Dynamic Interpretation of Emerging Systemic Risks

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ABSTRACT

We use computational linguistics to analyze risk factors in bank 10-Ks to develop an empirical model of dynamic, interpretable emerging risks that is grounded in the theory of Gorton and Ordonez (2014) and that successfully predicts financial instability. The model detects risks in advance of the 2008 financial crisis as early as late 2005. Risks related to interest rates, mortgages, real estate, capital requirements, rating agencies and marketable securities became highly elevated during this pre-crisis period, with individual bank risk exposures strongly predicting the probability of bank failure and future stock return volatility. Tests using very recent data indicate a rise in market instability since 2014 related to risks associated with sources of funding, marketable securities, regulation risk, and credit default. Overall, our model reliably assesses both the build-up of systemic risk in the financial system and bank-specific exposures in a timely fashion.

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Banks may be the black holes of the financial universe; hugely powerful and influential, but to some irreducible extent unfathomable."

Morgan (2002)

I Introduction

Understanding the nature of information production in the banking industry is critical to assessing whether financial instability is detectable and avoidable. Theories suggest that the incentives, and ultimately the timing, surrounding information production are nuanced. Information can be privately valuable to individual investors and depositors, but significant ongoing informational opaqueness can be socially optimal. For example, Gorton and Ordonez (2014) argue that the banking sector is more efficient when there is little or no information production on the quality of bank assets, as this economizes on information costs and, in so doing, leads to lower borrowing costs and greater economic growth. Yet opaqueness that is optimal in normal times exposes the economy to periodic crises following aggregate negative shocks to collateral values. Information production to ascertain collateral quality will then increase for a period of time until the crisis is resolved.

Models in this area assume that there are only two states of nature: normal times when there is no information generation, and crisis periods that induce information production. However, the path from stability to crisis is clearly not instantaneous given real world frictions. Slow information diffusion in asset pricing could be due, for example, to short sale constraints (Diamond and Verrecchia (1987)), limits to arbitrage (Shleifer and Vishny (1997)), information processing and awareness (Merton (1986)), and/or limited investor attention (Barber and Odean (2007)). Practically speaking, we suggest that there exist three states of information production: (1) no information production (normal period), (2) some information production as systemic risk is building (transition period), and (3) high information production (crisis period).

Although opacity may be useful in stimulating economic growth, existing regulation limits opacity because regulators require banks to disclose highly aggregated risk exposures in their annual 10-Ks. We conjecture that the initiation of information production and thus the start of the transition period can be detected by examining the link between financial market trading and the collective risks disclosed by financial institutions.[1]

[1] For example, Bui, Lin, and Lin (2016) find that short selling in bank stocks increased during the years leading up to the crisis and predicts bank outcomes. This provides support for the underlying assumption that trading by potential information producers occurs during our proposed transitional period.

We use computational linguistics to identify the presence of information production regarding systemic risks, and also to identify the specific channels through which systemic risks build. We focus these tools on bank stock price co-movements and their link to banks' disclosed verbal risk factors. If the transition period is sufficiently long, then specific systemic risk channels can, in principle, be identified early when it is possible to still mitigate the severity of financial instability. Our findings, based on the recent financial crisis, indicate that information production slowly builds for about three years during the transition period from stability to instability.

The use of qualitative information in the assessment of emerging risks is a complement to the many quantitative measures that have been proposed to monitor financial stability. Bisias, Flood, Lo, and Valavanis (2012) provide a survey of over 30 systemic risk metrics and this list continues to grow. The large number of proposed methods to monitor the build-up of systemic risk is related to the fact that there are many ways of defining systemic risk in a complex financial system. Examples include liquidity mismatch (Brunnermeier, Gorton, and Krishnamurthy (2014)), interconnectedness (Billio, Getmansky, Lo, and Pelizzon (2012), Allen, Babus, and Carletti (2012) and Elliot, Golub, and Jackson (2014)), and measures of bank risk (Adrian and Brunnermeier (2016) and Acharya, Pedersen, Philippon, and Richardson (2012)) to name only a few. In support of using many such measures, Bisias, Flood, Lo, and Valavanis (2012) argue that "a robust framework for monitoring and managing financial stability must incorporate both a diversity of perspectives and a continuous process for re-evaluating the evolving structure of the financial system and adapting systemic risk measures to these changes."

These existing risk measures can be categorized as general or specific. General measures include those based on financial market variables such as the correlation of stock returns, VIX, or CDS spreads. Specific measures obtain from a theoretical understanding of how systemic risk might manifest, for example, inadequate liquidity or under-capitalization. The drawbacks of general measures are twofold. First, they do not provide information on the economic determinants of systemic risks. Second, they often assume that the source of increased systemic risk is known, and that it is uniform across crises.

We begin by developing a framework that formalizes the ideal properties that systemic risk models should have. Our approach is cognizant of the fact that the financial system is complex, difficult for any one researcher to fully understand, and is constantly evolving. First, we suggest that the econometric model should be automated, replicable, and free from any bias imposed by the researcher. Second, the model must identify a set of emerging systemic risk channels that are clearly interpretable. Third, the model must be dynamic, and thus capable of identifying emerging risks that might not have been present in past periods or that might not be anticipated. Fourth, the methodology should be flexible enough to permit optional researcher exploration without loss of generality. Finally, the model must identify emerging risks in a timely fashion and with adequate power to eventually allow for regulatory intervention. As we argue below, each of these criteria are present in our model.

We propose that risk assessment of the disclosures of financial firms can provide valuable information on both the intensity and source of emerging systemic risks. Textual analysis using 10-Ks is well-suited to the task as firms are required to disclose a synopsis of risks facing the company.[2] For example, these include discussions of interest rate risk ("In a sustained rising interest rate environment the asset yields may not match rising funding costs, which may negatively impact interest margins."), capital adequacy (" Republic's failure to maintain the status of "well-capitalized" under our regulatory framework, or "well-managed" under regulatory exam procedures, or regulatory violations, could compromise our status as a FHC and related eligibility for a streamlined review process for acquisition proposals and limit financial product diversification.") and mortgage loan risk ("Our interest-only mortgage loans may have a higher risk of default than our fully-amortizing mortgage loans and, therefore, may be considered less valuable than other types of mortgage loans in the sales and securitization process.").[3]

We identify the list of potential systemic risks from 10-K text by extracting all text in sections or subsections of the 10-K that have the root word "risk." We use two text analytic tools in tandem: Latent Dirichlet Allocation (LDA), a dimensionality reduction algorithm, and Semantic Vector Analysis (SVA), which ensures interpretability while allowing for flexibility and standardization. A drawback of LDA, if used alone, is that it is not always interpretable and it produces a unique set of topics in each year making it difficult to track the evolution of individual risks through time. Therefore, we use SVA in a second stage to ensure interpretability and to standardize themes from LDA into a simple panel database containing bank-year observations of each risk exposure. This approach allows us to lock

[2] After 2005, the SEC requires a separate risk factors disclosure section, Item 1A. Prior to this time, these disclosures were made in different sections throughout the 10-K.

[3] Text analytics in finance is growing in popularity and has been shown to explain asset prices and corporate decisions in a variety of settings. For example, see Tetlock (2007), Tetlock, Saar-Tsechanksy, and Macskassy (2008), Tetlock (2010), Hanley and Hoberg (2010), Loughran and McDonald (2011), Hanley and Hoberg (2012), Loughran and McDonald (2014), Hoberg and Maksimovic (2015), and Hoberg and Phillips (2016).

in some risk factors that are stable through time while allowing flexibility for the model to detect newly emerging risks in any given period in our sample.

To identify the potential for systemic risk to emerge, we compute a pairwise covariance matrix based on daily stock return comovement in each quarter from 1998 to 2015. To determine which semantic risk themes are emerging in a given quarter, we examine the link between pairwise covariances and common bank-pair exposures to each verbal risk theme. We predict that return covariance will be significantly associated with common risk exposures, but only in transition periods where systemic risk is building.

