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Model Uncertainty and Systematic Risk in US Banking☆

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Abstract

This paper uses Bayesian Model Averaging to examine the driving factors of equity returns of U.S. Bank Holding Companies. BMA has as an advantage over OLS that it accounts for the considerable uncertainty about the correct set (model) of bank risk factors. We find that out of a broad set of 12 risk factors only the market, real estate, and high-minus-low Fama-French factors are reliably related to US bank stock returns over the period 1986-2010. Other factors are either only relevant over specific subperiods or for subsets of bank holding companies. We discuss the implications of our findings for empirical banking research.

JEL: G01, G20 G21, G28, L25

Keywords: Bayesian Model Average, Banking Risk, Bank Stock Returns
PACS: Bank Supervision, Financial Stability

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1. Introduction

The nature of their business exposes banks to various types of risk. Not only may these risks fluctuate over time as economic conditions change, also the exposure of banks to these risks may vary over time. Regulators and supervisors rely on a smorgasbord of tools to track these (time-varying) risk exposures. One set of indicators relies on market prices, such as bank stock market returns. These indicators can be obtained by relating bank stock returns to various risk factors, such as market, interest rate, and other relevant risks. The challenge for regulators and supervisors is to discover which risk factors are relevant for which types of financial institutions at a specific point in time. However, based on a broad literature survey, it is fair to state that there is little consensus on the risk factors, apart from the market factor, that drive bank stock returns. This is clear from Table 1 which gives an overview of the different (combinations of) risk factors that have been used in the literature so far. The 24 papers we refer to have related bank stock returns to various combinations of no less than 17 different risk factors. The uncertainty about which risk factors to include in a bank factor model is labeled "model uncertainty". In this paper, we implement a Bayesian framework that explicitly takes into account the uncertainty about the relevant set of factors ("model uncertainty"). We apply this methodology to US Bank Holding Companies over the period $1986 - 2010$.

Our paper contributes to an expanding literature that measures banking risk as the exposure of bank (sector) stock returns to some set of predefined risk factors. In contrast to other papers, we do not impose a specific return-generating process. When estimating only one model, the researcher imposes the chosen model on the data and the only uncertainty that is considered is parameter uncertainty, where one typically interprets the coefficients of significant variables. The uncertainty about which risk factors to include (model uncertainty) is typically ignored. In this paper, we explicitly take model uncertainty into account by using Bayesian Model Averaging techniques to estimate bank factor models. To the best of our knowledge, we are the first to apply Bayesian Model Averaging in the banking literature[1]. Suppose that the literature offers a list of k potential explanatory risk factors. In the set of linear factor models, 2^k different model combinations can be made, where each model consists of (a subset of) the explanatory variables. Using Bayesian Model Averaging techniques, we are able to account for this considerable model uncertainty. BMA compares all models simultaneously, as opposed to conditioning on a single individual model. Each individual model is attributed a posterior probability and the posterior parameter estimate is obtained as the weighted average of the pa-

[1]Bayesian Model Averaging (BMA) was first developed by Leamer [44], and has since been used in several disciplines, ranging from statistics (Raftery, Madigan, and Hoeting [52] and Hoeting, Madigan, Raftery, and Volinsky [36]), over a large literature on cross-country growth regressions (Fernandez, Ley, and Steel [24], Brock and Durlauf [8] and Sala-I-Martin, Doppelhofer, and Miller [53] among others) to finance (Cremers [14], Avramov [4] and Wright [66]).

rameters over the different models, where the posterior model probabilities are used as weights. Because this approach considers all models simultaneously, we obtain useful insight into the importance of each regressor. For each risk factor, we can compute its posterior inclusion probability, i.e. how likely it is that a particular risk variable is part of the model, making it a useful tool to evaluate the relevance of the different risk factors.

In the first part of the analysis, we compare the results of BMA versus OLS in explaining the impact of various risk factors on the returns of a banking index. More specifically, we relate weekly excess returns of an equally-weighted portfolio of the 50 largest (in terms of total assets) US Bank Holding Companies to innovations in the different risk factors. In the exposition of the advantages of BMA, we use an index of the 50 largest BHCs. In subsequent parts, we use various alternative indices (such as large, systemically important BHCs). We cover most of the candidate risk factors that have been previously used in the literature, but also introduce some risk factors that have received attention only in recent times, such as the volatility implied by option prices or indicators of interbank stress risk. Details on the motivation for including these factors and on their construction can be found in Section 1.2. Full sample $(1986-2010)$ results reveal that the market and real estate factor, as well as the high-minus-low book-to-market Fama-French factor, are the most important risk factors, with posterior inclusion probabilities close to a 100 percent. Other factors, maybe with the exception of the 3-month T-Bill rate, do not seem to be reliably related to the returns on the broad bank index. We show that our BMA approach that takes into account model uncertainty leads to different conclusions than one that does not (OLS). Moreover, our results indicate that there is no correct or dominant model. The most likely model has a posterior model probability of less than 25%, suggesting that accounting for model uncertainty is important.

In the second part of the analysis we investigate whether or not bank factor models vary over time or differ according to the type of bank holding companies. In a first step, we estimate the BMA model with the same set of risk factors on a pre- and post 2007 sample. In a more general analysis, we conduct rolling-window BMA regressions, basically re-estimating the BMA model each quarter using two years of weekly data. We find that factors such as the implied volatility index and term and default spread frequently switch between being economically and statistically relevant or not. Hence, specific periods (typically those characterized by increased financial market stress) may be associated with different bank risk exposures, which may have implications for, e.g., the supervision of bank risk or cost of capital considerations. Differences across studies with respect to the most relevant risk factors may hence not only be due to a failure to account for model uncertainty, but may also be the consequence of looking at different periods. In fact, some factors may be 'dormant' for a long time, and hence undetectable in short (tranquil) samples, to suddenly appear in times of market stress.

We also compare the results of our baseline portfolio of the 50 largest Bank Holding Companies with alternative portfolios of BHCs. In particular, within the sample of Bank Holding Companies (BHCs), we differentiate between various 'types' by constructing portfolios of BHCs according to size (largest 15 versus smallest 50), sound versus distressed BHCs and BHCs with a stable retail focus versus systemic stress-prone banks. Details on the construction of these portfolios are mentioned in Section 1.1. The general conclusion from this analysis is that while the relevant set of exposures does vary substantially over time, it is relatively stable across bank types.

Finally, we discuss some implications of our findings for empirical banking research based on stock returns. In fact, return-generating models of bank stocks are not only a useful (supervisory) tool to uncover risk exposures, but also serve as an input in various setups in empirical banking research. For example, computing abnormal returns in event studies requires the specification of a benchmark model. Additionally, residual-based measures of uncertainty (idiosyncratic volatility) or transparency (R-squared) require an accurate identification of risk factors and a correct specification of the factor model. Accurate measures of banks' exposures to stock market movements (e.g. to compute capital charges for systematic risk) also hinge on the correct specification of a factor model. In Section 4, we discuss the implications of our findings for these setups.

The paper is organized as follows. Since this paper is essentially empirical, we start with a detailed description of the data used in this paper. Subsection 1.1 explains how the overall bank index and the cross-sectional portfolios sorted on bank characteristics are constructed. Subsection 1.2 motivates our choice of the set of risk factors and discusses their construction. Section 2 presents the BMA framework we use to analyze the importance of the risk factors. Section 3 discusses the main empirical results. In subsection 3.1, we present results from models with time-invariant risk exposures. In subsection 3.3, we allow for time variation in the model specifications as well as time variation in the significance and magnitude of the factor exposures. We discuss the implications of our findings for different strands of empirical banking research (event studies, market risk, idiosyncratic volatility) in Section 4. Section 5 concludes.Data

1.1. Portfolio construction

Our initial analysis is conducted on a portfolio of the 50 largest (based on total assets) US Bank Holding Companies (BHCs, henceforth) over the period 1986 – 2010. The set of BHCs is rebalanced quarterly to reflect the actual, time-varying ranking. The portfolio return is an equally weighted average of the underlying weekly returns and measured in excess of the 3-Month Treasury Bill rate. In addition to this portfolio of large US BHCs, we also examine in Section *3.2* portfolios of BHCs with a specific business model.

We construct portfolios according to size (large versus small), sound versus distressed banks, and BHCs with a steady retail versus an expansionary, systemic risk-prone strategy. To define the universe of publicly traded BHCs and relate the stock price information to accounting data, we use the link provided by the New York Fed[2]. We construct two portfolios based on a size criterium:

[2]This link is only available until the end of 2007, but is manually extended until the end

the **largest** 15 BHCs and the **smallest** 50 BHCs, based on total assets (and quarterly rankings). In contrast to small BHCs, the largest 15 banks operate nationwide, are more interconnected through interbank payments or correlated exposures and may benefit from implicit too-big-to-fail guarantees. **Sound** versus **distressed** banks are determined based on two characteristics: profitability and leverage. A bank is considered to be sound (in a given quarter) if it belongs to the highest quartile in terms of both return on assets and the equity-to-total-assets ratio. Sound banks are hence profitable and protect this source of franchise value by means of prudent capitalization. A bank is categorized as distressed in a given quarter if it is combining low profits and high leverage (lowest quartile of ROA and equity to assets). We purposely identify sound and distressed BHCs using two dimensions to distinguish them from (successful) gambling (poorly capitalized with high profits) or bad luck (low profits while strongly capitalized). Finally, we construct a portfolio of BHCs with a steady **retail focus** and one of **expanding, tail risk-prone BHCs**. De Jonghe [15] and Fahlenbrach, Prilmeier, and Stulz [20] show which bank characteristics make banks more subject to extreme systematic risk. Large and expanding banks with low leverage, a reliance on wholesale funding and focused on non-interest income generating activities experienced the largest stock price drops in the 1998 and $2007-08$ crises (Fahlenbrach, Prilmeier, and Stulz [20]) and have higher tail betas (De Jonghe [15]). To construct these two portfolios, we take the following steps. First, we compute, by quarter, the quartiles of each of the following five dimensions: size, asset growth, leverage, wholesale funding and share of interest income; and allocate a score of 1 to 4 to the corresponding quartile. Subsequently, we sum the quartile-based scores and obtain an index between 5 and 20. Tail risk-prone banks are those with a score of at least 17, implying that they should score high in almost all dimensions, while retail banks are those with a score of eight or less.

Summary statistics of the returns on the various portfolios are reported in panel A of Table 2, while Table 3 provides more detailed information on the (variables used in the) construction of the portfolios. The average annualized return on the portfolio of the largest 50 BHCs is 14.1%. Systemic risk-prone BHCs earned a higher annualized return over the period $1986-2010$. While most portfolios yield an annualized return of almost 10% or higher, the distressed BHC portfolio's return is almost zero. Larger BHCs, sound or tail-risk prone BHCs yield a higher annualized return vis-à-vis small, distressed or retail-oriented BHCs. In general, the correlations between contrasting portfolios of BHCs (large versus small, sound versus distressed, and retail versus tail risk-prone) are slightly lower than the average pairwise correlation indicating that we are indeed identifying types of BHCs with different strategies.

More evidence on the heterogeneity between the identified BHC types is

of 2010. Similar to the procedure described by the NY Fed, we use information of the SNL financial database containing all publicly traded bank holding companies in a quarterly file format.

reported in Table 4. For each constructed portfolio of BHCs, we report the average value of a set of bank characteristics as well as the p-value of a difference in means test for the opposite portfolios. The largest 15 versus smallest 50 BHCs portfolios are determined only based on total assets, which is reflected in the large difference in the logarithm of their total assets. However, large and small banks also differ substantially in their level of capitalization, reliance on deposit funding and loan granting, and consequently also in the source of income (mainly interest income for small banks). Sound, high franchise value banks are contrasted with distressed banks based on their level of capitalization and profits. Distressed banks hold 50% less Tier 1 capital compared to sound banks and are loss-making over the sample period. In addition, the BHCs in these two portfolios differ markedly in the amount of loan loss provisions as well as their cost effectiveness. Poor credit risk management and inefficient cost management lead to undercapitalization and poor profitability. Retail banks are differentiated from diversified, wholesale-oriented banks in many dimensions. By construction, the retail banks are smaller, better capitalized, experience stable (near zero) growth, and focus more on retail deposits and interest income generating activities as compared to tail risk-prone financial conglomerates. Nevertheless, they are equally profitable and cost efficient and provision similarly for potential credit risk.

