Table 8. * significant at 10%; ** significant at 5%; *** significant at 1%

Panel A: Statistical and Economic significance

	(1) VaR	**(2) ES**	**(3) Equity Vol**	**(4) MES**
F-test that all manager fixed effects = 0	1.36	1.19	1.2	1.33
	(0.00)	(0.00)	(0.00)	(0.00)
% of R^2 attributable to manager risk fixed effects	3.73	5.00	2.92	5.26

Panel B: Regression of Manager Risk Fixed Effects on Manager Profiles

	(1) VaR	**(2) ES**	**(3) Equity Vol**	**(4) MES**
Cautious Innovator	0.010***	0.014***	0.131***	-0.000
	(0.001)	(0.002)	(0.011)	(0.001)
Aggressive Innovator	0.011***	0.019***	0.154***	0.010***
	(0.001)	(0.002)	(0.013)	(0.002)
Cautious Traditionalist	0.002	0.007***	0.050***	-0.001
	(0.001)	(0.002)	(0.015)	(0.002)
Aggressive Traditionalist	0.005***	0.012***	0.101***	0.001
	(0.002)	(0.002)	(0.019)	(0.002)
Prudent	0.005***	0.009***	0.085***	-0.003**
	(0.001)	(0.001)	(0.010)	(0.001)
Constant	-0.006***	-0.011***	-0.093***	0.000
	(0.001)	(0.001)	(0.009)	(0.001)
Observations	538	538	538	538
Adjusted R^2	0.150	0.102	0.180	0.119

Table 10: Bank-manager style matching: bank governance and bank manager profiles

The table shows probit regressions with robust standard errors on the manager style profiles. Manager profiles (*Cautious Innovators, Aggressive Innovators, Cautious Traditionalist, Aggressive Traditionalist, Prudent, Extremely Prudent*) 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-means clustering algorithm with the optimal number of groups determined by the Calinski and Harabasz (1974) index. *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. *significant at 10%; ** significant at 5%; *** significant at 1%

Manager Profile:	**(1) Cautious Innovator**	**(2) Aggressive Innovator**	**(3) Cautious Traditionalist**	**(4) Aggressive Traditionalist**	**(5) Prudent**	**(6) Extremely Prudent**
Entrenchment	-0.490***	-0.676***	0.643***	0.330	0.133*	0.764***
	(0.094)	(0.212)	(0.148)	(0.274)	(0.080)	(0.244)
Board independence	6.558***	-3.727**	-2.829**	-1.645	-2.151**	2.318
	(1.438)	(1.474)	(1.253)	(3.286)	(0.904)	(1.796)
Board size	0.022	0.049	0.074*	-0.267**	-0.030	-0.204***
	(0.034)	(0.042)	(0.039)	(0.121)	(0.031)	(0.073)
Female	-5.000***	-4.936*	0.370	5.619	1.378	12.706***
	(1.902)	(2.771)	(2.267)	(4.814)	(2.234)	(3.750)
Constant	-4.257***	-3.514***	-2.116*	-2.276	1.895*	-8.351***
	(1.259)	(1.280)	(1.127)	(3.190)	(0.999)	(2.611)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.271	0.355	0.283	0.394	0.105	0.454
Observations	212	212	212	212	212	212

Table 11. Manager Profiles and Bank CEOs

The table shows 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. Aggressive Traditionalist is a dummy equal to one f or managers that belong to the first cluster group, Cautious Traditionalist is a dummy equal to one for managers that belong to the third cluster group. Manager profiles (*Cautious Innovators, Aggressive Innovators, Cautious Traditionalist, Aggressive Traditionalist, Prudent Risk-Takers*) are binary variables and each manager is allocated to one manager profile based on 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)**
Dependent Variable		**Manager was CEO (0/1)**	
Birth year	-0.043***	-0.047***	-0.044***
	(0.013)	(0.013)	(0.013)
Male	0.328	0.432	0.471
	(0.396)	(0.386)	(0.389)
Depression baby	0.055	0.059	0.077
	(0.151)	(0.156)	(0.154)
Military service	-0.222	-0.234	-0.230
	(0.241)	(0.248)	(0.248)
MBA	0.243	0.239	0.205
	(0.262)	(0.265)	(0.260)
Ivy league	0.148	0.186	0.163
	(0.173)	(0.177)	(0.175)
Fast Track	-1.362***	-1.473***	-1.433***
	(0.437)	(0.432)	(0.433)
Nonbank experience (Non ex)	0.129	0.314	0.231
	(0.313)	(0.318)	(0.320)
Nonbank experience (Ex)	0.417**	0.530***	0.483***
	(0.176)	(0.181)	(0.176)
Generic	0.471**	0.632***	0.637***
	(0.218)	(0.228)	(0.225)
Cautious Innovators		0.037	
		(0.200)	
Aggressive Innovators		-0.224	
		(0.278)	
Cautious Traditionalist		0.202	
		(0.221)	
Aggressive Traditionalist		**1.018*** **	**0.976*** **
		(0.307)	**(0.287)**
Prudent Risk-Takers		0.110	
		(0.457)	
Constant	87.020***	94.252***	89.299***
	(26.173)	(26.666)	(26.268)
Pseudo- R^2	0.114	0.143	0.138
Observations	411	411	411