In order to assess whether a specific systemic risk emerges in the time-series leading up to the financial crisis, we first estimate the adjusted R^2 contribution of each of our 18 baseline candidate risks in explaining return covariance over the entire time series. We then standardize the resulting quarterly time series from 2004 to 2015 by the mean and standard deviation from a non-crisis baseline period (1998 to 2003). The resulting t-statistic indicates whether the contribution of a specific theme is statistically significant and provides an indication of importance. In addition, we also create an aggregate emerging risk score as the R^2 due to the contribution of all semantic themes in explaining return covariance.[4]

Our aggregate emerging risks score is shown in Figure 1. It becomes highly significant (t-statistic above 8.0) in the second quarter of 2005, far in advance of the financial crisis. It more than doubles to a level with a t-statistic exceeding 13.0 by the fourth quarter of 2006. Other indicators of systemic risk such as VIX or aggregate measures of volatility do not become significantly elevated until the crisis begins in 2008. We also note that our aggregate systemic risk score does not become elevated during other episodes of market volatility that were not ultimately systemic in nature for banks specifically. For example, the bursting of the technology bubble of 2000 and the events surrounding 9/11/2001 were both associated with volatile stock returns, but there were no serious spillovers to financial intermediaries and no threats to financial stability. We view these events as falsification tests. That is, our model does not produce elevated systemic risk themes simply when markets are volatile. Rather, our model is designed to measure systemic risks and to assess financial stability.

We next examine the specific types of risks that emerged in the lead-up to the financial crisis. We show that themes related to interest rates and mortgages (Mian and Sufi (2009)), rating agencies (White (2010)), dividends (Acharya, Gujral, Kulkarni, and Shin (2011)), risk

[4] Gao (2016) finds that including a text-based systematic risk factor into a four-factor Fama-French model increases R^2 and the factor is associated with a positive risk premium.

management (Aebia, Sabatob, and Schmid (2012)) and marketable securities rise in their ability to explain bank-pair return covariance as early as 2005.

Because our methodology allows for flexibility in the examination of risks, we further consider sub-themes known to be related to increased risk during the financial crisis. For example, sub-themes within the broader category of marketable securities include commercial paper (Covitz, Liang, and Suarez (2013)), cash (Cornett, McNutt, Strahan, and Tehranian (2011)), mortgage-backed securities (He, Qian, and Strahan (2011)), and municipal bonds (Dwyer and Tkac (2009)). We show a heightened impact of each of these sub-themes on bank-pair covariance in the period leading up to the crisis, especially mortgage-backed securities and commercial paper, indicating an early understanding (as early as late 2005) by investors that risks associated with these asset classes were of concern. Thus, our method can provide regulators with an early warning of specific emerging risks that might affect financial stability.

The aforementioned results are based on aggregate time series analysis. Our framework also enables us to measure the exposure of specific banks to systemic risk in the cross-section. We examine whether institution level exposure predicts subsequent stock returns, volatility and bank failures. We find that the more a bank is exposed to emerging risk factors from early 2006 until the second quarter of 2008, the greater is the negative return during the financial crisis from September 2008 to December 2012.

We analyze whether our methodology can predict subsequent bank failures. Using data on bank failures from the FDIC, we show that banks exposed to more emerging risk factors, as early as the beginning of 2006, are more likely to fail during the 2008 financial crisis and its aftermath.

Last, to assess the impact of emerging risk factors in the cross-section more generally, we use Fama and MacBeth (1973) regressions where the dependent variable is an ex post monthly stock return volatility and the independent variable of interest is the emerging risk exposure of each financial firm measured over one, two, three and four quarters. We find that both recent and deeply lagged exposures (up to 30 months) predict subsequent monthly volatility.

Collectively, our results indicate that text analytics can identify emerging risks and detailed semantic analysis can reveal the underlying mechanisms driving these risks that can be useful to researchers and regulators interested in assessing financial stability. Moreover, this might be possible years before systemic risks reach crisis levels.

Up to this point, our analysis has focused on historical events. But in order for our methodology to prove its dynamic properties, it must also provide insights regarding emerging risks in the future. Examining emerging risk factors in very recent data (through the beginning of 2016) indicates a substantial build-up of potential systemic risk at present.[5] Concerns about sources of funding, marketable securities, credit default, regulation risk, and capital requirements are examples of the risks we see emerge starting in early 2014. More importantly, we show that financial firms' exposure to these emerging risks predicts bank-specific negative stock returns from December 2015 to February 2016 (when financial firms were particularly volatile). While it is too early to tell whether a systemic event will occur in the future, our findings suggest that researchers and regulators should be aware about the potential impact of current emerging risks.

In addition to contributing to the research on systemic risk metrics and bank failures (Sarkar and Sriram (2001), Cole and White (2011), Fahlenbrach, Prilmeier, and Stulz (2012) and DeYoung and Torna (2013)), our paper is related to a growing literature on early warning systems.[6] Unlike many papers that propose metrics based upon variables known to affect financial institutions during the financial crisis, our methodology is not predicated on defining the source of systemic risk, and thus, does not suffer from a "post-crisis bias" (Bussiere and Fratzscher (2006)). Because of substantial reforms in the financial sector, the risks that emerge in the next crisis are unlikely to resemble those from previous financial crises. Our methodology is dynamic and free of researcher bias. Hence it allows for the identification even of emerging risks for which researchers or regulators have no ex-ante knowledge.

II Existing Theory and Motivation

We briefly explain how our paper is motivated directly from theories of systemic risk in the banking sector. Although we discuss specific theories of bank opacity below, we also note the presence of a broader literature that examines the impact of mandated disclosures on financial market regulation.[7] Our findings contribute to the debate of whether

[5]As with all predictive models, this is a joint test of the significance of the risks in the economy and the significance of the model to predict those risks.

[6]See for example, Huang, Zhou, and Zhu (2009), Giesecke and Kim (2011), Estrella and Mishkin (2016), Frankel and Saravelos (2012), and Duca and Peltonen (2013).

[7]See Verrecchia (2001), Dye (2001), Healy and Palepu (2001), and Beyer, Cohen, Lys, and Walther (2010) for additional reviews of the literature on collective disclosures and the informational environment.

enhanced financial disclosure is beneficial from the perspective of societal welfare (Kurlat and Veldkamp (2015)).

Early papers such as Diamond and Dybvig (1983) and Gorton and Pennacchi (1990) and more recently, Gorton and Ordonez (2014) and Dang, Gorton, Holstrom, and Ordonez (2016), suggest that the banking sector (or debt more broadly) generates the most value to society when there is no information production specific to underlying loans. Bank opacity avoids scenarios where banks issue sub-optimally small loans to avoid incentivizing information production, and allows uninformed investors to participate without paying information rents.[8] In turn, this reduces borrowing costs and increases economic growth.

Other papers theorize that opacity can create financial stability and contagion. Bouvard, Chaigneau, and Motta (2016) examine the interaction between opacity and the voluntary disclosure of private information of regulators. In this case, opacity signals good news because regulators will only disclose information in times of crisis.[9] Thus, markets appear to know some but not all of the relevant information about the risks facing banks. This creates under-reporting of information because the regulator makes the system opaque in more states than is optimal, creating instability. Alvarez and Barlevy (2015) agree that bank opacity can, at times, be optimal for bank risk sharing. However, if contagion is severe, requiring banks to disclose more information can improve welfare. Begley, Purnanandam, and Zheng (2016) show that banks under-report their market risks when they have incentives to save equity capital, and this coincides with periods of systemic risk.

Thus, the literature suggests that bank opacity can expose society to financial crises as an absence of information production can allow systemic risk to build unchecked, creating large panics ex post. This raises the question as to whether it is possible to enjoy an optimal level of bank opacity, and yet establish a mechanism for reducing crisis risk.

The benefits of bank opacity may be feasible to maintain if information produced about financial instability has the following three traits: (1) such information can be generated

[8] Whether banks are indeed opaque is subject to debate. Flannery, Kwan, and Nimalendran (2013) examine opacity using market trading patterns of banks. During normal times, larger banks do not appear to be more opaque than their non-financial control firms. However, during the crisis period, banks' microstructure diverges from non-banks, which increases opacity. Jeffrey S. Jones and Yeager (2013) find that bank investments in opaque assets create more systematic risk and increase price synchronicity.

[9] Peristian, Morgan, and Savino (2010) provide evidence on the release of stress test results and find that the market can distinguish between banks that did and did not have a capital gap before the stress test. They document a market reaction upon announcement only for banks with a capital gap and conclude that "the stress test produced information about the banks that private sector analysts did not already know." The fact that investors knew some of the risks facing banks, but not all, is a key requirement for a prolonged transition period leading up to crisis periods.

at little to no cost (Andolfatto, Berentsen, and Waller (2014)), (2) it is uninformative in normal times, and (3) it is uninformative about specific loan attributes. The ability to produce information having these traits is especially beneficial if the costs to society of large scale panics is high, and if preemptive regulatory interventions can potentially reduce the severity of impending crises.