1.2. Bank Risk Factors

Excess bank stock returns reflect changes in the market value or net worth of a (portfolio of) bank(s). Hence, stock returns reflect the market's assessment of the banks' profit potential and risk profile. Saunders and Cornett (2014) identify the following sources of risk that affect banks' net worth: interest rate, credit, liquidity, foreign exchange, sovereign, market, off-balance sheet, and technology risks.We follow the labelling of Saunders and Cornett [54] and classify innovations in a total of twelve factors, which have been used in the previous literature, to one of five broad risk categories. [3]

1.2.1. Interest Rate risk

A financial intermediary is, through its activity of maturity transformation, exposed to interest rate risk caused by differences in the duration of its assets and liabilities. Table 1 shows that, since Flannery and James [26], most studies include at least one interest rate factor. Usually, it is the short-term interest rate, but it is often combined with either the term spread or a long-term interest rate. As a short-term interest rate risk factor, we include the three-month Treasury bill rate (**TB3**). As a second interest rate risk factor, we include the term spread (**TS**), calculated as the difference between the yield on a 10-year government bond and the three-month Treasury bill rate[4]. In models with both the short rate and the term spread, the short rate captures the effect of a parallel shift in the term structure, while the term spread tests for the effect of a change in the slope of the term structure of interest rates. As the duration of bank liabilities is usually shorter than the duration of banks' assets, we expect rate increases to negatively affect bank stock returns. However, not finding a significant exposure does not necessarily mean that banks are not exposed to interest rate risk, but that they may have succesfully hedged their exposure, e.g. by means of interest-rate derivatives.

1.2.2. Credit Risk

We include two proxies for credit risk, one related to exposures to corporate credit risk and one related to real estate exposures. As a measure of economy-wide (corporate) default risk, we include the yield difference between Moody's BAA and AAA-rated corporate bonds (**DS**), i.e. the yield difference between bonds with the lowest and highest investment-grade rating. Because a rise in

[3] Saunders and Cornett [54] identify 8 risk factors, of which we include five. We do not include a proxy for country risk as all financial institutions in the sample are incorporated in the US. Furthermore, technology and operational risk are mostly idiosyncratic and discrete events, and are therefore also not included as a systematic risk factor. Off-balance sheet risk is not incorporated directly, but is indirectly captured by the five other risk categories. For example, market sentiment, proxied by the VXO implied volatility index, should provide an indication of the likelihood with which contingencies arise that mover off-balance sheet assets and liabilities on the balance sheet.

[4] We do not include the long-term interest rate to avoid perfect multicollinearity as we already include the short rate and term spread, defined as the difference between the long and the short rate.

the default spread increases the probability of losses in the bank's loan portfolio, we expect a negative relationship between bank stock returns and innovations in the default spread.

The largest share of loans in banks' overall loan portfolio are residential and commercial real estate loans. Hence, decreasing real estate prices may affect the value of banks negatively directly through their effect on the expected value of outstanding mortgages, or indirectly through the resulting drop in the value of mortgage-backed securities. While there exist several proxies for price movements in the US real estate market (such as the Case-Shiller index), none of them is available at a daily or weekly frequency. Inspired by the work of Adrian and Brunnermeier [2], we construct a value-weighted real estate index (**RE**) of all publicly traded real estate companies (with (header) SIC (major group) code 65[5]) from CRSP.

1.2.3. Liquidity risk

Banks provide liquidity to the economy (by financing illiquid assets with liquid claims) but this may pose a risk when liability holders demand immediate cash for the claims they hold with the banks. We include three liquidity risk factors, corresponding with the three main groups of liability holders: banks, retail depositors and wholesale financiers. Banks strongly rely on each other for their day-to-day liquidity management. Uncertainty about other banks' solvency creates tensions on the interbank market. As an indicator of credit risk in the financial system, potentially leading to interbank market freezes, we include the Treasury-EuroDollar spread (**TED** spread), defined as the difference between the three-month LIBOR and the three-month Treasury bill rate (IMF [38] and Garleanu and Pedersen [28]). We expect bank stocks to react negatively to shocks in the TED spread[6], because a widening of the spread is an indication of increased distress risk, and hence a loss of trust, in the financial sector.

As a measure of liquidity tightness in the market of deposits, we use the spread between the three month deposit rate (three month unregulated time deposit) and the three month Treasury Bill rate (**DepS**) (see e.g. Dewenter and Hess [17]). The sign is unpredictable. On the one hand, deposit inflows that are seeking a safe haven during crisis periods provide banks with a natural hedge to fund drawn credit lines and other commitments (Gatev and Strahan [29]). On the other hand, the banking system in its role as a stabilizing liquidity insurer acts as an active seeker of deposits via managing bank deposit rates (Acharya and Mora [1]). The third liquidity measure is the difference between

[5] SIC code 65 consists of the following subgroups: 6510 (real estate operators (no developers) & lessors), 6512 (operators of nonresidential buildings), 6513 (operators of apartment buildings), 6519 (lessors of real property), 6531 (real estate agents & managers (for others)), 6532 (real estate dealers (for their own account)), 6552 (land subdividers & developers (no cemeteries)).

[6] The three-month LIBOR-OIS (overnight index swap) spread would be an alternative to the TED spread (Giesecke and Kim [31]) but is unfortunately not available over the entire period 1986-2010.

the Federal Funds Overnight rate and the three month LIBOR rate (**MMS**, i.e. money market spread), which measures tightness in the wholesale funding market, in particular the money market (see e.g. Taylor and Williams [63]). Since MMS is related to funding conditions in the more volatile money market, we expect it to be a more important risk factor in times of financial market stress.

1.2.4. Foreign Exchange risk

Large banks may have exchange rate exposure, e.g. through foreign lending or derivative exposures. As a measure of currency risk (**FX**), we use the Nominal Major Currencies Index, available from the Federal Reserve Board's H 15 filings. An increase in the index is associated with an appreciation of the USD with respect to a trade-weighed basked of (main) currencies. Such appreciation of the USD will affect banks either negatively or positively, depending on whether they are long or short the foreign currency (see e.g. Chamberlain, Howe, and Popper [9]).

1.2.5. Market risk

As a proxy for market risk, we include returns on a broad equity market portfolio (**Market**), which is the only factor that is common to all studies explaining (bank) stock returns. This exposure, or 'market beta', measures how sensitive returns are to aggregate market movements, and hence to changes in general economic and financial market conditions. As a proxy for the market portfolio, we use the Non-Financial Market Index from Datastream (code TOTLIUS). We use a market index excluding the financial sector to avoid spurious results. We additionally include the VXO implied volatility index[7] to capture market sentiment. The **VXO** is a forward-looking risk measure that has predictive power for returns at relative short horizons (up to 3 months), and hence differs from other state variables that have predictive power (if any) beyond that horizon (see e.g. Londono [48]). We expect bank stock returns to have a negative exposure to VXO innovations.

Since the seminal work of Fama and French [22], a large literature has emerged showing that stock returns are not only related to market returns, but also to returns on a size and a value factor[8]. We use the size (**SMB**) and value (**HML**) factors made available by Kenneth French on his website. Both the size and value factor earn a positive risk premium, implying that risk increases

[7]This is a weighted index of American implied volatilities calculated from eight near-the-money, near-to-expiry, S&P 100 call and put options with a 1 month maturity. We use the VXO rather than the better known S&P500-based VIX index because the former is already available from 1986 on (compared to 1990 for the VIX index). Notice that the VIX and VXO index overlap perfectly until 22 September 2003, as until that date also the VIX was based on S&P100 option prices. In the post 2003 period, both indices remain highly correlated.

[8]The size factor is calculated as the difference in return between small and large stocks (SMB); the value factor is the difference in return between stocks characterized by high and low (HML) book-to-market value.

with exposures to both factors. Liew and Vassalou [46] argue that persistently high Book-to-Market stocks face a higher risk of distress and that they are more likely to survive when the economic outlook is good rather than bad. Similarly, small capitalization stocks are more likely to do well during periods of economic growth, and more likely to be the first to disappear during periods of economic slowdown. The vulnerability of high Book-to-Market and small capitalization stocks to changes in the economic cycle leads to a positive link between the performance of the HML and SMB strategies and future economic growth. In sum, both the size and value factor seem to contain information about the future state of the economy not captured by the market factor alone, and are hence also candidate risk factors for bank stock returns.

1.2.6. Summary

To summarize, we relate excess returns to a total of twelve risk factors, which are classified in five groups. According to the efficient market hypothesis, we only expect a relationship between bank stock returns and *unanticipated* changes in risk factors. To ensure that we capture unexpected movements in the risk factors, we take the residuals from an $AR(n)$ model for each risk variable, where n is determined by the Schwarz Bayesian Information Criterion. Panel B of Table 2 reports summary statistics for the different factor shocks (and reports both the name and abbreviation used throughout the paper), as well as the expected signs of the factor exposures.

2. Bayesian Model Averaging

This section outlines Bayesian Model Averaging in the normal linear regression model. We focus on the big picture and relegate a more detailed but technical discussion to an online appendix. As in Magnus, Powell, and Prufer [50], we start from:

$$y = x_1\beta_1 + x_2\beta_2 + \varepsilon, \quad \varepsilon \sim N\left(0, \sigma^2\right) \tag{1}$$

where y and ε are $(T \times 1)$ vectors of bank index returns and random disturbances, respectively. x_1 denotes the $(T \times k_1)$ matrix of regressors that are always included, i.e. for which no model uncertainty exists. In our application, x_1 is simply a constant term, so that $k_1 = 1$. x_2 is an $(T \times k_2)$ matrix of at most k_2 (contemporaneous) explanatory variables for bank stock returns. β_1 and β_2 are the unknown parameter vectors. We assume that the disturbances $(\varepsilon_1, ..., \varepsilon_T)$ are independently and identically distributed. Model uncertainty implies that the researcher does not know ex ante what regressors in x_2 are reliably related to the dependent variable y. Given k_2 explanatory variables, there are in total $K = 2^{k_2}$ different model combinations (in the linear case). Let $M^{(k)}$ denote model k under consideration, then

$$y = x_1\beta_1 + x_2^{(k)}\beta_2^{(k)} + \varepsilon \tag{2}$$

with $x_2^{(k)}$ a subset of matrix x_2 with dimension $(T \times k_2^{(k)})$, and $\beta_2^{(k)}$ the corresponding parameter vector.

We use standard non-informative priors for the parameters that are common to all models, namely σ^2 and β_1. The prior for β_2, Equation (3) is informative and centered around zero:

$$p\left(\beta_2^{(k)} | \beta_1, \sigma^2, M^{(k)}\right) \propto N\left(0, \sigma^2 V_0^{(k)}\right) \tag{3}$$

We specify the prior variance $V_0^{(k)}$ using Zellner's (1986) g-prior. Following Fernandez, Ley, and Steel [23] among others, we set $g = inv(\max(n, k_2^2))$ and assume

$$V_0^{(k)} = g^{-1}(x_2^{(k)} M_1 x_2^{(k)})^{-1} \tag{4}$$

where $M_1 = I_n - x_1(x_1^{'}x_1)^{-1}x_1^{'}$. The attractive feature of this prior is that it becomes weaker the more informative the data is, either because the sample size T or the number of explanatory variables k_2 is large. With respect to model prior probabilities, we simply follow standard practice and assume that each model $M^{(k)}$ is equally likely[9]:

$$p(M^{(k)}) = \frac{1}{K} \tag{5}$$

[9] We do check the robustness of our results to alternative priors, such as the collinearity adjusted dilution prior of George [30].

Under the normal linear regression framework, the likelihood function, assuming model $M^{(k)}$ is the most likely model, is given by

$$p\left(y \mid \beta_1, \beta_2^{(k)}, \sigma^2, M^{(k)}\right) \propto \left(\sigma^2\right)^{-n/2} \exp\left(-\frac{\left(y - x_1\beta_1 + x_2^{(k)}\beta_2^{(k)}\right)' \left(y - x_1\beta_1 + x_2^{(k)}\beta_2^{(k)}\right)}{2\sigma^2}\right) \tag{6}$$

By combining the likelihood function and the priors, given the data y and model M_k, one obtains the joint posterior density on a specific model. However, our goal is to combine information from multiple models. Given the data y and a prior model probability for model $M^{(k)}$ (Equation (5)), the posterior model probability[10] - the probability that model $M^{(k)}$ is the most likely model, after seeing the data and updating the prior belief - can be expressed as

$$p(M^{(k)}|y) = \frac{p(M^{(k)})p(y|M^{(k)})}{\sum_j p(M^{(j)})p(y|M^{(j)})} = \lambda^{(k)} \tag{7}$$

where $p(y|M_k)$ is the marginal likelihood, and $\sum_{k=1}^{K} \lambda^{(k)} = 1$.