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 CORP/MA	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 the Manger Risk-fixed effect							
Equity volatility	Volatility of daily returns measured at annual intervals	3689	0.321	0.265	0.207	0.127	1.282
Value at risk	5% Value at Risk measured on daily stock returns at annual intervals	3689	0.043	0.035	0.029	0.016	0.177
Expected shortfall	5% Expected Shortfall measured on daily stock returns at annual intervals	3689	0.321	0.265	0.207	0.127	1.282
Variable employed in Crisis test							
Buy and Hold Return	Negative buy and hold Returns between 07/ 2007 – 12/2008	133	0.533	0.661	0.294	-0.002	0.947
Volatility	Volatility of daily returns between 07/ 2007 – 12/2008	133	0.054	0.050	0.017	0.033	0.101
Value at risk	5% Value at Risk between 07/ 2007 – 12/2008	133	0.071	0.067	0.016	0.047	0.113
Expected shortfall	5% Expected Shortfall between 07/ 2007 – 12/2008	133	0.116	0.110	0.034	0.073	0.197
MES	5% Marginal Expected Shortfall between 07/ 2007 – 12/2008	133	0.084	0.079	0.025	0.050	0.151
Market leverage	Total bank liabilities divided market value of equity plus total liabilities	133	0.806	0.804	0.044	0.710	0.892
Probability of default	Bank probability of default computed as described in Appendix 5 and multiplied by 1,000	133	0.006	0.000	0.015	0.000	0.066
Beta	Market beta derived from a linear regression of bank daily stock return to market daily stock return from S&P 500 Composite Index Return	133	1.007	0.926	0.280	0.577	1.773
Stock return 2006	Buy and hold return in year 2006	133	0.039	0.052	0.145	-0.443	0.322
Board Governance							
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_t} is the risk-free rate (proxied by the 1-year US 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 DDt 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. The global crisis and bank policies

The table shows OLS regressions with robust standard error clustered at bank level. The dependent variables are observed from 07/ 2007 – 12/2008 and include negative 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 when on the worst 5% days in terms of market returns. Definitions of all other variables are reported in Appendix 3. Robust standard errors clustered at the firm level are reported in round brackets. *significant at 10%; ** significant at 5%; *** significant at 1%

	(1)	(2)	(3)	(4)	(5)
	negative BHR	**Volatility**	**VaR**	**ES**	**MES**
Size	0.099*	0.003	0.002	0.009	0.009**
	(0.051)	(0.003)	(0.003)	(0.005)	(0.004)
Market leverage	0.870	0.069*	0.101**	0.123	0.053
	(0.644)	(0.038)	(0.044)	(0.081)	(0.039)
Probability of default	0.015	0.000	0.001	0.001	0.001
	(0.013)	(0.001)	(0.001)	(0.001)	(0.001)
Beta	-0.006	0.010*	0.010	0.020	0.003
	(0.126)	(0.006)	(0.007)	(0.012)	(0.007)
Stock return 2006	-0.099	-0.012	-0.011	-0.023	-0.026
	(0.284)	(0.013)	(0.014)	(0.030)	(0.018)
Entrenchment	0.002	0.000	0.000	0.000	0.000
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Vega	-0.499*	-0.021	-0.015	-0.038	-0.013
	(0.280)	(0.016)	(0.015)	(0.033)	(0.022)
Delta	0.038	0.010	0.008	0.012	-0.006
	(0.140)	(0.010)	(0.011)	(0.019)	(0.013)
Bonus	0.001	-0.000	-0.000	0.001	0.000
	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)
Economy	0.034	0.000	0.001	0.000	0.003
	(0.031)	(0.002)	(0.001)	(0.003)	(0.002)
Non-Interest income	-0.456	-0.028**	-0.034**	-0.054*	-0.040*
	(0.315)	(0.013)	(0.017)	(0.029)	(0.020)
Mortgage-backed securities	0.834	-0.047	-0.056	-0.160	-0.128*
	(0.834)	(0.047)	(0.066)	(0.110)	(0.070)
Derivatives	-0.003	0.002	0.002	0.002	0.005
	(0.067)	(0.005)	(0.004)	(0.010)	(0.007)
Securities	-1.503***	-0.041**	-0.048**	-0.081**	-0.020
	(0.362)	(0.016)	(0.020)	(0.036)	(0.021)
Gap12	-0.721***	-0.034**	-0.040**	-0.095***	-0.043**
	(0.269)	(0.014)	(0.016)	(0.033)	(0.020)
Commercial/real estate	0.147	-0.002	0.000	-0.002	0.004
	(0.111)	(0.005)	(0.005)	(0.010)	(0.007)
Lending diversification	-0.784***	-0.022*	-0.034**	-0.053*	-0.013
	(0.265)	(0.012)	(0.015)	(0.027)	(0.018)
Lending risk	3.876	0.045	0.374	-0.120	-0.665
	(9.720)	(0.395)	(0.456)	(0.924)	(0.698)
Wholesale funding	0.321	0.039	0.026	0.031	0.024
	(1.055)	(0.048)	(0.060)	(0.100)	(0.067)
Other short term funding	0.415	0.014	0.024*	0.037	0.027
	(0.309)	(0.013)	(0.014)	(0.027)	(0.019)
Constant	-1.216	-0.043	-0.046	-0.091	-0.089*
	(0.748)	(0.038)	(0.046)	(0.085)	(0.053)
Observations	82	82	82	82	82
Adj. R^2	0.523	0.316	0.356	0.349	0.354