The information generated by our risk model generally satisfies these three criteria. First, because it is automated, information gathering costs are negligible. Second, the model is designed to produce no information about individual loans or assets, and it is also designed to produce no information in normal times. That is, the model is designed to produce aggregate information about systemic risk, and only when systemic risk is building. These unique properties are made possible because we focus only on co-movement in returns that might plausibly be driven by candidate emerging systemic risk factors, which are not specific to any particular asset.

The empirical framework adopted in our paper is motivated by the aforementioned theory that suggests that in normal times investors will not find it profitable to produce information. As financial instability increases, investors will invest in information production regarding the risks facing banks and will begin to trade on this information. If investors are trading on specific emerging risks, the key prediction is that pairs of banks exposed to the same risk will experience aberrational co-movement. This will, in turn, create elevated return covariance for bank pairs exposed to the same emerging risks allowing our methodology to predict the potential for financial instability.

The benefits of such an emerging risk model are highest if the social planner can be made aware of emerging risks before they reach crisis levels. This would allow the social planner to fix the systemic flaws through regulatory change, which would then allow the economy to return to normal times without a full-fledged panic. Thus, in order for our methodology to be useful for researchers and policymakers, it must identify emerging risks in a dynamic, flexible and comprehensive manner even in changing market conditions. We propose that an ideal model should satisfy the following five requirements:

Requirement 1 (Bias-Free): The model should be automated, replicable, and fast to execute. Non-automated approaches are likely intractable given the large volume of verbal risk factor data disclosed in 10-Ks. In addition, the method should not require user input as to the selection of the emerging topics.

Requirement 2 (Interpretable): The output from the model must produce a set of emerging risk factors that are clearly interpretable without ambiguity. Empirical research requires that identification of specific textual themes should be easily interpretable in order to measure their impact. Precision in isolating the type of emerging risk is particularly critical when considering policy interventions.

Requirement 3 (Dynamic): The model must be dynamic, and capable of identifying emerging risks in the current period that might not have been present in past periods. Generally, empirical asset pricing focuses on stable risk factors. In contrast, systemic risks are by nature unique, and they can be spontaneous in nature. This requirement is particularly relevant when specific emerging systemic risks might not be ex ante known to the researcher.

Requirement 4 (Flexible): Although the model should be capable of identifying emerging risk factors without any researcher input (per Requirement 1), the model should nevertheless allow the user to delve more deeply into the sources of risk using their knowledge of current economic conditions. An ideal model will permit deeper analysis without loss of generality.

Requirement 5 (Timely): The model must be able to detect emerging risks well in advance of a systemic event. In order for the model to be useful for regulatory intervention, the model must provide an early warning sign of areas of concern.

These requirements set a high bar, which cannot be met using many standard computational linguistic methods. For example, many studies use fixed vocabulary lists to score documents (see Loughran and McDonald (2011) and Tetlock (2007) for example). This approach is useful in addressing many existing questions in the literature, and is automated. However, the approach does not satisfy the bias free component of Requirement 1 in our setting because the researcher must provide the word lists. The approach also is not dynamic (Requirement 3) because it offers no guidance regarding how the word lists might change over time.

Given Requirement 1 in particular, the most suitable tools should be those that are automated and that create content organically. Support vector regression (SVR) is an example of a text analytic method used in the finance and accounting literature (Manela and Moreira (2016) and Frankel, Jennings, and Lee (2016)) that does not require researcher input regarding content. However, this method does not satisfy the rather critical Requirement

2 of interpretability. SVR only identifies single words or commongrams, and the results are difficult to interpret. For example, Hoberg (2016) shows that SVR words tend to be common words, words with multiple interpretations, and shorter words.

Latent Dirichlet Allocation (LDA), like SVR, also generates content automatically without researcher bias. However, because the focus of LDA is on identifying specific topics based on clusters of vocabulary, the algorithm comes closer to identifying links that are interpretable. LDA is also fully automated and can be rerun in any period, making it dynamic as well. However, one drawback to this approach lies in the dynamic continuity of LDA models. Because LDA regenerates themes in each time period, there is no thematic continuity year-to-year, making it difficult to identify exposure to consistent themes over time. In addition, the LDA algorithm is not flexible as it does not accept researcher input beyond simple parameter specifications, and hence it does not satisfy Requirement 4.

As a result of these challenges, we consider a model of emerging risks that uses two tools in tandem. The approach first runs LDA on the risk factor corpus to identify a set of themes in each year. The model then uses Semantic Vector Analysis (SVA) to generate fully interpretable output and to provide year-over-year continuity of common themes. The pairing of these tools generates a model of semantic themes that can identify plausible emerging risks in a timely fashion (Requirement 5) thus, satisfying all five requirements. We now discuss how we implement our methodology using LDA and SVA .

III Methodology

We consider the corpus of verbal risk factors disclosed by U.S. banks in their 10-Ks from 1997 to 2014.[10] In its raw form, the text is in paragraph form and is very high-dimensional (many thousands of paragraphs and unique words). This complexity precludes using the corpus to detect interpretable emerging risk factors without some dimensionality reduction. We consider two text analytic tools to address this problem. The first, Latent Dirichlet Allocation (LDA), is a dimensionality reduction algorithm. The second is Semantic Vector Analysis (SVA), which ensures flexibility and direct interpretation of emerging risks.

[10]Following convention, we only use the initial 10-K filed in each fiscal year, and do not consider amended 10-Ks which can be filed at a much later time.

A Extracting 10-K Risk Factors

Our sample of 10-K's is extracted by web-crawling the Edgar database for all filings that appear as "10-K," "10-K405," "10-KSB," or "10-KSB40." The document is processed for text information, fiscal year, and the central index key (CIK). Although all of the text-extraction steps outlined in this paper can be programmed using familiar languages and web-crawling techniques, we utilize text processing software provided by meta Heuristica LLC. The advantage of doing so is that the technology contains pre-built modules for fast and highly flexible querying, while also providing direct access to analytics including Latent Dirichlet Allocation and Semantic Vector Analysis (discussed in the next section).[11] We use all available fiscal years in the metaHeuristica database from 1997 to 2014.

One benefit of using metaHeuristica is that the discussion of risk factors in the 10-K are time consuming to extract using standard programming methods. Starting in 2005, risk factors became more standardly placed in Item 1A. Prior to 2005, however, most firms discussed risk factors in many different parts of the 10-K with heterogeneous subsection labels. metaHeuristica's dynamic querying tools allow us to identify and query directly sections and subsections of the 10-K containing the word root "risk" regardless of where they are in the 10-K.

The output from these metaHeuristica queries is the full set of paragraphs that contain discussions of risk factors for all banks in our sample in all years from 1997 to 2014. Each paragraph is linked to key identifiers including the bank's central index key (CIK), the file date of the given 10-K, the bank's fiscal year end, and the filer's SIC code. This database of paragraphs is the central input to the text analytic methods we discuss.

B Latent Dirichlet Allocation

LDA is a dimensionality-reducing algorithm used extensively in computational linguistics that was developed by Blei, Ng, and Jordan (2003). The method was created from an underlying model in which each document is assumed to be generated from a probability distribution over topics. Suppose there are T topics that a document writer might choose from. The vocabulary corresponding to each topic, when written, is assumed to be generated using a distribution of vocabulary associated with an individual topic. LDA algorithmically

[11]For interested readers, the metaHeuristica implementation employs "Chained Context Discovery" (See Cimiano (2010) for details). The database supports advanced querying including contextual searches, proximity searching, multi-variant phrase queries, and clustering.

derives both a measure of how much text in each document corresponds to each topic, and the topic vocabularies for each topic.[12]

Each LDA topic is defined as a probability distribution over 100 individual words and 100 commongrams. For example, the word "mortgage" might occur with a higher probability in a discussion of financing risk than in a discussion of internal risk management. Suppose that there are a fixed number of T such topics that banks draw upon when writing their risk factors (RFs). Potential topics might include interest rate risk, deposit risk, and risks relating to sources of funding. When writing the 10-K and discussing risk factors, LDA assumes that managers draw words from topic-specific vocabularies. Although readers of 10-Ks might expect specific risk factors to appear as topics, LDA does not require the user to specify any topics ex ante. They are determined algorithmically by LDA using likelihood analysis. This fact is critical to our requirements, as it implies that the algorithms can detect an emerging risk even if the user is entirely unaware of the existence of the risk.

LDA requires only one decision from the user, i.e. the number of topics T to be generated. To maintain parsimony, in this study, we focus on 25 topics (although we consider 50 topics for robustness and find similar results). The choice of 25 topics reflects the multi-faceted nature of RF text and allows us to identify higher-dimensional topics without significant overlap.