The posterior parameter estimates are calculated as the weighted average of the parameter estimates over the different models, using the posterior model probabilities $\lambda^{(k)}$ as weights:

$$E(\beta_{2i}|y) = \sum_{k=1}^{K} \lambda^{(k)} \cdot E(\beta_{2i}^{(k)}|y, M^{(k)}) \tag{8}$$

where $E(\beta_{2i}^{(k)}|y, M^{(k)})$ is the estimate for the slope parameter β_{2i} given model $M^{(k)}$. Following Leamer [45], the posterior variance is defined as

$$V(\beta_{2i}|y) = \sum_{k=1}^{K} \lambda^{(k)} \cdot V(\beta_{2i}^{(k)}|M^{(k)}) + \sum_{k=1}^{K} \lambda^{(k)} \cdot \left[E(\beta_{2i}^{(k)}|y, M^{(k)}) - E(\beta_{2i}|y)\right]^2 \tag{9}$$

The posterior variance of β_{2i} consists of two terms: the first is the weighted sum of the variances across all models, whereas the second terms depends on the difference between the posterior mean (equation 8) and the model specific estimates $E(\beta_{2i}^{(k)}|y, M^{(k)})$. Hence, if the parameter estimate is very dispersed across models, this implies larger model uncertainty which is translated into larger parameter uncertainty.

[10] In a traditional setup, researchers may use the Akaike's information criterion (Akaike [3]), the Schwarz's criterion (a Bayesian information criterion, Schwarz [57]) or the Fisher's information criteria (Wei [65]), among others (Bossaerts and Hillion [7]) to select a single, most likely model. Because researchers may 'search' for the best specification among a set of alternatives, data snooping and overfitting are genuine concerns, in particular when there are many plausible risk factors that are potentially correlated. Our approach, on the other hand, does not seach for a unique model, but averages over all possible linear models giving a higher weight to more likely models.

The key ambition of this paper is to determine what regressors are reliably related to bank stock returns. For this reason, one of the most important metrics for our purpose is the "Posterior Inclusion Probability (PIP)", which measures the likelihood that a certain regressor should be included in the "true" model. Following Leamer [45], the PIP is calculated as the sum of the posterior model probabilities of the models that include variable x_{2i} with $i = 1, ..., k_2$:

$$p(x_{2i}|y) = \sum_{k=1}^{K} \lambda^{(k)} \cdot I(x_{2i} \in x_2^{(k)}|y, M^{(k)}) \tag{10}$$

where I is an indicator equal to one if the variable x_{2i} is present in model $M^{(k)}$ and zero otherwise.

3. Empirical Results

3.1. Bayesian Model Averaging: Full Sample Results

3.1.1. Baseline Results

Table 5 reports estimation results for our baseline specification, which relates returns on the index of the 50 largest BHCs to the 12 bank risk factors discussed in Section 1.2. In the top panel, we report for each risk factor (12 columns) the OLS factor exposure and t-statistic, the BMA factor exposure and t-statistic as well as the Posterior Inclusion Probability of that factor. The most striking finding is that only three factors, namely the market, HML, and real estate factor, have a Posterior Inclusion Probability (PIP)[11] close to a 100 percent, strongly suggesting that these three factors should always be included in a model for bank stock returns. All other factors, including the interest rate factors, have PIPs and factor exposures close to zero. The PIP of the short rate is slightly higher (47%), but still below 50%. This finding is surprising, and challenges the predictions of many (theoretical) models of banking risk that give a prominent role to interest rate risk (see e.g. Flannery and James [26]). The fact that the market factor is important is not suprising, and neither is its magnitude (close to 1). The HML and real estate factor are absent in all but 2 and 1 of the papers listed in Table 1, respectively. Our results suggest that they are more reliably related to bank stock returns than more frequently used regressors. The HML exposure has a positive sign, as expected given its positive (negative) association with future economic growth (distress risk). Given that booming and subsequently rapidly decreasing housing prices were one of the key causes of the financial crisis that started in 2007, our finding of a positive and significant association of our real estate factor with bank stock returns is neither surprising.

BMA also provides information on how likely a given model is. In fact, an individual regressor will have a large PIP to the extent that it is part of the most likely models. Panel C of Table 5 reports the 10 specifications with the highest model probability. For each model, we report the model's likelihood, what factors it contains, as well as its adjusted R-squared. A first observation is that the 12 factor model is not among the top 10 models. The richest top 10 model contains at most 5 factors. Not surprisingly, the market, HML, and real estate factor are part of all these models (thus leading to a PIP of 100%). Second, a model consisting of only these three factors is the most likely.

[11] In addition to the posterior mean and the posterior inclusion probability of the coefficient, we also compute the sign certainty statistic, as used in Sala-I-Martin, Doppelhofer, and Miller [53] and Doppelhofer and Weeks [18]. This is a measure of the posterior confidence in the sign of the coefficient, and it is calculated as the posterior probability that the coeffcient is on the same side of zero as its mean conditional on inclusion. We find that the sign certainty statistic is very much in line with the posterior inclusion probability of the risk factors. When the posterior inclusion probability of a variable is high (such as for the market factor, the HML and the real estate factor), the sign certainty statistic is also high, meaning that we can be quite confident about the direction of the impact of a change in the risk factor on bank stock returns.

Nevertheless, it has a posterior model probability of 'only' 23.83%. One other specification (which also includes the T-bill rate) is almost as likely and has a PMP of 23.5%. None of the other models has a posterior model probability exceeding 7.5%. Alternative models include other factors (2 of the top-10 models include the default spread or money market spread; the TED spread, the deposit spread, the effective exchange rate, and the VXO each appear once), but have much lower PMPs (7.3 percent for the $3rd$ most likely model to only 1.8 percent for the $10th$ most likely model). Fourth, while PIPs are in general much better in discriminating between good and bad models (see e.g. Ciccone and Jarocinski [13]), it is still worth noting that the differences in adjusted R^2 between a specification with just the market, HML, and real estate factor and more elaborate models is rather small, casting serious doubt on the usefulness of these additional factors in explaining bank stock returns.

3.1.2. BMA versus OLS

To what extent does BMA lead to different conclusions than plain OLS, i.e. to a model that ignores model uncertainty? Clearly, as can be seen from Panel A, the risk factors with PIPs of 100 percent (market, HML, real estate) also have the largest OLS t-statistics, and are all significant at the 1 percent level. Yet, the results based on an OLS estimation of the model that imposes all 12 risk factors to be present would have concluded that also the 3 month T-bill, interbank distress (MMS) and market sentiment (VXO) are significantly related to bank stock returns, while the PIPs of especially the latter two are far below 50%.

To better understand the difference between OLS and BMA, Panel B reports for each specific risk factor the proportion of significant coefficients (at the 10, 5, 1 percent level) obtained from OLS regressions of the banking sector returns on a constant, the market, and the specific risk factor on the one hand, and all other potential combinations of the remaining 10 risk factors on the other hand. This exercise confirms the relevance of the HML and real estate factor, as they are significant at the 1 percent level irrespective of the (combination of) other risk factors included. What is striking, however, is that a significant relationship (at the 5% level) is found in 87.8% of model combinations for the 3-month Treasury bill rate, in 53.6% of cases for the SMB factor, 50.6% for the market sentiment indicator, and 21.9% for the money market spread. The low PIPs for these risk variables indicate, however, that the model combinations for which OLS finds significance must have a very low posterior model probability. In other words, a researcher that imposes a particular model has a high probability of finding a signifcant slope estimate for these risk factors, but is unaware that the imposed model has a very low model probability within the (large) potential set of model specifications.

Ignoring model uncertainty may not only lead to false conclusions about what the relevant risk factors are, but may also have strong effects on the estimated magnitude of the economic relations. For instance, the OLS slope coefficient for the three-month Treasury bill is more than three times as large as the one estimated using BMA (-2.37*** versus -0.69). We observe similar differences for many of the other risk factors. The magnitude of the BMA slope coefficients is lower because the models with large estimated parameters (in absolute magnitude) happen to have a much lower model probability than those with small and insignificant estimates. In contrast, the low uncertainty about the inclusion of the market, HML, and real estate factor is reflected in the small differences between the OLS and BMA factor exposures.

To analyze whether BMA does also lead to better out-of-sample performance, we follow an 3-step procedure. First, we estimate the factor exposures using either OLS or BMA, over the last m quarters of weekly data. As before, we set $m = 8$, but test the robustness of our results to using 6 or 12 quarters instead. Second, we calculate the explanatory power (Mean Absolute Deviation (MAD), Root Mean Squared Error (RMSE), R^2) of our model over the next quarter $(t + 1)$, using the exposures estimated using data until the current quarter t. Third, we move the observed sample with one quarter, and repeat the analysis until the end of the sample has been reached. The first 2columns of Table 6 compare the out-of-sample performance for specifications, either estimated using BMA or OLS, that include all 12 risk factors. We find that BMA leads to substantially lower MAD's and RMSE's, and higher R2's. Reducing the models only to factors that have either PIP's larger than 50% (BMA, column 3) or are significant at the 5% level (OLS, column 4) does not lead to better performance. Increasing window length from 8 till 12 quarters or reducing it instead till 6 quarters has a negative effect on the out-of-sample performance statistics, indicating that our choice for 8 quarters implies an optimal trade-off between estimation noise and timeliness (shorter windows lead to higher estimation noise, but estimates reflect more quickly new information). The last two columns compare out-of-sample performance between a model that only contains what we identified as the most important risk factors, namely the market, high-minus-low, and real estate factors, and one that contains all but the latter two. As expected, the performance statistics deteriorate substantially when the real estate and high-minus-low factor are excluded from the model.

3.1.3. Multicollinearity

Multicollinearity between the regressors could prevent us from finding the correct significant relationships, as it tends to blow up standard errors. To test the robustness of our results to multicollinearity, we replace the TED, money market, and deposit spread – all measures of some aspect of liquidity stress – with their first principal component. Additionally, we orthogonalize the VIX and the real estate indicator to innovations in the market and Fama-French portfolio returns. Our BMA results remain qualitatively the same. The change in posterior inclusion probability between the results in Table 5 and the results with this new set of regressors is 2% at most (for the three month Treasury Bill rate). Second, we test the robustness of our results with respect to a different model prior. One could argue that the uninformative model prior, giving equal prior probability to all models, puts too much weight on redundant models with correlated regressors, and too few weight on good but unique models. To address this critique, we use the collinearity adjusted dilution prior (George (2010)) to downweight models with highly collinear regressors. Again, our conclusions remain unchanged. The highest difference in posterior inclusion probability between the two different model priors is 3% (for the VIX). Results of these additional tests are available upon request.

3.2. Empirical evidence for different types of BHCs

The findings discussed above for the portfolio of the 50 largest BHCs are largely replicated for the various BHC portfolios (Columns 2-7 of Table 8). The preferred models now also include the SMB Fama-French factor next to the market, HML, and real estate factor. Again, other factors have PIPs close to zero with very few exceptions. The volatility index VXO has PIPs of 85 and 90 percent for the portfolios of smallest 50 and retail BHCs, respectively, while the difference between the Federal Funds Overnight Interest Rate and the 3-month Treasury Bill rate seems significantly related to the portfolio returns of the smallest 50 BHCs. Some interesting differences in risk exposure can be found between the different types of BHCs. The exposure to market risk of the smallest 50 banks is smaller than the market risk exposure of the largest 15 banks, and the difference is statistically significant. The market risk exposure of distressed banks is statistically significantly larger than the market risk exposure of sound banks. Similarly, the market risk exposure of tail risk-prone banks is larger than the upper bound of the confidence band of the market risk exposure of retail banks. Regarding the SMB factor, it is not surprising that the exposure to the SMB factor of the smallest 50 banks is significantly larger (and positive) than the SMB exposure of the largest 15 banks (negative). This holds also for the distressed versus sound banks. We confirm the importance of the default risk factor for distressed banks. The exposure to default risk of the distressed banks is significantly different (and negative) from the exposure to default risk of the sound banks (which is estimated to be zero, and has a PIP of only 3%). The importance of the MMS factor is different between the index constructed for the largest 15 and the 50 smallest banks. More specifically, the PIP of the MMS is 17% for the largest banks, and only 3% for the smallest banks. This is in line with our intuition that it is usually the largest banks that can draw on funds from the money market. Moreover, we find for the smallest banks that the exposure to the MMS factor is estimated to be zero, whereas it is negative for the largest banks. Regarding the exposure to real estate risk, we find that the tail risk-prone banks are statistically significantly more exposed to real estate risk than the retail banks. The PIP of real estate risk is 100% for tail risk-prone banks, whereas it is 67% for retail banks, and the magnitude of the exposure is also statistically significantly larger (0.13 versus 0.03).