Appendix 5: Results: Three way fixed effect model on the connectedness sample with sample selection correction

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 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 km 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. Definitions of all variables are reported in Table 2. *significant at 10%; ** significant at 5%; *** significant at 1%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	**Non interest income**	**Mortgage Backed**	**Derivatives**	**Securities**	**Gap12**	**Comm/real estate loans**	**Lending diversification**	**Lending Risk**	**Wholesale Funding**	**Other short funding**
Size $_{t-1}$	-0.021**	-0.012***	-0.046	-0.031**	-0.023	0.181***	0.013*	0.005***	0.002	0.023***
	(0.009)	(0.004)	(0.047)	(0.014)	(0.015)	(0.066)	(0.008)	(0.002)	(0.006)	(0.008)
Equity$_{t-1}$	-0.015	-0.019	-2.467***	-0.371***	-0.360	7.737***	0.268*	0.233***	-0.249**	-0.596***
	(0.138)	(0.039)	(0.579)	(0.137)	(0.246)	(2.310)	(0.144)	(0.045)	(0.100)	(0.156)
Market to book$_{t-1}$	0.006	0.003*	0.030	0.035***	0.031***	-0.111**	-0.002	-0.011***	0.016***	0.015**
	(0.006)	(0.002)	(0.032)	(0.008)	(0.011)	(0.051)	(0.005)	(0.002)	(0.005)	(0.006)
Core deposits $_{t-1}$	-0.025	0.052***	0.411*	0.140**	-0.149*	-0.790**	-0.030	0.008	0.073**	-0.048
	(0.058)	(0.020)	(0.247)	(0.058)	(0.087)	(0.332)	(0.037)	(0.011)	(0.030)	(0.046)
Loans $_{t-1}$	-0.062***	-0.010***	-0.080***	-0.024***	-0.011	-0.005	-0.022***	-0.004***	-0.006	0.004
	(0.008)	(0.002)	(0.019)	(0.009)	(0.010)	(0.016)	(0.003)	(0.001)	(0.004)	(0.006)
Vega $_{t}$	0.023*	-0.004	0.155***	-0.024**	-0.038	-0.087	0.001	0.005	0.011**	0.003
	(0.013)	(0.004)	(0.044)	(0.011)	(0.031)	(0.068)	(0.012)	(0.005)	(0.005)	(0.011)
Delta$_{t}$	-0.018	0.003	-0.105***	0.023**	0.040	0.084	0.000	-0.005	-0.008*	0.003
	(0.012)	(0.004)	(0.039)	(0.011)	(0.030)	(0.065)	(0.011)	(0.005)	(0.005)	(0.011)
Bonus $_{t}$	0.000	0.001***	-0.007**	-0.000	-0.001	0.010**	-0.000	-0.001***	-0.000	0.001
	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.000)	(0.000)	(0.001)
Economy $_{t}$	0.000	0.000***	0.004*	-0.000	-0.000	0.000	-0.000	0.000**	0.001***	-0.001
	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Inverse Mills ratio	-0.012	**-0.017****	**-0.252****	**-0.056****	**-0.139****	**0.573*****	**0.038***	-0.010	**-0.042*****	**-0.050****
	(0.024)	**(0.008)**	**(0.100)**	**(0.025)**	**(0.057)**	**(0.205)**	**(0.021)**	(0.007)	**(0.014)**	**(0.022)**
Observations	3,689	3,193	2,793	3,689	3,689	3,689	3,689	3,689	3,689	3,689
R^2	0.921	0.738	0.984	0.828	0.791	0.866	0.953	0.829	0.672	0.921
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 6: Comparing manager fixed effects estimated with and without sample selection correction