LDA output is in the form of two data structures. The first data structure describes the distribution of topics discussed by each bank in each year of our sample. These firm-year specific distributions are commonly referred to as "topic loadings". LDA generates a vector of length 25 for each firm-year in our sample, scoring the document based on the extent to which it discusses each of the 25 topics. This data structure is a reduced dimension summary of the aggregate content of the RFs discussed throughout the 10-K. Raw 10-Ks have a dimensionality exceeding 100,000, on average, corresponding to the number of unique words. The output of LDA summarizes each document using vectors of length of 25.

The second data structure is a set of word frequency probabilities for each topic. For LDA based on 25 topics, this data structure contains 25 individual word lists with corresponding word probabilities. In other words, each topic is described as a vector of probabilities of individual words. The word lists associated with each topic can be evaluated to

[12] We provide only a summary level discussion of LDA here. We refer more advanced readers interested methods to the original study by Blei, Ng, and Jordan (2003) for a complete treatment, or to the Appendix A in Ball, Hoberg, and Maksimovic (2016) for a less technical treatment.

determine the most important risk factors that appear in the sample of banks in a given year.

Figure 2 displays a summary of the output of an LDA model using our sample of banks in 2006. Overall, we find the choice of 25 topics to be both parsimonious and informative. The figure shows that bank risk factors contain many topics that imply sensible risk factors being disclosed by banks. These include interest rate risk, economic conditions, mortgage loan risk, regulation risk, fair value, and corporate governance. However, the quality of an LDA model needs to be assessed more deeply by looking at the full vocabulary lists associated with each topic. Only if each topic can be cleanly interpreted as having only one meaning, would we declare success regarding the "clear interpretation" requirement that we discussed earlier as an ideal property of a risk model.

For example, the risk topic labeled "r-10" in the summary Figure 2 suggests that it is related to real estate loans. The list contains phrases such as "real estate," "loan portfolio," and "commercial real estate". This topic is an example of a highly interpretable emerging risk, as it is straightforward to understand that this source of this risk is related to real estate loans.

Not all of the topics in the time-series, however, are easily interpretable, and some tend to blend themes. For example, the topic labeled "r-08" in the summary Figure 2 contains phrases such as "fair value," "interest rate risk," and "financial instruments." Although any one of these items individually might indicate an interpretable risk factor, the blending of these in one LDA topic suggests ambiguous content.[13] Thus, we conclude that LDA only partially succeeds in satisfying Requirement 2, interpretability.

Another limitation is that LDA creates a unique list of emerging risk factors in each year, and each is related to the emerging risk factors in prior years in a different way, making it difficult compare topics over time. In order to identify stable risk factors, the researcher would need to manually assess the similarity of topics from year to year. Such an assessment can lead to the introduction of researcher bias, violating Requirement 3.

The final limitation of LDA is that it fails to deliver flexibility (Requirement 5 above). LDA, as a canned algorithm, and does not accept input regarding the types of risk factors that a user might like to explore further. For example, upon reviewing the results in Figure

[13] A deeper dive into the complete word lists comprising this topic confirm this assertion. It contains additional terms such as "rate risk," "financial instruments," "cash flows" and "hedge," making its overall categorization ambiguous.

2, a researcher might wish to further understand the properties of an individual sub-risk such as "commercial real estate" with more granularity. Because LDA does not address this issue, we propose an extended formulation that satisfies all five requirements.

C Semantic Vector Analysis

We propose a second stage procedure using Semantic Vector Analysis (SVA) based on a module provided in the metaHeuristica software package to address the aforementioned limitations of LDA. The SVA algorithm draws upon research in the area of "Distributional Semantics", a probabilistic approach used to uncover the semantics of natural language. The intuition for this approach is that "a word is characterized by the company it keeps" as popularized by linguist John Rupert Firth (1957).

The SVA algorithm first collects distributional information (on a per word or a per phrase basis) from the 10-K and stores it in high-dimensional vectors. The vectors can then be used as a representational framework to characterize how any given word or phrase is semantically related to other words in the corpus. This step is done using neural networks as in Mikolov, Chen, Corrado, and Dean (2013) and Mikolov, Sutskever, Chen, Corrado, and Dean (2013). In particular, we use a two-layer neural network to learn the contextual use of words. The algorithm learns contextual use by using features of the text to (A) predict a single word given its immediate surround words and (B) predict the surrounding words of a single word. This approach allows us to generate a more flexible, interpretable mechanism to identify risk factors.

We use the first stage LDA results to extract a list of economically relevant risk factors by reviewing the results of the LDA model in detail, both at the summary level (Figure 2) and at the detailed level for the 25 topics. However, this step is not fully automated because the user must prune the list of LDA phrases to eliminate any boilerplate or redundant information. Although user input is required (which might violate Requirement 3), it is a necessary condition to ensure interpretability of the results (Requirement 2). Also note that the extent of human interaction in this case is limited to pruning a list of essential terms, which likely poses a more modest level of bias compared to methods that require researchers to propose such a list without any guidance.

Our examination of the LDA topics results in 18 themes[14] and the SVA algorithm

[14] We originally identified 21 themes but reduced the number to 18 after noting that three were highly correlated with other themes and were vague in interpretation. We dropped themes related "Economic

converts each of the 18 themes into a vector of 100 words and commongrams that best represent the given theme in the corpus. The resulting vectors are lists of words and phrases, each accompanied by a cosine similarity indicating how strongly linked the given word or phrase is to the semantic theme.

Table I we displays these "semantic vectors" for a sample of six of our baseline 18 semantic themes. For example, the first two columns illustrate that the "Mortgage Risk" theme loads on the words including "mortgages", "originated", "FNMA", "single family" etc. Intuitively, these words would be expected to appear in a discussion about Mortgage Risk. The theme "Derivative & Counterparty Risk" loads on phrases including four words having the root "counterparty", and also terms like "swaps", "netting arrangements", and "exposure".

In all, the word lists associated with each semantic theme, by design, are interpretable. This is because the lists are designed to maximize the identification of effective synonyms to the specified theme itself (the key input to SVA is a theme, expressed as a concise phrase, such as "mortgage risk"). Hence, the algorithm directly satisfies the interpretability Requirement 2. This approach also offers flexibility because the user can add any risk factors to this list even if they did not appear visibly in the LDA topics (therefore, satisfying Requirement 5, flexibility). Because the SVA algorithms are run every year, it is dynamic and therefore, the method also satisfies Requirement 4.

D Linking LDA to SVA

Our last step is to map the LDA topic model data structures to the SVA themes in order to determine an individual bank's exposure to each emerging risk. This is done for each SVA theme, one at a time, by computing the cosine similarity between each SVA theme and the raw text corresponding to each bank's total risk factor disclosure.

In particular, for each year t, suppose there are n_{ikt} unique words that are in the union of firm i's risk disclosure and theme k. We represent the risk factor disclosure for the firm as a vector with n_{ikt} elements, which we denote $W_{i,t}$. Each element is populated by the number of times firm i uses a given word in its risk factor disclosure in year t and the vector is normalized to have a length of 1. For any word that appears in SVA theme k but not in firm i's risk disclosure, the element is set to zero. Analogously, we represent the vocabulary

Conditions", "Board of Directors", and "Products and Services".

of theme k as a vector also with n_{ikt} elements, which we denote $T_{k,t}$. Each element of this vector contains the numerical theme loadings as shown in Table I for words that are part of the theme and this vector is also normalized to length 1. For any word that appears in firm i's risk disclosure but not in SVA theme k, the element is set to zero. Note that the vectors $W_{i,t}$ and $T_{k,t}$ have the same length.

We thus compute firm i's loading on semantic theme k in year t as $S_{i,k,t}$ as the normalized cosine distance:

$$S_{i,k,t} = \frac{W_{i,t}}{||W_{i,t}||} \cdot \frac{T_{k,t}}{||T_{k,t}||} \tag{1}$$

We compute the loading for firm i for each of the 18 semantic vectors. We thus have a panel database with one observation being a single bank-year containing 18 semantic theme loadings ($S_{i,k,t} \forall k = 1, ...18$).[15] The resulting data structure allows us to observe the intensity of every bank's discussion of each of the 18 themes and how it changes over time.

A final note is that most of the 18 semantic theme loadings $S_{i,l}$ are not highly correlated in the firm-year panel database. In particular, Table II reports the Pearson correlation coefficients between each pair of loadings. The pairwise correlations are generally less than 40%. However, there are some exceptions as some pairwise correlations are in the 50% to 60% range. For example, there is a 66.7% correlation between capital requirements and regulatory risk, and a 63.2% correlation between funding sources and capital requirements. These correlations indicate that some risk factors tend to co-appear in the same bank disclosures.