In sum, our full-sample BMA results suggest that the market, Fama-French, and real estate factors are the most relevant factors for bank stock returns, and that most other factors, maybe with the exception of the volatility index VXO, are largely unimportant. While the limited support for many of the additional risk factors confirms previous evidence of e.g. Schuermann and Stiroh [56], the lack of finding significant exposures over the full sample may just reflect structural instability in the parameters. For instance, factors mimicking stress in the interbank or deposit market may only become important during business cycle downturns or financial crises. The focus on liquidity risk, for instance, intensified since the collapse of the UK-based bank Northern Rock, which failed mainly because it was too heavily reliant on wholesale funding, and hence, could not refund itself in case of a dry-up in the interbank market. Therefore, we introduce time variation in the model selection and factor exposures in the next subsection.

3.3. Modelling Time Variation in Model Uncertainty

To show the importance of allowing for time variation, we proceed in two steps. In a first step, we show in Table 9 the composition of the top-10 models before and after the start of the financial crisis in 2007 for the portfolio of the largest 50 BHCs. That is, we now split the sample period in two: January 1986 - July 2007 and August 2007 - December 2010. We notice a number of interesting differences between the full and subsample results. First, the optimal number of factors seems to be somewhat larger in the pre-2007 period, suggesting that the lack of accommodating for structural breaks may indeed be one of the reasons for the lack of significant factor exposures. The VXO volatility index, the T-Bill rate as well as the difference between the three month deposit rate and the three month Treasury Bill rate (DepS) are part of most, if not all, top-10 models pre-2007. Hence, in the pre-2007 period, banks were exposed to market sentiment (VXO) as well as interest rate risk, but not to credit risk. Either banks were able to properly hedge against defaults, or more likely, credit risk was not properly priced in the pre-2007 period. Most of these factors disappear after 2007, but are replaced by the default spread factor, which is part of all of the top-10 models in the post-2007 period. As the banking crisis started to spill over to the real economy, default risk started to increase, further depressing bank stock returns. Second, while before August 2007 the top-3 models have a joint probability of nearly 60 percent (23.5% for the top model), this drops to less than 22 percent in the post-2007 period (8.06% for top model). Somehow it seems that the uncertainty induced by the financial crises also leads to higher model uncertainty. Relying on a single model during a crisis to assess and monitor bank risk is clearly insufficient. Third, the adjusted R^2 of the top-10 models is much higher in the post-2007 period (83% versus 51%), which is consistent with the notion that common factors (and hence correlations between banks) become more important in times of high volatility. A final piece of information regarding the time variation in factors, comes from a sample split analysis based on NBER recession dates. The full sample period is split according to an NBER recession indicator (equal to one on recession dates, and zero otherwise). From the 1247 datapoints, 142 have been recorded as in recession by the NBER. Table 7 shows the result of the BMA analysis on the split samples. Over the full sample period, the market index, the real estate factor, the HML Fama-French factor and the three-month Treasury bill rate (PIP of 50%) have been found to be the important variables. Splitting the sample between NBER recession and non-recession data shows us that two variables become important in addition to the previously listed ones: the default factor and the SMB Fama-French factor. This is interesting, and in line with our hypothesis that both variables contain default related information. Furthermore, we notice some variation in other factors between recession and non-recession dates, but the difference in importance is less clear. Interesting enough, the VIX implied volatility index is a more important driver of bank stock returns during non-recession dates. The importance of the TED spread (PIP of 12% over the full sample period) seems to be driven by its importance during periods of recession.

In a second step, we investigate the time-varying factor inclusion and exposures in more detail. We estimate our BMA model over quarterly rolling windows of two years using weekly data[12]. Panel A of Table 10 shows for each 'bank type-risk factor' pair the percentage of observations with a PIP larger than 50 percent. Panel B of the same Table 10 shows for each 'bank type-risk factor' pair the corresponding marginal R^2. The latter is calculated as the average (over time) difference in R^2 between a model that does and a model that does not include a particular risk factor, conditional on that risk factor having at that point in time a PIP larger than 50 percent[13] In panel C, we report the average factor exposure for a given portfolio, conditional on that risk factor having at that point in time a PIP larger than 50 percent. Figure 1 gives a graphical representation of when which factors are important and for which types of banks.

On average across all portfolios, the market factor has in 92% of times a PIP larger than 50 percent, with an interquartile range (difference between value of 75^{th} and 25^{th} percentile) of 14%. The smallest percentage is observed for the portfolio of 50 smallest BHCs (66%). Panel A of Figure 1 shows that small banks were mainly disconnected from the market over the 2000-2008 period, after which the connection was restored again. For large banks (both 50 or 15 largest BHCs), we find, on the other hand, that the market factor loses significance from the second half of 2009 onwards (which corresponds with an estimation window of 2007Q2-2009Q2). In the last six quarters of our sample period, the HML factor, which captures distress and credit risk, becomes more important than the market factor for the (larger and) largest BHCs.

Panel A of Table 10 confirms the result from the full-sample analysis that the Fama-French and real estate factors are the most important bank risk factors other than the market. The HML factor is on average 'on' in 58.3% of observations, with a tight interquartile range of 27%. The rolling-window estimates reveal that the SMB factor enters the optimal model in on average 53.5% of observations, though with a rather broad interquartile range (44%). Not including the HML and SMB factors in times their PIP is larger than 50 percent would lead to a substantial (absolute) loss in R^2 of 7.9% and 6.3%, respectively. De-

[12]The first estimate is obtained for the last quarter of 1987.

[13]The marginal R^2 is calculated as follows: for each risk factor and in each estimation window, we take the difference between the model weighted R^2 (where the weights are given by the posterior model probabilities), and the model weighted R^2 of all models, excluding the specific risk factor. In the latter case, the posterior model probabilities are rescaled to ensure that the posterior model probabilities sum up to one.

spite having a PIP of 100% in the full-sample analysis, our time-varying analysis reveals that the real estate factor has a PIP larger than 50% in on average 25% of observations, with an interquartile range of 19%. Wrongly excluding the real estate factor would lead to a moderate loss in R^2 of 2.2% on average. Figure 1 shows that nearly all cross-sectional BHC portfolios disconnect from the HML factor in the 2004-2007 period, to reconnect again during the global financial crisis. The HML is 'on' most of the other times. The SMB risk factor seems to mainly affect the cross-sectional portfolios of BHC's. The largest BHCs are, however, most frequently exposed to real estate shocks. The marginal increase in R^2 from including the real estate factor is largest for the portfolio of 50 smallest BHCs (5%).

The other factors exhibit a considerably smaller proportion of observations with a PIP larger than 50%. The implied volatility index (VXO) is 'on' in on average 13.8% of cases. The VXO seems most relevant during the LTCM-Russian crisis and to some lesser extent during the global financial crisis. We observe the largest proportions for the distressed BHCs (18.7%) and 50 largest banks (17.6%). The marginal increase in R^2 is comparable to that of the real estate factor, about 2.2%, with a narrow interquartile range. The term spread factor is part of the preferred model in 11.9% of cases, and increases the R^2 with on average 3.1% (interquartile range of 1%). The largest 15 banks are more exposed to term spread shocks than the smallest 50 banks (12.1% versus 4.4%). Similarly, tail risk-prone have a more frequent exposure than retail banks (12.1% versus 4.4%).

To further investigate whether other factors than the market are significantly related to bank stock returns, Figure 2 plots at each point in time the number of factors with a PIP larger than 50 percent, (left axis) and the average difference in R^2 between the 'optimal' and a simple market model (dotted line with scale on the right axis). The optimal number of factors seems to vary mostly between 1 and 6 (in some exceptional cases 0 or 7), and seems to be highest on average in the aftermath of the Russian/LTCM crisis and subsequent burst of the technology bubble, and since the start of the financial crisis (third quarter of 2007). The lowest number of relevant factors is observed during the relatively tranquil 2004-2006 period. The increase in adjusted R^2 from including risk factors other than the market ranges from slightly negative[14] to more than 10%. For the portfolio of 50 largest BHCs (Panel A of Figure 2), the marginal R^2 peaks to values close to 10% in the mid-nineties, directly after the Russian/LTCM crisis, and during the global financial crisis. The increase in R^2 is not purely the result of increased explanatory power of existing factors, as the increase in R^2 seems also associated with an increase in the optimal number of factors. We obtain similar results for the cross-sectional portfolio analysis. For the various portfolios of BHCs, we find similar results with respect to the number of factors (with a maximum of seven relevant factors around the turn of the millennium for small BHCs, tail-risk prone BHCs and sound BHCs). The

[14] Because we look at adjusted R^2s, this difference can indeed be negative.

gains in R-squared can be even more substantial, with maximal gains of 20% (for distressed BHCs) and 15% for the smallest BHCs and tail risk prone BHCs. The main conclusion drawn from Figure 2 is that factors other than the market are important. Moreover, how many factors are important and their impact on explanatory power varies over time (especially in times of market stress) and across types of BHCs and FIs.

4. Implications for empirical bank research using stock returns

Models of bank stock returns are used as inputs in various types of empirical banking research, e.g., event studies, the decomposition of total bank risk in relevant components, proxies for bank opacity, and various related types of analysis. We document that the optimal combination of relevant risk factors may vary over time and may differ according to the type of bank holding company under investigation. This implies that due diligence is required in the specification of the bank factor model and that each empirical setup has to be tailored to the specific research question.

Many empirical banking studies examine the impact of an exogenous event on banks' valuation. These events could be bank-specific, such as mergers and acquisitions (Kane [41] and Hankir, Rauch, and Umber [32]), or sector-wide; e.g. banking or financial crises or regulatory changes (Johnson and Sarkar [40] and Mamun, Hassan, and Maroney [51]). To conduct such an event study, it is crucial to obtain an accurate measure of the (cumulative) abnormal return in response to the announced event. Our study yields three suggestions for the computation of cumulative abnormal returns. First, it is important to control for other risk factors in addition to returns on a broad market portfolio. For example, for the set of the 50 largest banks, the optimal number of factors varies over time between one and six. The explained variation in bank stock return can be increased by as much as 10%. Not controlling for other factors may yield a misspecified factor model leading to incorrect abnormal returns. A simple exercise gives an indication of the potential magnitude. For the portfolio of 50 largest BHCs, we compute for each quarter (event window) the cumulative abnormal return, using the previous 8 quarters as the estimation window, based on our BMA approach as well as a single factor model. The average difference over the 91 events (quarters) is small (-0.4%)[15]. However, the bias can be quite substantial during specific quarters and especially during NBER-dated recessions. In recessions, the average deviation in quarterly CARs is -4.9%. Second, the BMA implied model specification varies over time. Hence, in an ideal setup, the specification of the factor model changes for events that take place at different points in time (for example, M&As). Third, imposing the same model for various types of BHCs in a given time period may yield biased (cumulative) abnormal returns, since different types of BHCs sometimes imply different models. For example, in 2000, a model with a single factor (the market) is sufficient for retail BHCs, but would underestimate the R-squared of the richest model by almost 14% for tail risk-prone BHCs. Hence, abnormal returns (or other performance indicators such as alpha), based on a single factor model, could lead to an incorrect comparison between tail risk-prone banks and retail banks at the turn of the millennium.

[15] This difference in abnormal returns between our model and a single factor model is conceptually the same as the difference in one-quarter ahead forecast errors between these two models.

The flip side of the above comment is that idiosyncratic volatility is overestimated whenever R-squared is underestimated. Using BMA, we document that this measurement is heterogeneous in two dimensions. Model uncertainty (both in terms of number of factors and the goodness of fit) varies over time, but more importantly, also in the cross-section. Many studies try to explain the cross-section of banks' idiosyncratic volatility. For example, Stiroh [60] and Baele, De Jonghe, and Vander Vennet [5] document that banks with more non-interest income have lower idiosyncratic risk up to a turning point (at which they become overexposed to non-traditional banking activities). In both studies, a similar return-generating model is used for the entire set of banks. However, we document that the model specifications (and increased goodness of fit) for retail and tail risk-prone BHCs can be substantially different from each other over certain episodes, which may affect the results of the aforementioned studies.