The table compares the results of regressions in Table 3, Panel A (not corrected for potential selection bias) and Appendix 5 (after correcting for selection bias using a Heckman (1979) two-step framework). *Non interest income* is divided by operating income, *MBS* are mortgage backed securities over total assets, *Derivatives* are trading contracts over total assets, *Securities* are held-to-maturity plus available for sale securities over total assets, *Gap12* is the 12-month liquidity gap by total assets. *Comm/real estate loans* is the Log of the ratio between commercial and real estate loans. *Lending diversification* is 1-Herfindahl index of the shares of real estate, C&I, consumer, and other loans out of total loans. *Lending risk* are loans that are past due ≥90 days or are on a nonaccrual basis over total loans. *Wholesale funding* is commercial paper and other borrowed funds with a remaining maturity of ≤1 year while *Other short funding* includes large deposits. *Correlation Coefficients* is the correlation between manager fixed effects in in Table 3, Panel A and Appendix 6. *Explained Variance* refers the % contribution of manager fixed effects (styles) to the R^2 of bank policy variables after decomposing the policy variables into the fitted components, manager fixed effects, firm fixed effects and the residuals.

	N	Correlation Coefficients	Explained Variance due to Manager FE No Correction (%)	Explained Variance due to Manager FE After Correction (%)
1. Non interest income	774	0.9999	23.20	23.19
2. Mortgage-backed Securities	667	0.9967	23.70	22.73
3. Derivatives	585	0.9995	44.29	44.90
4. Securities	774	0.9967	28.64	28.43
5. Gap12	774	0.9947	37.11	36.56
6. Commercial over real estate loans	774	0.9732	23.56	22.91
7. Lending diversification	774	0.9983	23.35	23.61
8. Lending risk	774	0.9972	14.01	14.35
9. Wholesale funding	774	0.9935	22.78	22.89
10. Other short term funding	774	0.9977	20.06	20.52
Average		**0.9947**	**26.07**	**26.01**

Appendix 7 Manager Profiles and Risk

The table shows OLS regressions with robust standard error clustered at bank level. The dependent variables are observed from 07/ 2007 – 12/2008 and include negative 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 when on the worst 5% days in terms of market returns. Definitions of all other variables are reported in Appendix 3. *Innovator* is equal to one if manager are classified as either a Cautious Innovator or an Aggressive Innovators. *Traditionalist* equals to one for managers classified as Cautious or Aggressive Traditionalists. Robust standard errors clustered at the firm level are reported in round brackets. *significant at 10%; ** significant at 5%; *** significant at 1%

	(1)	(2)	(3)	(4)	(5)
	negative BHR	**Volatility**	**VaR**	**ES**	**MES**
Size	0.090	0.001	-0.001	-0.000	0.008**
	(0.058)	(0.003)	(0.002)	(0.007)	(0.004)
Market leverage	2.836**	0.250***	0.275***	0.453***	0.197**
	(1.303)	(0.050)	(0.057)	(0.109)	(0.080)
Probability of default	6.114**	0.172**	0.311***	0.400**	0.052
	(2.277)	(0.075)	(0.096)	(0.156)	(0.108)
Beta	-0.263	-0.008	-0.016	-0.027	0.003
	(0.245)	(0.011)	(0.010)	(0.025)	(0.014)
Stock return 2006	0.054	-0.028	-0.020	-0.045	-0.015
	(0.434)	(0.016)	(0.016)	(0.037)	(0.022)
Entrenchment	0.071*	0.004*	0.003**	0.007	0.007**
	(0.040)	(0.002)	(0.002)	(0.005)	(0.003)
Vega	-0.569**	-0.018	-0.007	-0.034	-0.030
	(0.235)	(0.016)	(0.012)	(0.031)	(0.018)
Delta	0.141*	0.009	0.003	0.013	0.011
	(0.074)	(0.006)	(0.004)	(0.011)	(0.007)
Bonus	0.009	-0.000	0.000	0.001	-0.000
	(0.011)	(0.001)	(0.001)	(0.001)	(0.001)
Economy	-0.000	0.000	0.000	0.000	0.000
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Innovator	0.054	**0.016****	**0.011****	**0.033***	0.013
	(0.113)	**(0.008)**	**(0.005)**	**(0.017)**	(0.012)
Traditionalist	0.024	0.001	0.004	-0.004	-0.011
	(0.132)	(0.004)	(0.006)	(0.011)	(0.007)
Constant	-2.634***	-0.162***	-0.146***	-0.279***	-0.189**
	(0.704)	(0.052)	(0.033)	(0.098)	(0.082)
Observations	145	145	145	145	145
Adjusted R^2	0.455	0.549	0.570	0.497	0.671