Despite some higher correlations, many banks still disclose one related theme without disclosing the other, giving us power to separate the impact of each factor. To ensure that multicollinearity is not affecting our results, we carefully inspect variance inflation factors when we estimate our covariance regressions containing all 18 factors. Because these regressions have a very large number of observations (the database is based on permutations of all bank pairs and we have over 55 million bank-pair-quarter observations in total), our ability to estimate variance inflation is high. We find that variance inflation factors never exceed 3.5, well below the problematic threshold of 10 and conclude that multicollinearity is not a first-order concern.

[15] Cosine similarity is bounded between 0 and 1 with observations closer to one indicating greater similarity between the SVA theme and the firm's risk factor disclosure. Thus, if a particular SVA theme's cosine similarity with firm i's risk factor disclosure is close to one, this means that the bank's discussion of the theme is highly relevant and the opposite is true if the cosine similarity is close to zero.

IV Data and Sample

Our initial sample of publicly traded financial institutions are identified from the Center for Research in Security Prices (CRSP) and Compustat databases as companies having SIC codes in the range 6000-6199. To be included in our final database, a bank must also have a link between its Compustat gvkey and its central index key (CIK), the unique identifier used to track firms on the Edgar database provided by the Securities and Exchange Commission. The gvkey to CIK links are obtained from the SEC Analytics database. Observations must also have a machine readable discussion of risk factors in its 10-K as identified by the metaHeuristica database. To satisfy this latter requirement, we query the metaHeuristica database to find any 10-K section titles, or subsection titles, containing the word "risk" or "risks".

Our final sample contains 9,046 bank-year observations from 1997 to 2014 that satisfy these requirements. We have an average of 503 publicly traded banks per year in our sample. Figure 3 displays the composition of our sample over time. The figure shows that there are 483 banks in the first year of our sample, and the number of banks peaked in 1999 at 617 banks. One reason for this initial increase might be that banks did not consistently disclose risk factors in the first two years of our sample, but more reliably disclosed risk factors after 1999. After the peak in 1999, the number of banks in our sample slowly declined to roughly 523 by the onset of the financial crisis in 2008 and further declined steeply to 315 by the end of our sample in 2014. This reflects the well-known finding that many banks failed or were acquired in the aftermath of the crisis.

A Financial Market Variables and Bank Characteristics

The literature on measurement of systemic risk often relies on financial market variables to measure intertemporal changes in the financial stability of the economy. For example, stock market returns capture common risk factors (Fama and French (1993)) that allow for the identification of potentially systemic events in real-time using readily accessible data (Brunnermeier and Oehmke (2013)). We consider stock market variables that either capture the stock return co-movement among financial institutions, or that identify the overall build-up of risk within the financial system. Our primary variable of interest is the pairwise covariance based on daily returns from CRSP for pairs of financial firms in our sample in a given quarter.

We then consider four additional measures to capture overall market risk or uncertainty. The first measure is the cross-sectional standard deviation of monthly returns for all stocks in the CRSP database in a given quarter. The second is an analogous measure based on financial firms only. The third is the implied volatility of the European-style S&P 500 index options (VIX). The fourth is the average pairwise covariance of banks in our sample.

Our primary measure of the informational relationship between banks is the pairwise covariance for every permutation of bank i and j in every quarter t. We compute the covariance using daily returns of bank pairs in each given quarter, and denote this as $C_{i,j,t}$.[16]

We collect information from Call Reports on bank characteristics that have been used in the literature (Cole and White (2011) and Cornett, McNutt, Strahan, and Tehranian (2011)) as control variables in our covariance model. In addition, we also separately explore the extent to which these accounting variables predict systemic risks. We aggregate Call Report data at the holding company level if the bank has a parent ID, otherwise, data is at the individual commercial bank level. In order to identify an identifier that can be used to identify banks in our data, we merge the RSSD ID in the Call Report Data with the New York Federal Reserves list of publicly listed institutions to obtain a CRSP PERMCO. We use this field as a key to merge with our sample. If an institution does not have a Call Report, we collect data on bank characteristics from COMPUSTAT.

Specifically, we construct the following variables (all but *Assets* are scaled by assets): *Cash* and *CatFat* from Berger and Bouwman (2009) as measures of liquidity[17], *Loans* and *Ln(Assets)* as indicators of the size of the bank, *Non-Performing Assets*, the sum of loans that are 30 days and 90 days past due and *Loan Loss Prov & Allow*, the sum of loan loss provision and allowances to capture potential problem lending, *Bank Holding Co. Dummy*, an indicator variable equal to one if the bank has a parent, zero otherwise, *Neg. Earnings Dummy* an indicator variable equal to one if net income is negative, zero otherwise as a measure of profitability, and *Capital*, the ratio of equity to assets as this measure has been shown to predict subsequent bank performance (Berger and Bouwman (2013) and Cole and White (2011)). Finally, we include *Bank Age* and it is constructed as the time since the first appearance in CRSP.

[16] We winsorize these covariance estimates in each quarter at the 1/99% level to reduce the impact of any outliers.

[17] Generously provided by Christa Bouwman at `https://sites.google.com/a/tamu.edu/bouwman/data`.

We augment the database with Compustat industry data, which is based on SIC codes, and with textual network (TNIC) industry data from Hoberg and Phillips (2016). Because our framework naturally controls for industry as we limit our sample to banks, our additional controls for TNIC are conservative, and allow us to control for additional variation in product market offerings within the sample of banks (we also note that our results are robust to excluding this step). Overall, the purpose of examining bank and industry characteristics is to provide an array of control variables in our covariance regressions, as these variables should explain a material amount of variation in bank-pair-quarter covariances. Hence, any emerging risk factors we find can be seen as significant even relative to these existing drivers of covariance.

B Summary Statistics

Table III displays summary statistics. Panel A reports statistics for bank-pair-quarter variables. Because of the large number of permutations in this sample, there are over 55 million observations during our entire sample period. The Panel shows that the average pair of banks, not surprisingly, has a high positive covariance. Because all of our sample firms are financial institutions, 87.2% are in the same two-digit, 50% in the same three-digit and 46.8% are in the same four-digit SIC code. The average TNIC pairwise similarity from Hoberg and Phillips (2016) is 0.090, indicating a material amount of product similarity among the banks in our sample. As a basis for comparison, the average pairwise similarity of peer firms in the baseline TNIC network that is calibrated to be as granular as three digit SIC is 0.064.

Panels B and C of Table III display summary statistics for the bank characteristics that we consider. Most of the financial institutions in our sample, 85%, are bank holding companies. The average bank has loans to assets of almost 50%. Loan loss provision and allowances as well as non-performing assets are both close to zero (0.05% and 0.02%, respectively). Most of the banks in our sample are bank holding companies and, on average, have a capital ratio of 10%. Only 5% of banks have negative net income.

Panel D displays summary statistics for the quarterly time-series variables and we have 72 observations in our sample from 1997 to 2015. The average VIX index during our sample is 21.2, and it reaches a high of 51.7 in the 4th quarter of 2008. The average cross sectional standard deviation of monthly returns in our sample is 15.5% for all firms, and 9.1% for banks only. The lower result for banks only is because (A) firms in a specific industry have lower cross sectional variance due to the industry component being common to the included firms and (B) banks are highly regulated and insured.

Although their construction is explained in the next section, we report the summary statistics for two time series variables obtained from our emerging risk model. The first is the average accounting variable (bank characteristics and industry) adjusted R^2, 7.7%, indicating the explanatory power that standard bank characteristics and industry controls have in explaining bank pairwise covariances. We also report the incremental R^2, 0.8%, that textual risk factors have in explaining pairwise covariance beyond the accounting controls. Hence, the verbal risk factor metrics improve explanatory power by a material 10.4%. We note that the accounting variable adjusted R^2 has a higher R^2 contribution because it is well known that industry and firm characteristics, particularly size, are first-order drivers of comovement.

Another observation from Panel C is that both R^2 variables have substantial variation. For example, the marginal R^2 from the inclusion of verbal risk factors ranges between 0% and 2.3%. This variation illustrates a crucial property of our emerging risk model: it can detect time varying changes in the relationship between disclosed risk factors and bank pair covariances.

Table IV displays Pearson correlation coefficients for our time series variables. The standard time series variables used in past studies (VIX, cross sectional return volatility, and average covariance) tend to be strongly, positively correlated. For example, the average pairwise covariance, and both metrics of average cross-sectional standard deviation of monthly returns, are more than 50% correlated with the VIX. In contrast, the two R^2 variables, text and accounting, from the risk model have lower and sometimes negative correlations with the VIX and other volatility variables. This suggests that the measure of systemic risk we propose is not highly correlated with other quantitative systemic risk measures. Our later results will show that this is because our risk model R^2 variables lead these other measures in time series, reducing their simultaneous correlations.