There is a large literature that studies the link between opacity and R-squared (see e.g. Jin and Myers [39] and Hutton, Marcus, and Tehranian [37]). Firms with more opaque financial reports have stock returns that are more synchronous with market-wide factors and hence have a higher R-squared. In addition, there is theoretical and empirical evidence that opaque firms (with higher R-squared) are more prone to stock price crashes. Our results in Table 9 indicate that opacity is substantially larger in the post-2007 period compared with the pre-2007 period. When the R-squared is based on a single factor model, substantial mismeasurement can occur. For the portfolio of the 50 largest BHCs the underestimation of the R-squared ranges between 0% and 10%. More important, however, is that ignoring model heterogeneity for different banking types can lead to imprecise (but not necessarily incorrect) conclusions. For example, the difference in R-squared between distressed and sound banks is underestimated (based on a single factor, market model) by 5 to 10 percent over the period 1999-2002. Based on an extended and more appropriate model, the difference in opacity and crash risk between distressed and sound banks would be estimated more precisely.

Finally, omitting important risk factors may lead to biased estimates of market betas. Accurate estimation of the market beta is important for several reasons. First, the estimate of a bank's systematic risk directly affects the bank's cost of capital[16]. A second reason is that the estimate of systematic risk may affect the bank's (regulatory) provisions for market risk. Finally, systematic risk is used as a measure of risk in several studies (see e.g., Stiroh [59] and Saunders, Strock, and Travlos [55]). In these papers, the estimate of market risk exposure (obtained in a first step) is used in a second step as a dependent variable, and related to the riskiness of non-interest related sources of income, or the bank's

[16]This paper does not provide evidence on the pricing of the risk factors. To do so, one would need to set up cross sectional asset pricing tests such as in Fama and French [21], or in Viale, Kolari, and Fraser [64] in the empirical banking literature. However, such an analysis is beyond the scope of this paper.

ownership structure. Hence, it is important that systematic risk is properly measured in the first step.

Figure 3 shows the divergence in market beta estimated in a benchmark one-factor model versus our posterior estimates of market risk exposure in the BMA analysis. During the period between 2000 and 2006, we find a steady increase in the market beta from 0.5 to 0.9, a finding that has also been documented by Bhattacharyya and Purnanandam [6], who report an increase in market beta from 0.4 in 2000 to 1 in 2006. During this period, both market beta estimates are very similar, suggesting a minor role for the other risk factors. However, during the most recent financial crisis, we find that the market beta obtained from a benchmark one-factor model increases, whereas the BMA market beta decreases; a clearly opposite pattern (see Figure 3). This suggests that the other risk factors gain in importance, as discussed in Section 3.3. In the recent crisis, the HML Fama-French factor, an indicator of distress, becomes more important. A similar pattern emerges during the period of the millennium change, where the market beta estimated in a one-factor model is overestimated with respect to our BMA estimate, although to a lesser extent.

The figure shows that both measures are not always equal and that the largest differences arise during periods of market stress, such as the period around the millennium change, and most strikingly during the recent financial crisis. In a single factor model, the market beta "absorbs" information contained in the (missing) risk factors and tends to increase[17]. Yet, as is reflected by the substantially higher R-squared of the multifactor model and the many significant factor exposures, information is lost in this "absorption" process. We believe that studies trying to understand bank risk should not just relate bank-specific variables to the market beta, but to exposures of the full set of risk factors that are found to be relevant at a particular point in time.

5. Conclusion

Banks are exposed to various risks by the nature of their business. Through interconnectedness and contagion, individual bank defaults may affect financial system stability and ultimately spill over to the real economy. Therefore, prudential regulation in the banking industry tries to limit banks' risk taking incentives. However, regulation did not prevent the $2007-9$ crisis. Therefore, it remains important for supervisors to adequately track bank risk over time. The identification of relevant bank risks and their measurement remains an important challenge.

This paper contributes to the literature that measures banking risk as the exposures of bank stock returns to a set of pre-defined risk factors. We start

[17]To show this, we also run our time-varying BMA analysis on the twelve factors, in which each of the factors (except the market factor) is orthogonalized with respect to the market. Even in this setup, some of the other factors are significant and the fit of the regression is improved, indicating that these factors contain additional information.

by arguing that there is no consensus on what the correct set of risk factors is. The 24 previous papers that we identify relate bank stock returns in various combinations to no less than 17 different risk factors. All models include a market and (combinations of different) interest rate factor(s).

Factor exposures are typically estimated using ordinary least squares (OLS) with a fixed set of risk factors. There is, however, considerable uncertainty about what the appropriate set of risk factors is. Missing important factors may lead to underperforming models at best and wrong conclusions at worst. We apply an empirical technique, Bayesian Model Averaging (BMA), which explicitly takes into account this 'model uncertainty'. BMA compares all models (potential combinations of the different risk factors) simultaneously, instead of focusing on just one specification, and attaches a posterior probability to each model. Individual factors will only be considered important (have a high posterior inclusion probability) to the extent that the models in which they appear have a high posterior model probability.

We apply BMA to a benchmark portfolio of Bank Holding Companies, as well as to returns on portfolios of Bank Holding Companies with different characteristics (large/small, retail/diversified, and sound/distressed BHCs). Our set of 12 candidate risk factors includes most of the risk factors used in previous papers, as well as some that recently emerged, such as the implied volatility on S&P500 options (as a measure of sentiment) and the TED spread (as a measure of financial sector credit risk).

Full sample ($1986-2010$) results reveal that the market, real estate, and the high-minus-low (HML) Fama-French factor are the most important drivers of bank stock returns, with posterior inclusion probabilities close to 100 percent. Other factors do not seem to be reliably related to bank stock returns. In a small simulation exercise, we show that when the econometrician ignores model uncertainty and impose a fixed set of risk factors, she would frequently assume a risk factor to be statistically important. She would be unaware though that the models for which significance is found have a very low posterior model probability relative to models that do either not include that risk factor, or where it is found not to be statistically significant. The importance and positive and significant sign of the HML factor exposure is consistent with the findings of Liew and Vassalou [46] that the HML factor is positively (negatively) associated with news about the future state of the economy (distress risk) that is not captured by the market portfolio. Given that booming and subsequently rapidly decreasing housing prices were one of the key causes of the financial crisis that started in 2007, our finding of a positive and significant association of our real estate factor with bank stock returns is a relevant finding for bank supervisors. What is more surprising is that other factors, and in particular interest rate factors, do not seem to be reliably related to bank stock returns. This may suggest that changes in the risk factors were largely anticipated by market participants or that financial institutions are expected to hedge their associated exposures. Overall, we find limited evidence that the relevant set of risk factors varies significantly across different types of BHCs.

Our time-varying analysis shows that our failure to find significant exposures to risk factors other than the market, HML and real estate factor in the full sample is at least to some extent caused by structural instability in the estimated parameters. Other factors, such as the implied volatility, term spread, and SMB factor, which remained undetected in the full sample estimations, frequently switch between the 'on' and 'off' state. The optimal number of factors varies between 1 (just the market) and 7, and tends to increase with market uncertainty. The increase in (adjusted) R-squared from including risk factors other than the market amounts at times to more than 20 percent. Hence, relevant bank risk exposures vary over time, which may have implications for bank management (e.g., the cost of capital), investors (e.g., expected returns from investing in bank stock) and supervisors (e.g., time-varying exposures of BHCs to unexpected economic or financial market shocks).

A final section explores the implications of our findings for empirical banking research based on stock returns and for bank supervisors. Using a simple simulation exercise, we show that abnormal returns typically used in event studies are meaningfully affected by a (suboptimal) choice of risk factors, especially in bad times. Failing to include relevant risk factors also biases residual-based measures of uncertainty (idiosyncratic volatility), measures of opaqueness (R-squared), and, as we show, also indicators of systematic risk (betas). Our most pragmatic advice for future research is to complement the market factor with at least a real estate and high-minus-low Fama-French factor. As a robustness check, one should examine the relevance of the small-minus-big Fama-French factor as well as the short-rate, default spread, and VIX factors.

[1] Acharya, V. V., and N. Mora, 2012, "Are Banks Passive Liquidity Backstops? Deposit Rates and Flows during the 2007-2009 Crisis," *National Bureau of Economic Research Working Paper Series*, No. 17838.

[2] Adrian, T., and M. Brunnermeier, 2009, "CoVar," *Federal Reserve Bank of New York Staff Report Nr 348.*

[3] Akaike, H., 1974, "New Look at Statistical-Model Identification," *Ieee Transactions on Automatic Control*, Ac19(6), 716–723.

[4] Avramov, D., 2002, "Stock return predictability and model uncertainty," *Journal of Financial Economics*, 64(3), 423–458.

[5] Baele, L., O. De Jonghe, and R. Vander Vennet, 2007, "Does the stock market value bank diversification?," *Journal of Banking and Finance*, 31(7), 1999–2023.

[6] Bhattacharyya, S., and A. Purnanandam, 2012, "Risk-Taking by Banks: What Did we Know and When Did We Know it?," *AFA 2012 Meetings Paper.*

[7] Bossaerts, P., and P. Hillion, 1999, "Implementing statistical criteria to select return forecasting models: What do we learn?," *Review of Financial Studies*, 12(2), 405–428.

[8] Brock, W. A., and S. N. Durlauf, 2001, "Growth empirics and reality," *World Bank Economic Review*, 15(2), 229–272.

[9] Chamberlain, S., J. S. Howe, and H. Popper, 1997, "The exchange rate exposure of US and Japanese banking institutions," *Journal of Banking and Finance*, 21(6), 871–892.

[10] Chaudhry, M. K., R. Christie-David, T. W. Koch, and A. K. Reichert, 2000, "The risk of foreign currency contingent claims at US commercial banks," *Journal of Banking and Finance*, 24(9), 1399–1417.

[11] Choi, J. J., and E. Elyasiani, 1997, "Derivative exposure and the interest rate and exchange rate risks of US banks," *Journal of Financial Services Research*, 12(2-3), 267–286.

[12] Choi, J. J., E. Elyasiani, and K. J. Kopecky, 1992, "The Sensitivity of Bank Stock Returns to Market, Interest and Exchange-Rate Risks," *Journal of Banking and Finance*, 16(5), 983–1004.

[13] Ciccone, A., and M. Jarocinski, 2010, "Determinants of Economic Growth: Will Data Tell?," *American Economic Journal-Macroeconomics*, 2(4), 222–246.

[14] Cremers, M., 2002, "Stock Return Predictability: A Bayesian Model Selection Perspective," *Review of Financial Studies*, 15(4), 1223–1249.

[15] De Jonghe, O., 2010, "Back to the basics in banking? A Micro-Analysis of Banking System Stability," *Journal of Financial Intermediation*, 19(3), 387–417.

[16] Demsetz, R., and P. Strahan, 1997, "Diversification, Size and Risk at Bank Holding Companies," *Journal of Money, Credit and Banking*, 29(3), 300–313.

[17] Dewenter, K. L., and A. C. Hess, 1998, "An international comparison of banks' equity returns," *Journal of Money, Credit and Banking*, 30(3), 472–492.

[18] Doppelhofer, G., and M. Weeks, 2009, "Jointness of Growth Determinants," *Journal of Applied Econometrics*, 24(2), 209–244.

[19] Elyasiani, E., and I. Mansur, 1998, "Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate: A GARCH-M model," *Journal of Banking and Finance*, 22(5), 535–563.

[20] Fahlenbrach, R., R. Prilmeier, and R. M. Stulz, 2012, "This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance during the Recent Financial Crisis," *The Journal of Finance*, 67(6), 2139–2185.

[21] Fama, E. F., and K. R. French, 1992, "The Cross-Section of Expected Stock Returns," *Journal of Finance*, 47(1992), 427–465.

[22] Fama, E. F., and K. R. French, 1996, "Multifactor explanations of asset pricing anomalies," *Journal of Finance*, 51(1), 55–84.

[23] Fernandez, C., E. Ley, and M. F. J. Steel, 2001a, "Benchmark priors for Bayesian model averaging," *Journal of Econometrics*, 100(2), 381–427.

[24] ——— , 2001b, "Model uncertainty in cross-country growth regressions," *Journal of Applied Econometrics*, 16(5), 563–576.

[25] Flannery, M. J., A. S. Hameed, and R. H. Harjes, 1997, "Asset pricing, time-varying risk premia and interest rate risk," *Journal of Banking and Finance*, 21(3), 315–335.

[26] Flannery, M. J., and C. M. James, 1984a, "The Effect of Interest-Rate Changes on the Common-Stock Returns of Financial Institutions," *Journal of Finance*, 39(4), 1141–1153.

[27] ——— , 1984b, "Market Evidence on the Effective Maturity of Bank Assets and Liabilities," *Journal of Money, Credit and Banking*, 16(4), 435–445.