V Determination of Emerging Risks

To determine which semantic risk themes are emerging or receding in a given quarter, we examine the link between exposures to each risk theme and the monthly pairwise covariance of banks i and j. Our central hypothesis is that stock return covariance, which is a measure of co-movement of banks i and j, should become significantly associated with bank i and bank j's exposure to a given semantic risk theme if that specific risk is emerging. This hypothesis relies on the assumption that a strictly positive number of investors are aware of emerging risks, and trade on them, before they become prominent. If so, their aggregate trading patterns will be detectable in the covariance data. Thus, banks jointly exposed to a given risk factor should comove in a significant way in a given quarter.

The key independent variables we consider are the extent to which banks i and j are exposed to the 18 semantic themes ($S_{i,l}$ and $S_{j,l}$ $\forall l = 1, ..., 18$). Specifically, we take the product of bank i and j's loadings (cosine similarity) on each of the semantic themes S (expressed here in vector form for all 18 risks):

$$S_{i,j} = S_i \ S_j \tag{2}$$

The resulting pairwise semantic theme loadings capture the extent to which banks i and j are exposed to the same emerging risks. We regress the quarterly return covariance of banks i and j on each of these 18 semantic theme loadings and we also include controls for industry, size, and accounting characteristics using the following is the regression equation:[18]

$$Covariance_{i,j,t} = \alpha_0 + \beta_1 S_{i,j,t,1} + \beta_2 S_{i,j,t,2} + \beta_3 S_{i,j,t,3} + ... + \beta_T S_{i,j,t,18} + \gamma \mathbf{X_{i,j,t}} + \varepsilon_{i,j,t}, \tag{3}$$

This model produces 18 β coefficients for each of the 18 pairwise semantic theme loadings, and also a set of γ coefficients for industry and bank characteristics. These slopes are computed separately in each quarter.

In the time series analysis that follows, we consider the R^2 from the above regression and decompose it into parts. First, we compute the R^2 attributable to the industry and accounting controls $X_{i,j,t}$ by running the regression in equation (3) without the semantic themes:

$$Covariance_{i,j,t} = \alpha_0 + \gamma \mathbf{X_{i,j,t}} + \varepsilon_{i,j,t}, \tag{4}$$

Then we compute the marginal R^2 that is attributable solely to the textual semantic themes by taking the R^2 from equation (3) and subtracting the R^2 from equation (4).[19] Note that both R^2 variables are now time-series variables, as each is derived from the regression

[18] We estimate pairwise control variables as the dot product of the variable for bank i with bank j.

[19] For robustness, we also consider a variation where we use the 25 LDA topic loadings ($T_{i,j,t}$) instead of the 18 semantic theme loadings ($S_{i,j,t}$) and obtain similar results. This indicates that the 18 semantic themes are correctly capturing information in the LDA loadings.

once per quarter. As a result, we are able to compare the time series properties of these R^2 variables to standard financial market variables that are typically used to assess systemic risk such as VIX or measures of aggregate volatility and comovement.

A Aggregate Time Series Results

We begin our analysis of whether our measures of emerging risk are informative in predicting the build-up of systemic risk. We do so by comparing the time series R^2 contribution of the accounting and textual variables from our risk model in Equation 4 to the time series variables that have been proposed as measures of systemic risk intensity. We define the initial part of our sample (1998 to 2003) as a calibration period, and use this period to compute each variable's baseline quarterly mean and standard deviation. In each of the subsequent quarters from 2004 to 2015, we compute a t-statistic based on how many standard deviations the current value is from the baseline mean. A high t-statistic indicates the likely presence of emerging risks.

We plot each variable's time series of t-statistics in Figure 4, rather than reporting them in tabular format, for ease of viewing. The benefit of the figure is that it makes it very clear when each risk begins to emerge. In particular, we can see the relative importance of each variable in the period leading up to the crisis and more recently.

Panel A of Figure 4 displays the time series of these t-statistics for four variables thought to be indicative of systemic risk: the VIX, quarterly average pairwise covariance among bank-pairs and the quarterly average standard deviations of returns for all firms and financial firms. Panel B plots the analogous time-series of t-statistics for the accounting and text R^2 variables used in our risk model. All variables are defined in Table III.

Examining the significance of financial market variables in Panel A, it is apparent that the VIX, average covariance and both measures of cross sectional return volatility do not become elevated above baseline levels until after Lehmann Brothers fails in September of 2008. We conclude that using these basic financial market variables as measures of emerging risks, or as an early warning system, is problematic. This is because they do not become prominent until the crisis has already emerged in full, too late to serve as an early warning indicator.

When we consider the time series of t-statistics for the accounting variables in Panel B of Figure 4, we find that it becomes different from the baseline period just after the first quarter in 2007. From the end of the second quarter of 2007 through the first quarter of 2009, the R^2 from accounting variables rises significantly above pre-crisis levels. Because the financial market variables in Panel A do not emerge until late 2008, we conclude that bank and industry characteristics are important in explaining variation in emerging risks, and can be a leading indicator of financial instability.

More importantly, Panel B of Figure 4 shows that semantic themes emerge earlier than both the financial market variables and the accounting variables used in the risk model. In particular, the elevation of the textual semantic theme variables' R^2 becomes apparent as early as late 2005 and strongly so by mid 2006. This is well before the crisis itself emerges, and also before the accounting variables emerge. The semantic theme contribution remains elevated as the crisis materializes in 2008, and tapers off as financial conditions begin to improve.[20]

These preliminary results indicate that an aggregate measure of textual themes related to risk can be an important ex ante indicator of emerging systemic risk. In the next section, we examine the contribution of individual emerging risks to bank-pair covariance.

B Individual Emerging Risk Factor Time Series

The preceding analysis provides evidence that semantic themes that capture emerging risks can provide an early warning of future periods of financial instability. A primary advantage of sematic themes as a measure of emerging risk compared to accounting or financial market variables is the ability to further interpret the text to identify the specific economic underpinnings of systemic risk build-up. Because accounting variables are low dimensional, they cannot be interpreted with greater depth to identify specific manifestations. For example, it is not clear what action should be taken to monitor systemic risk if firm size explains a significant amount of comovement.

In this section, we examine the contribution of each specific semantic theme in explaining how emerging risks affect the comovement of bank stocks. By doing so, we are able to identify the content of specific emerging risks and when they begin to emerge.

As with the aggregate time series results in Figure 4, we first estimate the time series of the marginal R^2 contribution of each individual semantic theme in explaining pairwise bank covariance using the model in Equation (3). This is done by computing the adjusted

[20] Using the R^2 due to LDA topics rather than SVA themes results in a similar pattern. Thus, for the remainder of the paper, we concentrate on SVA textual themes.

R^2 of the full model including all accounting variables and semantic themes, and then recomputing the adjusted R^2 with a single semantic variable excluded. This calculation is done separately for each of the 18 semantic themes, and the result is a single quarterly time series of R^2 contributions for each semantic theme.

To generate a plot of statistical significance regarding each theme's importance, we define the initial part of our sample (1998 to 2003) as a calibration period, and use this period to compute each semantic themes' R^2 baseline quarterly time series mean and standard deviation. In each of the subsequent quarters from 2004 to 2015, we compute a t-statistic based on how many standard deviations the current value is from the baseline mean. We then plot the quarterly t-statistics for each semantic theme. We consider an increase in the t-statistic to be indicative of an emerging risk factor.

Appendix A reports a fully detailed set of figures displaying the time series of t-statistics for each of our 18 text-based emerging risk factors. In Figure 5, we restrict the presentation to only the most prominent emerging risks in the period leading up to the 2008 financial crisis. The figure shows large increases in the t-statistics for semantic themes related to mortgages, real estate and interest rate risk, consistent with the build-up of risk in mortgage credit in the period preceding the crisis (Mian and Sufi (2009)). Demyanyk and Hemert (2011) suggest "that the seeds for the crisis were sown long before 2007, but detecting them was complicated by high house price appreciation between 2003 and 2005 - appreciation that masked the true riskiness of subprime mortgages." Notably, our methodology detects the emergence of these risks in 2005, well before delinquencies in the 2006 and 2007 loan vintages became apparent.

We also observe elevated risks for marketable securities, indicative of worries by some investors regarding the quality of these securities during the crisis. This finding is most likely due to concerns about mortgage-backed securities and risks to the liquidity of various short-term assets (Covitz, Liang, and Suarez (2013)).

We find that the semantic theme related to dividends is also prominent in the pre-crisis period. Acharya, Gujral, Kulkarni, and Shin (2011) present evidence that banks, even at the height of the financial crisis, continued to pay dividends to equity holders. The paying of dividends further depletes regulatory capital at precisely the time as banks were experiencing significant losses. The risk associated with the payment of dividends under potentially adverse circumstances is reflected in the rise in the t-statistic for this theme before the financial crisis.

It is well-known that credit rating agencies played a role in the crisis and we find an emergence of this risk in early 2005 that dies down at the end of 2006 but becomes prominent again in 2007. It re-emerges strongly before the Lehman bankruptcy in the first quarter of 2008. Our finding of a link to ratings supports the literature's identification of problems with the rating process such as ratings shopping (Benmelech and Dlugosz (2009), Skreta and Veldkamp (2009), Bolton, Freixas, and Shapiro (2012), and Griffin and Tang (2012)), ratings catering (Griffin, Nickerson, and Tang (2013)), rating agency competition (Becker and Milbourn (2011)), and rating coarseness (Goel and Thakor (2015)).

The risk management theme is heightened as early as 2004 and remains elevated until late 2007. This risk factor is less specific than those discussed above and likely captures overall concerns about banks' ability to manage increased exposure to systemic risk, and the extent to which banks had robust risk management procedures in place. This theme is important because the mitigation of risk is often discussed in conjunction with the disclosure of such risks, making it a prominent leading indicator of the build-up of collective risks.

Finally, regulation risk begins to be elevated in late 2005 perhaps reflecting concern about Federal Reserve intervention to chill an overheated housing market. In remarks to the American Bankers Association Annual Convention on September 26, 2005, Chairman Alan Greenspan expressed concern that the "apparent froth in housing markets may have spilled over into mortgage markets."[21] Also note the significant increase in 2010 corresponding to the passage of the Dodd-Frank Act.

Also noteworthy is that some risks do not appear to emerge around the 2008 crisis. In Appendix A, we do not find elevated themes prior to the 2008 crisis related to credit default, capital requirements, fair value, funding sources, bank deposits, or executive compensation even though some of these risks were identified as contributing to the crisis ex post. For example, concerns about executive compensation were raised, suggesting that bank managers might have engaged in excessive risk taking because federal deposit insurance provides a hedge against downside risk. Alan Blinder "refer(s) to the perverse incentives built into the compensation plans of many financial firms, incentives that encourage excessive risk-taking with OPM – Other People's Money."[22]

[21] `http://www.federalreserve.gov/boardDocs/Speeches/2005/200509262/default.htm`

[22] Crazy Compensation and the Crisis, *Wall Street Journal*, May 28, 2009 `http://www.wsj.com/articles/SB124346974150760597`. Note that Fahlenbrach and Stulz (2011) do not find evidence that worse compensation incentives were correlated with bank performance during the crisis.

Derivative and counterparty risk is only slightly elevated prior to the crisis despite the fact that counterparty risk associated with credit default swaps might have enabled an "unsustainable credit boom" that might have lead to excessive risk-taking on the part of financial institutions (Stulz (2010)).

In summary, our examination of interpretable text-based emerging risks indicates that many of the risks identified during the crisis as being systemically important were visible in the confluence of trading patterns by investors and the financial disclosures of banks many months (and sometimes years) in advance of the crisis itself. Financial regulators currently consider a plethora of financial market indicators to determine whether systemic risk is increasing. Our analysis suggests that this reliance on financial market indicators might reveal financial instability too late. The ability to identify specific sources of increased systemic risk early using semantic themes can be beneficial not only to scholars interested in examining systemic risk and episodes of stochastic volatility, but also to those who monitor financial stability, especially when standard metrics might be difficult to interpret and may not reveal increases in volatilty in a timely fashion.

Although our research question uses the financial crisis as an experiment to assess the efficacy of our approach, its ultimate viability depends on being able to identify future emerging risks before they become crises. In this spirit, we first note that there is a notable decline in the contribution of most semantic themes to bank-pair covariance after the crisis period, and Figure 1 shows analogous low R^2 in the earlier parts of our sample. The decline in significant themes after the crisis is consistent with the ultimate recovery that was observed, and with government interventions to reduce systemic risk.

Predicting future events in real-time is a high threshold for academic research. Because our methodology meets Requirement 5 as being timely, we are also able to examine the contribution of emerging risks to covariance as late as 2015. As can be seen in both Figure 1 and Figure 6, a substantial number of risks are emerging throughout 2014 and 2015. In Figure 6 for example, we see evidence of increased systemic risk though the end of 2015 that presage current economic conditions at the time this draft is written, notably the recent uncertainty in emerging markets, the rally in gold prices, potential defaults in the energy sector, slowing growth, poor performance of financial firm stock indices, and the threat of negative interest rates.

In support of the build-up of systemic risk due to these issues, themes related to funding sources, credit default and short-term securities emerge very strongly (t-statistic based on comparison to pre-crisis distribution exceeded 30 in some cases by late 2013). This perhaps indicated that conditions such as negative interest rates might pose challenges for traditional funding sources of banks. The *Wall Street Journal* notes that earnings for banks in the first quarter of 2016 were expected to decline 8.5% from the same period last year.[23]

Real estate risk declines after the financial crisis but re-emerges in late 2012 as the housing market begins to rally, particularly in areas hard hit by the recession. For example, a *New York Times* article on the housing rebound in Phoenix notes that an influx of newcomers to the state are having difficulty finding housing because of a contraction in the supply of houses and the lack of construction workers who left the state to find work elsewhere. Backlogs of foreclosures also continued to rise during that time creating uncertainty in the balance sheets of financial institutions.[24]

Derivative and counterparty risk has been a focus for financial regulators recently. Federal Reserve chair, Janet Yellen notes "Indeed, in the 21st century, a run on a failing banking organization may begin with the mass cancellation of the derivatives and repo contracts that govern the everyday course of financial transactions."[25] The increase in the importance of this theme in late 2013 is consistent with concerns over the importance of this risk to the financial system.

The capital requirement theme begins to be elevated after 2012 as regulators continue to stress test banks and evaluate appropriate capital levels. Related to this, regulation risk is also highly elevated in the recent period (although less so by the end of 2015). This semantic theme likely captures the heightened regulatory scrutiny faced by financial institutions in the wake of the implementation of the Dodd-Frank Act, and uncertainty surrounding monetary policy.

Finally, the risk management theme is also significant after a decline post-crisis signaling the potential build-up of risk in financial institutions. Although it is too soon to tell whether these emerging risks will lead to a systemically important event, our results suggest that some investors are trading in a way consistent with crisis-like expectations. As such, it is

[23] Kuriloff, Aaron, Miserable Year for Banks: Stocks Suffer as Rates Stay Low, *Wall Street Journal* April 10, 2016.

[24] See `http://www.nytimes.com/2013/10/10/us/real-estate-boom-in-phoenix-brings-its-own-problems.html?_r=0` and `http://www.forbes.com/sites/morganbrennan/2013/01/17/worst-of-foreclosure-crisis-is-over-but-problems-remain/#13bac1435748`.

[25] See `http://www.federalreserve.gov/newsevents/press/bcreg/yellen-opening-statement-20160503.htm`

valuable for researchers and regulators to be aware of potential threats to financial stability.

C Researcher Identified Themes

In this section, we depart from the main semantic themes generated by our methodology and demonstrate how the use of LDA and SVA, in tandem, offers the researcher a high degree of flexibility. Suppose a researcher observes that marketable securities are an emerging risk factor. A relevant question to ask is which marketable securities are driving this result? One might be interested in semantic sub-themes related to securities that were affected during the financial crisis and are likely be affected under current market conditions, for example, mortgage-backed securities, commercial paper, municipal bonds and cash. By querying the semantic vector directly on additional key phrases of interest, additional themes can be added directly to the risk model.

Figure 7 presents results for the added semantic themes using a graphical presentation akin to that in Figure 5. The figure shows that mortgage-backed securities and commercial paper, two asset classes that were at the heart of the financial crisis, have the most significant increase in the period preceding the crisis. The rise in emerging risks relating to these two types of securities begins as early as late 2005. Cash is also elevated during this time consistent with concerns about the liquidity of financial institutions.