[28] Garleanu, N., and L. H. Pedersen, 2011, "Margin-based Asset Pricing and Deviations from the Law of One Price," *Review of Financial Studies*, 24(5).

[29] Gatev, E., and P. E. Strahan, 2006, "Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market," *The Journal of Finance*, 61(2), 867–892.

[30] George, E. I., 2010, "Dilution priors: Compensating for model space redundancy," *IMS Collections, Borrowing Strength: Theory Powering Applications; A Festschrift for Lawrence D. Brown*, 6, 158–165.

[31] Giesecke, K., and B. Kim, 2011, "Systemic Risk: What Defaults are Telling Us," *Management Science*, 57(8), 1387–1405.

[32] Hankir, Y., C. Rauch, and M. P. Umber, 2011, "Bank Mergers and Acquisitions: A market power story?," *Journal of Banking and Finance*, 35(9), 2341–2354.

[33] He, L. T., F. C. N. Myer, and J. R. Webb, 1996, "The sensitivity of bank stock returns to real estate," *Journal of Real Estate Finance and Economics*, 12(2), 203–220.

[34] Hess, A. C., and K. Laisathit, 1997, "A market-based risk classification of financial institutions," *Journal of Financial Services Research*, 12(2-3), 133–158.

[35] Hirtle, B. J., 1997, "Derivatives, portfolio composition, and bank holding company interest rate risk exposure," *Journal of Financial Services Research*, 12(2-3), 243–266.

[36] Hoeting, J. A., D. Madigan, A. E. Raftery, and C. T. Volinsky, 1999, "Bayesian model averaging: A tutorial," *Statistical Science*, 14(4), 382–401.

[37] Hutton, A. P., A. J. Marcus, and H. Tehranian, 2009, "Opaque financial reports, R-2, and crash risk," *Journal of Financial Economics*, 94(1), 67–86.

[38] IMF, 2009, "Responding to the Financial Crisis and Measuring Systemic Risks," *Global Financial Stability Report*, April 2009.

[39] Jin, L., and S. C. Myers, 2006, "R-2 around the world: New theory and new tests," *Journal of Financial Economics*, 79(2), 257–292.

[40] Johnson, S. A., and S. K. Sarkar, 1996, "The valuation effects of the 1977 Community Reinvestment Act and its enforcement," *Journal of Banking and Finance*, 20(5), 783–803.

[41] Kane, E. J., 2000, "Incentives for banking megamergers: What motives might regulators infer from event-study evidence?," *Journal of Money, Credit and Banking*, 32(3), 671–701.

[42] Kane, E. J., and H. Unal, 1988, "Change in Market Assessments of Deposit-Institution Riskiness," *Journal of Financial Services Research*, 1(3), 207–229.

[43] Lajeri, F., and J. Dermine, 1999, "Unexpected inflation and bank stock returns: The case of France 1977-1991," *Journal of Banking and Finance*, 23(6), 939–953.

[44] Leamer, E. E., 1973, "Multicollinearity - Bayesian Interpretation," *Review of Economics and Statistics*, 55(3), 371–380.

[45] ——— , 1978, "Specification Searches: Ad Hoc Infererence with Nonexperimental Data," *Wiley*, New York.

[46] Liew, J., and M. Vassalou, 2000, "Can book-to-market, size and momentum be risk factors that predict economic growth?," *Journal of Financial Economics*, 57(2), 221–245.

[47] Lloyd, W. P., and R. A. Shick, 1977, "Test of Stones 2-Index Model of Returns," *Journal of Financial and Quantitative Analysis*, 12(3), 363–376.

[48] Londono, J. M., 2011, "The variance risk premium around the world," *International Finance Discussion Papers*, 2011-1035.

[49] Lynge, M. J., and J. K. Zumwalt, 1980, "An Empirical-Study of the Interest-Rate Sensitivity of Commercial Bank Returns - a Multi-Index Approach," *Journal of Financial and Quantitative Analysis*, 15(3), 731–742.

[50] Magnus, J., O. Powell, and P. Prufer, 2010, "A comparison of two model averaging techniques with an application to growth empirics," *Journal of Econometrics*, 154(2), 139–153.

[51] Mamun, A., M. K. Hassan, and N. Maroney, 2005, "The Wealth and Risk Effects of the Gramm-Leach-Bliley Act (GLBA) on the US Banking Industry," *Journal of Business Finance and Accounting*, 32(1-2), 351–388.

[52] Raftery, A., D. Madigan, and J. A. Hoeting, 1997, "Bayesian Model Averaging for linear regression models," *Journal of the American Statistical Association*, 92, 179–191.

[53] Sala-I-Martin, X., G. Doppelhofer, and R. I. Miller, 2004, "Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach," *American Economic Review*, 94(4), 813–835.

[54] Saunders, A., and M. Cornett, 2014, *Financial Institutions Management: A Risk Management Approach*. McGraw-Hill/Irwin Series in Finance, Insurance and Real Estate.

[55] Saunders, A., E. Strock, and N. G. Travlos, 1990, "Ownership Structure, Deregulation, and Bank Risk Taking," *Journal of Finance*, 45(2), 643–654.

[56] Schuermann, T., and K. Stiroh, 2006, "Visible and hidden risk factors for banks," *Federal Reserve Bank of New York Staff Report Nr 252.*

[57] Schwarz, G., 1978, "Estimating Dimension of a Model," *Annals of Statistics*, 6(2), 461–464.

[58] Song, F. M., 1994, "A 2-Factor Arch Model for Deposit-Institution Stock Returns," *Journal of Money, Credit and Banking*, 26(2), 323–340.

[59] Stiroh, K., 2006, "A portfolio view of banking with interest and noninterest activities," *Journal of Money, Credit and Banking*, 38(5), 1351–1361.

[60] ——— , 2006b, "New evidence on the determinants of bank risk," *Journal of Financial Services Research*, 30(3), 237–263.

[61] Sweeney, R. J., and A. D. Warga, 1986, "The Pricing of Interest-Rate Risk - Evidence from the Stock-Market," *Journal of Finance*, 41(2), 393–410.

[62] Tarhan, V., 1987, "Unanticipated Interest-Rates, Bank Stock Returns and the Nominal Contracting Hypothesis," *Journal of Banking and Finance*, 11(1), 99–115.

[63] Taylor, J. B., and J. C. Williams, 2009, "A Black Swan in the Money Market," *American Economic Journal-Macroeconomics*, 1(1), 58–83.

[64] Viale, A., J. Kolari, and D. Fraser, 2009, "Common risk factors in bank stocks," *Journal of Banking and finance*, 33(3), 464–472.

[65] Wei, C. Z., 1992, "On Predictive Least-Squares Principles," *Annals of Statistics*, 20(1), 1–42.

[66] Wright, J. H., 2008, "Bayesian Model Averaging and exchange rate forecasts," *Journal of Econometrics*, 146(2), 329–341.

Table 1: Independent variables used in factor models for bank stock returns: a summary of 24 studies

This table presents an overview of the independent variables that have been included in models for bank stock returns. The independent variables are numbered from 1 to 17, indicating 1 (market risk), 2 (interest rate risk, short term), 3 (term spread risk), 4 (default risk), 5 (liquidity risk), 6 (market volatility), 7 (real estate risk), 8 (small-minus-big), 9 (high-minus-low), 10 (momentum), 11 (market dividend yield), 12 (inflation risk), 13 (interest rate risk long term), 14 (deposit demand), 15 (exchange rate risk), 16 (bank portfolio return) and 17 (money supply).

	Period	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
Lloyd and Shick [47]	1969-1972	X												X				
Lynge and Zumwalt [49]	1969-1975	X	X											X				
Flannery and James [26]	1976-1981	X	X											X				
Flannery and James [27]	1976-1981	X	X											X				
Sweeney and Warga [61]	1960-1979	X	X											X				
Tarhan [62]	1979-1982	X	X															X
Kane and Unal [42]	1975-1985	X												X				
Saunders, Strock, and Travlos [55]	1978-1985	X	X											X				
Choi, Elyasiani, and Kopecky [12]	1975-1987	X	X													X		
He, Myer, and Webb [33]	1986-1991	X	X					X										
Song [58]	1976-1987	X	X															
Demsetz and Strahan [16]	1980-1993	X	X	X	X													
Hess and Laisathit [34]	1981-1988	X		X	X	X								X	X			
Chamberlain, Howe, and Popper [9]	1986-1993	X														X	X	
Hirtle [35]	1986-1994	X												X				
Choi and Elyasiani [11]	1975-1992	X	X													X		
Flannery, Hameed, and Harjes [25]	1973-1990	X												X				
Dewenter and Hess [17]	1984-1996	X		X	X	X												
Elyasiani and Mansur [19]	1970-1992	X												X				
Lajeri and Dermine [43]	1977-1991	X	X										X					
Chaudhry, Christie-David, Koch, and Reichert [10]	1989-1993	X	X											X		X		
Stiroh [59]	1997-2004	X	X	X	X													
Schuermann and Stiroh [56]	1997-2005	X	X	X	X	X	X		X	X								
Viale, Kolari, and Fraser [64]	1986-2003	X	X	X	X				X	X	X	X						

Table 2: Summary statistics of the dependent and independent variables

This table reports summary statistics of the returns on the different bank indices in Panel A. All series have a weekly frequency and span the period 1986-2010. We report the annualized mean and volatility as well as the skewness and kurtosis of the portfolio returns. Each portfolio return is constructed as an equally weighted return (with quarterly rebalancing of the portfolio). Below the summary statistics, we present a correlation table of the returns on the seven portfolios. Theseseven portfolios are the benchmark portfolio and six portfolios of various 'types' of bank holding companies. The numbers correspond with: (1) Largest 50 BHCs, (2) Largest 15 BHCs, (3) Smallest 50 BHCs, (4) Sound BHCs, (5) Distressed BHCs, (6) Retail BHCs, (7) Tail Risk-prone BHCs. In panel B we report the innovations in the different risk factors included in the analysis. Innovations are the residuals from a AR(n) model estimated on the different risk variables, where n is the optimal lag chosen by the Schwarz Bayesian Information Criterion. We also report the expected sign of the impact of a given risk factor on bank stock returns.

Panel A: Summary Statistics for Bank Portfolio Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Portfolio Returns - Summary Statistics							
Annualized Average Return	0.141	0.134	0.103	0.146	0.004	0.093	0.170
Annualized Volatility	0.274	0.308	0.113	0.148	0.242	0.129	0.232
Skewness	1.014	1.338	-0.636	0.237	1.356	-0.726	1.360
Kurtosis	17.005	22.774	13.107	10.213	30.517	14.536	22.179
Portfolio Returns - Correlation Table							
(2) Largest 15	0.962						
(3) Smallest 50	0.568	0.555					
(4) Sound Banks	0.839	0.777	0.604				
(5) Distressed Banks	0.711	0.680	0.722	0.644			
(6) Retail Banks	0.649	0.614	0.780	0.748	0.687		
(7) Tail risk-prone Banks	0.925	0.896	0.612	0.835	0.787	0.692	

Panel B: Summary Statistics Risk Variables

	mean	**st. dev**	**min**	**max**	**expected sign**
Market	0.0010	0.0240	-0.1765	0.1185	+
Small minus Big (SMB)	0.0001	0.0133	-0.0935	0.0642	+
High minus Low (HML)	0.0007	0.0135	-0.0695	0.0983	+
3-month T-Bill (TB3)	0.0000	0.0013	-0.0163	0.0061	-
Term Spread (TS)	0.0000	0.0015	-0.0057	0.0089	"+/-"
Default Spread (DS)	0.0000	0.0005	-0.0036	0.0051	-
TED spread (TED)	0.0000	0.0014	-0.0083	0.0103	-
3-month unregulated time deposit - 3-month T-Bill (DepS)	0.0000	0.0013	-0.0088	0.0146	"+/-"
FF Overnight - 3 month LIBOR (MMS)	0.0000	0.0020	-0.0147	0.0167	"+/-"
Effective Exchange Rate (FX)	-0.0003	0.0099	-0.0375	0.0446	"+/-"
Market Volatility (VXO)	-0.0001	0.0362	-0.1889	0.6613	-
Real Estate returns (RE)	0.0028	0.0357	-0.2132	0.2404	+

Table 3: Data Description, Source codes and Construction of Portfolios

Portfolio Construction

Portfolio Name	*Description (for each portfolio, we allow for quarterly rebalancing)*
Largest 15	The 15 largest publicly traded BHCs (BHCs) measured by Total Assets
Smallest 50	The 50 smallest publicly traded BHCs measured by Total Assets
Sound Banks	The intersection of the 25% best capitalized and 25% most profitable (ROA) BHCs in a given quarter
Distressed Banks	The intersection of the 25% worst capitalized and 25% least profitable (ROA) BHCs in a given quarter
Retail Banks	We sort BHCs in quartiles according to five characteristics: Size (=ln(Total Assets), Growth in Total Assets, the leverage ratio (Total Assets/Total Equity), wholesale funding share and the share of non-interest income in total income. We attach a score of 1, 2, 3 or 4 for each quartile sort. If the sum of the scores is at most 8, we classify a BHC as a retail BHC, which is a small, well-capitalized, slow-growing BHC, that is relying on core funding and interest generating activities
Tail Risk-prone Banks	We sort BHCs in quartiles according to five characteristics: Size (=ln(Total Assets), Growth in Total Assets, the leverage ratio (Total Assets/Total Equity), wholesale funding share and the share of non-interest income in total income. We attach a score of 1, 2, 3 or 4 for each quartile sort. If the sum of the scores is at least 17, we classify a BHC as a diversifeid BHC, which is a large, highly leveraged and expanding BHC, that is relying on wholesale funding and diversified into non-interest generating activities

Bank Characteristics

Variable Name	*Corresponding Codes*
Size (=ln(Total Assets))	ln(BHCK2170)
Growth in Total Assets	Δ(ln(BHCK2170))
Return on Assets	BHCK4340 / BHCK2170
Equity to Total Assets	BHCK3210/BHCK2170
Cost to Income ratio	BHCK4093 / (BHCK4074 + BHCK4079)
Non-Performing Loans over Total Loans	(BHCK5525 - BHCK3506 + BHCK5526 - BHCK3507 + BHCK1616) / BHCK2122
Deposits to Total Assets	(BHDM6631 + BHDM6636 + BHFN6631 + BHFN6636)/ BHCK2170
Core Deposits Share	$\frac{((BHCB3187 + BHOD3187) + (BHCB2389 + BHOD2389) + (BHCB6648 + BHOD6648) + BHFN6636)}{(Deposits + FedFundsPurchased)}$
Wholesale Funding Share	(BHCB2604 + BHOD2604) + FFpSs / (Deposits + FedFundsPurchased)
Loans To Total Assets	BHCK2122 / BHCK2170
C&I Loans Share	(BHCK1763 + BHCK1764) / BHCK2122
Interest Income Share	BHCK4074 / (BHCK4074 + BHCK4079)

Table 4: Definition and Summary Statistics of the Bank Holding Company portfolios

This table presents descriptive statistics on the characteristics of the constituents of the six portfolios we construct. We present information on the average value of a number of bank characteristics. For each portfolio, we first compute an equally weighted average bank characteristic per quarter for the constituent banks. Subsequently, we average over time. We also report p-values of differences in means test for contrasting portfolios: i.e., Small vs Large, Sound vs Distressed and Retail vs Tail Risk-prone BHCs. The definition and construction of the characteristics and portfolios are described in Table 3.

	Largest 15	(2) Smallest 50	Diff Mean (pval)	(3) Sound Banks	(4) Distressed Banks	Diff Mean (pval)	(5) Retail Banks	(6) Tail Rik-Prone Banks	Diff Mean (pval)
Size (=ln(Total Assets))	18.524	12.795	0.000	14.352	14.432	0.039	13.142	16.346	0.000
Growth in Total Assets	0.019	0.023	0.020	0.023	0.022	0.399	-0.002	0.055	0.000
Return on Assets	0.009	0.007	0.000	0.016	-0.002	0.000	0.010	0.010	0.198
Equity to Total Assets	7.537	9.097	0.000	11.600	5.973	0.000	10.343	6.931	0.000
Cost to Income ratio	0.657	0.719	0.000	0.563	0.813	0.000	0.667	0.666	0.791
Non-Performing Loans	0.021	0.018	0.000	0.011	0.027	0.000	0.015	0.015	0.751
Deposits to Total Assets	0.606	0.824	0.000	0.766	0.763	0.412	0.824	0.666	0.000
Core Deposits Share	0.616	0.684	0.000	0.687	0.664	0.000	0.747	0.563	0.000
Wholesale Funding Share	0.242	0.163	0.000	0.174	0.213	0.000	0.111	0.299	0.000
LoansTo Total Assets	0.567	0.660	0.000	0.638	0.633	0.120	0.651	0.579	0.000
C&I Loans Share	0.263	0.197	0.000	0.190	0.194	0.211	0.168	0.234	0.000
Interest Income Share	0.543	0.809	0.000	0.745	0.759	0.000	0.849	0.605	0.000

Table 5: BMA versus OLS

This table summarizes estimation results for the static linear model estimated over the full sample (January 1986 to December 2010). Panel A reports results when using the portfolio of the 50 largest bank holding companies. Each column corresponds with a different risk factor. Panel A reports the OLS factor exposure and t-statisitc, the BMA factor exposure and corresponding t-statistic, as well as the risk factor's Posterior Inclusion Probability. Panel B reports for a specific risk factor the proportion of significant coefficients (at the 10, 5, 1 percent level) estimated for a model that includes apart from a constant, the market, and the specific risk factor all other potential combinations of risk factors. Panel C provides the specification of the top 10 models, ranked in terms of posterior model probability. The inclusion of a variable is indicated with a X. The table also contains the number of factors (all explanatory variables except the constant), the posterior model probability (PMP) and the adjusted R-squared.

Panel A: Full sample: OLS versus BMA

Nr.	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE
β-OLS	0.96	0.04	1.15	-2.37	-0.47	2.17	0.49	-0.91	-0.8	0.1	-0.05	0.2
t-stat OLS	19.22	0.73	20.06	-3.15	-0.88	1.61	0.45	-0.87	-2.07	1.50	-1.75	7.13
β-BMA	0.99	0.00	1.14	-0.69	0.00	0.32	0.12	0.01	-0.13	0.01	0.00	0.20
t-stat BMA	24.33	0.06	21.03	-0.84	-0.03	0.34	0.31	0.06	-0.43	0.22	-0.17	7.83
PIP	100%	3%	100%	47%	3%	13%	12%	5%	19%	7%	5%	100%

Panel B: Percentage significant across various model specifications (OLS)

	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE
10% level	-	63%	100%	96.3%	13.6%	32.9%	14.9%	2%	34.2%	6.3%	64.2%	100%
5% level	-	53.6%	100%	87.8%	6.3%	1.9%	4.4%	0.4%	21.9%	0%	50.6%	100%
1% level	-	50%	100%	57.2%	0%	0%	0%	0%	1.2%	0%	37.6%	100%

Panel C: Top 10 models, full sample

Nr.	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE	# factors	PMP	Adj R2
1	X		X									X	3	23.83%	61.67%
2	X		X	X								X	4	23.45%	61.86%
3	X		X	X					X			X	5	7.30%	61.97%
4	X		X				X					X	4	7.05%	61.78%
5	X		X						X			X	4	5.24%	61.77%
6	X		X			X						X	4	4.16%	61.75%
7	X		X	X		X						X	5	3.49%	61.93%
8	X		X	X						X		X	5	2.00%	61.90%
9	X		X					X				X	4	1.81%	61.70%
10	X		X	X							X	X	5	1.76%	61.89%

Table 6: BMA vs OLS: Out-of-Sample Performance

This Table reports average Mean Absolute Deviation (MAD), Root Mean Squared Error (RMSE), and R^2 for BMA and OLS regressions of returns on our benchmark bank index on our 12 risk factors. We first estimate the factor exposures using either OLS or BMA over the last $m = \{6, 8, 12\}$ quarters of weekly data. Subsequently, we calculate the performance of our model over the next quarter $(t+1)$, using the exposures estimated using data until the current quarter t. Third, we move the observed sample with one quarter, and repeat the analysis until the end of the sample has been reached. #1 to #3 refer to specifications that are estimated using all risk factors (#1), only the market, HML, and Real Estate factor (#2), or all risk factors but HML and Real Estate. Columns 'BMA #1 PIP>50%' and 'OLS #1 (5%)' report results for a model that only includes risk factors that either have a Posterior Inclusion Probability (PIP) larger than 50% or that are significant at the 5% level, respectively.

	BMA #1	OLS #1	BMA #1 PIP>50%	OLS #1 (5%)	BMA #2	BMA #3
Mean Absolute Deviation (in %)						
8 quarters	1.8074	1.9152	1.8238	1.9847	0.0184	0.0191
12 quarters	1.8256	1.8875	1.8364	1.8776		
6 quarters	1.8320	2.0000	1.8474	2.0181		
Root Mean Squared Error (in %)						
8 quarters	2.6732	2.7561	2.6934	2.8277	0.0272	0.0284
12 quarters	2.6760	2.7237	2.7022	2.7163		
6 quarters	2.6860	2.8937	2.7164	2.9472		
R-squared						
8 quarters	50.5%	47.4%	49.8%	44.6%	48.7%	44.0%
12 quarters	52.1%	50.3%	51.1%	50.6%		
6 quarters	50.5%	42.5%	49.3%	40.4%		

Table 7: Sample split between NBER recession dates and non-recession dates

This table summarizes estimation results for the static linear model estimated over different sample periods. The estimation results reported in Panel A are based on the NBER recession dates selected from the full sample period, whereas the results reported in Panel B refer to the NBER non-recession dates. For all the factors, we report the coefficient estimates of the OLS regression (on the full set of regressors) and the BMA regression. The corresponding t-statistics are reported. The PIP corresponding to the BMA regression is reported.

Panel A: NBER recession dates					
	β_{OLS}	β_{BMA}	PIP	t-stat OLS	t-stat BMA
constant	0.00	0.00		-0.51	-0.02
MARKET	1.10	1.00	100%	5.18	4.26
SMB	0.48	0.25	43%	1.92	0.74
HML	2.09	2.01	100%	10.05	7.99
TB3	-8.41	-4.78	77%	-2.77	-1.46
TS	-0.69	0.04	10%	-0.32	0.05
DS	8.83	5.30	59%	2.25	1.01
TED	1.98	0.18	12%	0.55	0.19
DepS	-3.00	-0.11	10%	-1.09	-0.14
MMs	-0.30	-0.04	9%	-0.21	-0.12
FX	0.47	0.13	27%	1.69	0.50
VXO	0.01	0.01	11%	0.12	0.20
RE	0.23	0.24	76%	2.05	1.46
Panel B: NBER non-recession dates					
	β_{OLS}	β_{BMA}	PIP	t-stat OLS	t-stat BMA
constant	0.00	0.00		-0.08	-0.40
MARKET	0.84	0.92	100%	18.60	20.13
SMB	-0.08	-0.01	11%	-1.56	-0.29
HML	0.73	0.76	100%	13.14	14.23
TB3	-1.92	-0.05	7%	-2.79	-0.21
TS	-0.44	-0.01	4%	-0.92	-0.13
DS	-0.56	0.00	3%	-0.41	-0.01
TED	-0.44	0.00	3%	-0.42	-0.02
DepS	-0.90	-0.01	3%	-0.79	-0.08
MMs	-0.65	-0.02	5%	-1.82	-0.17
FX	0.09	0.01	7%	1.48	0.21
VXO	-0.08	-0.02	32%	-3.25	-0.61
RE	0.12	0.11	100%	4.66	4.39

Table 8: Bayesian Model Averaging in the static linear model

This table summarizes estimation results for the static linear model estimated over the full sample (January 1986 to December 2010). The columns correspond with the seven portfolios we use. These seven portfolios are the benchmark series (column 1), and six portfolios of various 'types' of bank holding companies (columns 6-11). For each risk factor-portfolio pair, we report 5 statistics, i.e. the OLS factor exposure and t-statisitc, the BMA factor exposure and corresponding t-statistic and the Posterior Inclusion Probability.

		Largest 50	Largest 15	Smallest 50	Sound	Distressed	Retail	Tail risk-prone
Market	β_{OLS}	0.96	1.07	0.23	0.51	0.67	0.33	0.9
	t_{OLS}	19.22	18.75	8.43	18.52	12.41	11.49	21.02
	β_{BMA}	0.99	1.11	0.23	0.53	0.74	0.36	0.88
	t_{BMA}	24.33	22.27	7.38	22.69	12.14	9.58	24.43
	PIP	100%	100%	100%	100%	100%	100%	100%
SMB	β_{OLS}	0.04	-0.21	0.23	0.39	0.51	0.36	0.33
	t_{OLS}	0.73	-3.18	7.40	12.24	8.24	11.07	6.71
	β_{BMA}	0.00	-0.22	0.23	0.39	0.52	0.37	0.3
	t_{BMA}	0.06	-2.8	7.35	12.57	7.93	10.44	6.17
	PIP	3%	95%	100%	100%	100%	100%	100%
HML	β_{OLS}	1.15	1.19	0.35	0.61	1.03	0.52	0.97
	t_{OLS}	20.06	18.27	11.19	19.31	16.60	15.92	19.78
	β_{BMA}	1.14	1.19	0.35	0.62	1.05	0.53	0.95
	t_{BMA}	21.03	17.95	11.07	19.74	15.58	14.86	19.59
	PIP	100%	100%	100%	100%	100%	100%	100%
TB3	β_{OLS}	-2.37	-2.23	-0.17	-0.68	-1.1	-0.84	-2.18
	t_{OLS}	-3.15	-2.60	-0.41	-1.62	-1.34	-1.94	-3.34
	β_{BMA}	-0.69	-0.2	0	-0.06	0.01	-0.02	-0.52
	t_{BMA}	-0.84	-0.38	-0.06	-0.3	0.04	-0.15	-0.74
	PIP	47%	16%	3%	11%	3%	5%	42%
TS	β_{OLS}	-0.47	-0.62	-0.33	0.13	-1.05	-0.34	-0.89
	t_{OLS}	-0.88	-1.02	-1.14	0.43	-1.80	-1.11	-1.93
	β_{BMA}	0.00	-0.01	-0.01	0.03	-0.24	-0.02	-0.06
	t_{BMA}	-0.03	-0.05	-0.15	0.25	-0.47	-0.2	-0.25
	PIP	3%	3%	5%	8%	22%	6%	9%
DS	β_{OLS}	2.17	2.12	-0.8	0.22	-1.96	-0.18	-0.06
	t_{OLS}	1.61	1.38	-1.10	0.29	-1.33	-0.24	-0.05
	β_{BMA}	0.32	0.25	-0.04	0	-0.15	-0.01	0.01
	t_{BMA}	0.34	0.28	-0.17	0.04	-0.22	-0.04	0.07
	PIP	13%	10%	5%	3%	7%	3%	3%
TED	β_{OLS}	0.49	0.73	0.51	-0.54	-0.53	-0.69	-0.16
	t_{OLS}	0.45	0.59	0.88	-0.90	-0.45	-1.12	-0.18
	β_{BMA}	0.12	0.11	0	0.04	-0.12	-0.22	0.01
	t_{BMA}	0.31	0.29	0	0.25	-0.32	-0.58	0.06
	PIP	12%	11%	4%	9%	12%	30%	4%
DepS	β_{OLS}	-0.91	-1.1	-1.7	0.58	-0.5	-0.45	-0.55
	t_{OLS}	-0.87	-0.92	-3.02	1.00	-0.44	-0.74	-0.61
	β_{BMA}	0.01	0.01	-1.4	0.11	-0.12	-0.27	-0.01
	t_{BMA}	0.06	0.07	-4.22	0.41	-0.31	-0.65	-0.07
	PIP	5%	4%	99%	18%	12%	35%	4%

Figure 8 continued

		Largest 50	Largest 15	Smallest 50	Sound	Distressed	Retail	Tail risk-prone
MMS	β_{OLS}	-0.8	-0.87	0.14	-0.33	0.02	-0.21	-0.65
	t_{OLS}	-2.07	-1.97	0.69	-1.57	0.05	-0.97	-1.97
	β_{BMA}	-0.13	-0.13	0	-0.02	0.02	0	-0.03
	t_{BMA}	-0.43	-0.39	0.1	-0.23	0.15	0	-0.22
	PIP	19%	17%	3%	8%	5%	3%	7%
Exchange	β_{OLS}	0.1	0.09	-0.02	0.02	0.04	-0.01	0.12
	t_{OLS}	1.50	1.19	-0.48	0.57	0.49	-0.36	1.94
	β_{BMA}	0.01	0	0	0	0	0	0.01
	t_{BMA}	0.22	0.16	-0.1	0.06	0.04	-0.09	0.28
	PIP	7%	5%	3%	3%	3%	3%	10%
VXO	β_{OLS}	-0.05	-0.06	-0.05	-0.03	-0.05	-0.06	0
	t_{OLS}	-1.75	-1.98	-3.05	-1.68	-1.69	-3.59	0.06
	β_{BMA}	0.00	0	-0.04	0	-0.01	-0.04	0
	t_{BMA}	-0.17	-0.17	-1.89	-0.18	-0.3	-2.16	0.14
	PIP	5%	5%	85%	5%	11%	90%	4%
RE	β_{OLS}	0.2	0.22	0.06	0.09	0.09	0.05	0.13
	t_{OLS}	7.13	6.89	3.75	5.78	3.02	2.87	5.65
	β_{BMA}	0.20	0.22	0.05	0.09	0.08	0.03	0.13
	t_{BMA}	7.83	6.62	3.14	5.8	1.67	1.21	5.69
	PIP	100%	100%	97%	100%	81%	67%	100%

Table 9: The top 10 models, ranked in terms of posterior model probability

This table provides the specification of the top 10 models, ranked in terms of posterior model probability, for two subperiods. In panel A, we estimate the model on the portfolio of 50 largest BHCs over the period 1986 until July 2007. In panel B, we report post August 2007 results for the same portfolio. The inclusion of a variable is indicated with X. The table also contains the number of explanatory variables (except the constant), the posterior model probability (PMP) and the adjusted R squared.

Panel A: Top 10 models, pre-2007

Model Nr.	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE	# factors	PMP	Adj R2
1	X		X	X				X			X	X	6	23.54%	50.60%
2	X		X	X	X			X			X	X	7	18.25%	50.85%
3	X	X	X	X				X			X	X	7	15.77%	50.84%
4	X	X	X	X	X			X			X	X	8	4.91%	51.01%
5	X		X	X	X		X				X	X	7	4.44%	50.72%
6	X		X	X	X						X	X	6	3.43%	50.43%
7	X	X	X					X			X	X	6	2.42%	50.39%
8	X		X	X			X				X	X	6	2.17%	50.38%
9	X		X					X			X	X	5	2.00%	50.10%
10	X		X								X	X	4	1.76%	49.81%

Panel B: Top 10 models, post-2007

Model Nr.	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE	# factors	PMP	Adj R2
1	X		X			X						X	4	8.06%	82.54%
2	X		X	X		X						X	5	6.77%	82.94%
3			X			X						X	3	6.63%	82.05%
4	X		X		X	X						X	5	5.56%	82.89%
5	X		X			X	X					X	5	5.12%	82.88%
6	X		X			X					X	X	5	4.53%	82.85%
7			X		X	X						X	4	3.06%	82.33%
8	X		X			X		X				X	5	2.95%	82.76%
9	X		X	X		X					X	X	6	2.08%	83.12%
10	X		X	X		X				X		X	6	2.03%	83.11%

Table 10: Time-Varying BMA Estimation Results

This table summarizes estimation results for the time-varying BMA analysis over the period 1986-2010, using quarterly rolling windows of two years of weekly data. The table consists of three equally designed panels. The columns correspond with a risk factor, whereas the rows correspond with a bank type. Panel A (top panel) shows for each bank type-risk factor pair the percentage of observations with a PIP larger than 50 percent. In panel B, we report a marginal R-squared. The latter is calculated as the average (over time) difference in (model weighted) R-squared between a model that does and one that does not include a particular risk factor, conditional on that risk factor having at that point in time a PIP larger than 50 percent. Finally, the lower panel C contains for each bank type-risk factor pair the average factor exposure, conditional on the pair having a PIP $>$ 50 percent. In each panel, we also report for each risk factor the average and the interquartile range of the results for the eleven portfolios.

	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE
						Panel A: Percentage of PIP's $>$ 50%						
Largest 50	0.93	0.36	0.65	0.16	0.19	0.10	0.11	0.07	0.09	0.02	0.18	0.26
Largest 15	0.93	0.43	0.63	0.12	0.12	0.02	0.05	0.07	0.14	0.01	0.15	0.35
Smallest 50	0.66	0.74	0.63	0.05	0.04	0.02	0.03	0.10	0.11	0.04	0.09	0.26
Sound	0.98	0.78	0.70	0.15	0.07	0.08	0.05	0.02	0.09	0.09	0.16	0.21
Distressed	0.85	0.79	0.77	0.05	0.01	0.01	0.08	0.04	0.04	0.02	0.19	0.20
Retail	0.85	0.78	0.74	0.01	0.04	0.07	0.14	0.04	0.08	0.08	0.13	0.15
Tail Risk-prone	1.00	0.68	0.73	0.09	0.12	0.02	0.07	0.03	0.07	0.03	0.16	0.25
mean	0.92	0.54	0.58	0.09	0.12	0.05	0.07	0.06	0.08	0.04	0.14	0.25
IQR	0.14	0.44	0.27	0.09	0.14	0.05	0.04	0.04	0.03	0.02	0.08	0.19
						Panel B: Contribution to R-squared						
Largest 50	0.11	0.06	0.09	0.02	0.03	0.01	0.03	0.03	0.02	0.01	0.02	0.01
Largest 15	0.09	0.06	0.08	0.03	0.05	0.01	0.03	0.03	0.02	0.01	0.02	0.03
Smallest 50	0.09	0.08	0.09	0.05	0.02	0.02	0.07	0.02	0.03	0.04	0.03	0.05
Sound	0.11	0.08	0.09	0.04	0.03	0.02	0.03	0.01	0.02	0.02	0.02	0.02
Distressed	0.12	0.09	0.13	0.03	0.03	0.01	0.01	0.01	0.03	0.02	0.05	0.03
Retail	0.09	0.10	0.10	0.00	0.03	0.02	0.03	0.01	0.03	0.04	0.02	0.01
Tail Risk-prone	0.11	0.04	0.09	0.02	0.04	0.01	0.03	0.04	0.02	0.01	0.02	0.01
mean	0.10	0.06	0.08	0.02	0.03	0.01	0.03	0.02	0.02	0.02	0.02	0.02
IQR	0.02	0.05	0.04	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01
						Panel C: Beta						
Largest 50	0.91	0.33	1.10	-1.74	-2.53	7.99	18.52	-26.48	2.52	0.34	-0.22	0.31
Largest 15	1.02	-0.15	1.26	-1.57	-4.56	8.38	25.74	-20.68	-0.05	0.31	-0.22	0.33
Smallest 50	0.38	0.39	0.46	-2.48	-1.40	-0.83	4.48	-3.77	-0.63	-0.25	-0.11	0.18
Sound	0.50	0.47	0.54	-0.38	-1.86	3.64	4.23	3.21	1.00	0.08	-0.12	0.16
Distressed	0.73	0.74	1.00	-2.92	-1.77	4.75	-3.12	-2.52	1.95	-0.27	-0.22	0.21
Retail	0.39	0.47	0.52	0.97	-1.33	-1.51	1.68	-2.95	0.46	-0.07	-0.07	0.15
Tail Risk-prone	0.85	0.47	0.92	-2.78	-2.76	6.39	12.12	-22.19	1.49	0.05	-0.01	0.24
mean	0.83	0.42	0.80	-1.80	-2.73	5.35	9.43	-15.47	0.11	0.04	-0.19	0.25
IQR	0.52	0.14	0.58	2.04	2.36	7.10	21.84	23.96	2.83	0.56	0.24	0.13

Figure 1: Relevance of Risk Factors for different Bank Types over time

This Figure shows for each quarter whether or not a particular bank type - risk factor pair has a PIP larger than 50 percent (grey) or not (white). It thus contains a geographical representation of when which factors are important and for which types of banks.

Panel A: Market, SMB, HML, TB3, TS, DS

Figure 1 continued...

Panel B: TED, DepS, MMS, FX, VXO, Real Estate

Figure 2: Number of Factors and Marginal R2: Cross-sectional and Time variation

This Figure plots at each point in time the optimal number of factors (left axis) as well as the contribution of other factors than the market to the total (adjusted) R-squared (dotted line, scale on the right axis). Panel A reports results for our benchmark portfolio of the 50 largest BHCs and Panel B for different types of BHCs.

Panel A: 50 Largest BHCs

Panel B: Cross-Section of BHCs

Figure 3: Estimates of the market beta in the benchmark one-factor model and in the BMA analysis

This Figure plots the market exposure obtained via two different approaches. The solid line depicts the time-varying market beta from a single factor model. The dashed line depicts the exposure to market risk estimated in the BMA analysis with eleven additional factors. The beta reported for a given quarter is obtained by using weekly stock returns of the preceding two years.