After the financial crisis, the contribution of most of the sub-themes declines but both the cash and commercial paper themes increase in early 2014, reflecting current economic conditions perhaps related to low interest rates and worries about a possible increase in the federal funds rate. Municipal bond risk elevates particularly in late 2011 possibly reflecting concerns about potential budget cuts to states and municipalities during the debate regarding the debt ceiling.[26]

These findings underscore the flexibility inherent in the combined LDA/SVA methodology: the researcher can explore themes or risks even if they were not prominent in the LDA topics. This feature can be particularly valuable in two different settings. First, researchers who have a particular hypothesis about a specific emerging risk can determine whether their priors are valid. Second, regulators may be able to use the knowledge gained from prudential supervision of banks to explore whether anecdotal references to risk can be seen in a larger cross-section.

[26] `http://www.barrons.com/articles/SB50001424052702303389204576483952427623210`.

VI Cross-Sectional Implications

The preceding analysis is all based on time series tests, and it provides evidence that an early warning of interpretable systemic risks is feasible. While this is important from a macroeconomic financial stability perspective, intervention might only be needed if such emerging risks actually predict negative financial outcomes.

We begin by exploring the determinants of financial institutions' exposure to each of the themes identified in Appendix A. We run an OLS regression where the dependent variable is a bank's loading on a given SVA theme in each year and the independent variables include bank characteristics (scaled by assets) such as loans, loss provision and allowances, capital, an indicator variable for negative earnings, CatFat and non-performing assets. Panel A is based on our baseline model, where the semantic themes are driven purely by a review of the topics appearing in the LDA model. Panel B lists four additional topics used in an extended version of the baseline model based upon user defined sub-themes from an examination of the key words for the emerging risk factor "Marketable Securities".

For example, banks have a higher loading on mortgage risk when they have greater loans to assets, low liquidity, more loan loss provision and allowances. They are also more likely to have negative earnings. This could mean that unprofitable banks are increasing their exposure to risky loans. Smaller banks, those with low capital but high liquidity, have more exposure to risks associated with credit default. Consistent with the role of mortgage-backed securities in the financial crisis, in Panel B, financial institutions with more loans, lower liquidity, negative earnings but slightly greater capital have higher loadings on risk associated with these assets.

By determining the type of firm that may be most exposed to a particular semantic theme, one can assess which financial institutions might be more exposed to specific risk factors. Although we have tried to capture the most salient characteristics that may be related to risks facing financial institutions, our methodology allows flexibility in the choice of independent variables to include in the specification. This flexibility can be particularly useful to regulators who can use their supervisory information to determine whether a particular type of bank has the potential to contribute to financial instability.

Next, we examine whether an individual financial institution's exposure to emerging risks can predict subsequent outcomes. We do so in three different ways. First, we examine whether each bank's total exposure to emerging risk factors can predict bank stock returns during the crisis period from September 2008 to December 2012. This time period is meant to cover the most intense period of the financial crisis beginning with the failure of Lehman Brothers and through the period during which most banks failed. In addition, we also test whether an institution's exposure to emerging risk factors predicts its return during the period December 2015 to February 2016, the end of our sample, and a time when banks experienced high levels of volatility and sharply negative returns compared to the S&P 500.

Second, we use the FDIC's Failures and Assistance Transactions List to ascertain whether banks that are exposed to more *ex-ante* emerging risks are more likely to fail.[27]. Finally, we use rolling three month Fama and MacBeth (1973) regressions, where the dependent variable is the monthly volatility of daily stock returns, to examine whether increasing lags in a bank's exposure to quarterly risk factors predicts future volatility.

In each of these tests, we use a measure of each individual bank's quarterly exposure to emerging risks, *Emerging Risk Exposure*, as our primary independent variable of interest. This variable is computed, as the average predicted covariance bank i has with all other banks j using the main covariance model in Equation 3. This is computed separately in each quarter and for each bank using the following two step procedure. First, for each bank-pair in a given quarter, we take the product of the fitted coefficients for each SVA theme (β_1 to β_{18}) from the estimation of the main covariance model, and multiply it by the given bank-pair's product of SVA theme loadings ($S_{i,j,t,1}$ to $S_{i,j,t,18}$). We then sum the resulting 18 products for each bank-pair to get the total predicted covariance of bank i with each bank j. Finally, we average the predicted covariances over banks j to get the total *Emerging Risk Exposure* due to only to the semantic themes of bank i in quarter t.

A Predicting Crisis and Current Period Returns

In Table VI, we examine whether an individual institution's exposure to emerging risks can predict stock returns in the period after the financial crisis begins from September 2008 until December 2012 and the current period of economic volatility from December 2015 to February 2016. In Panel A, we regress the financial crisis stock returns on *Emerging Risk Exposure* measured in the specific quarter indicated in the column titled "Quarter". We include, but do not display in order to conserve space, controls for bank characteristics, momentum (month t-12 to t-2), log book-to-market ratio, the log market capitalization and a dummy variable for negative book-to-market ratio in each regression. For example,

[27] `https://www5.fdic.gov/hsob/SelectRpt.asp?EntryTyp=30&Header=1`

row (9) examines whether information about bank-level exposures to emerging risks in the first quarter of 2006 can explain which banks experienced the most negative stock returns during the crisis. We also indicate whether the emerging risk exposure is measured prior to the estimation period for the stock returns (these regressions are *Predictive*) or after (these regressions are *Non-Predictive*).

In order for our methodology to be useful, emerging risks must predict the returns of affected banks both significantly and in a timely fashion. An examination of Panel A in the table indicates that exposure to emerging risk factors significantly predicts negative stock returns during the aftermath of the financial crisis *as early as the second quarter of 2006*. For every quarter from 2006 until the beginning of the stock return estimation period in the third quarter of 2008, the *Emerging Risk Exposure* coefficient is negative and generally highly significant.

When we previously examined the current period of economic instability in Figure 6, we found that a number of new risk factors were emerging. Panel B of Table VI shows that the seeds for the current economic situation were sown as early as 2010. This period was characterized by the market trough after Lehman's bankruptcy and the passage of the Dodd-Frank Act. This was then followed by a period of concern regarding the European debt crisis, eventually leading up to negotiations over the U.S. government's raising of the debt ceiling in 2011. The results in Table VI support the conclusion that the economic uncertainty seen today might be linked to these events in 2011.

More recent uncertainty regarding the potential impact of raising the federal funds rate in mid-2015 versus the threat of negative interest rates if growth remains low, most likely further contributes to the highly significant relationship between emerging risk exposures and December 2015 to February 2016 returns. Thus, banks with greater exposure to these emerging risks are more affected in terms of experiencing lower ex post stock returns.

B Predicting Bank Failures

In addition to analyzing whether our methodology can be used to predict returns during the crisis, we also examine whether financial institutions that are more affected by emerging risk factors are more likely to experience bank failure. Table VII reports the results of cross-sectional regressions examining whether emerging risk factors can predict which banks fail during the period following the Lehman bankruptcy.

We restrict the sample of failed banks from the FDIC website to include only publicly traded banks. The first bank failure following the Lehman bankruptcy in September 2008 occurs in November of 2008. The last occurs in June of 2012. There are 41 such failures, with 2, 12, 19, 6 and 2 occurring in the years 2008, 2009, 2010, 2011, 2012, respectively. We note that results are unchanged if we limit the sample of banks to those that failed in the narrower window between 2008 and 2010. However, we believe that even later failures during this longer interval are likely related to emerging risks associated with financial crisis and its aftermath.

We define the dependent variable as a dummy variable, *Failure*, equal to one if the given bank was assisted or failed during the crisis period, zero otherwise. This dependent variable is regressed on the *Emerging Risk Exposure* in the period specified in the first column.[28] We include controls for bank characteristics (scaled by assets) such as loans, loss provision and allowances, capital, an indicator variable for negative earnings, CatFat and non-performing assets. We also control for industry fixed effects based on four-digit SIC codes. The regressions in the Table use ex ante data and are predictive when noted in the "Predictive Timing" column.

We find in Table VII that when financial institutions have higher exposure to emerging risk factors, the more likely the bank will fail in the period after the onset of the financial crisis. This relationship is predictive in an intermittent way as early as 2005 and 2006, and the predictive relationship becomes more reliable starting in the third quarter of 2006. These results are consistent with Table VI that shows that the greater a bank's exposure to emerging risks, the more negative are bank stock returns during and after the crisis.

Consistent with studies of the determinants of the probability of bank failure examine the fundamental characteristics of banks (see Sarkar and Sriram (2001)), we find evidence that specific bank characteristics aid in predicting which banks fail after controlling for the bank's exposure to emerging risks. For example, banks are more likely to fail if they have more loans and greater loan loss provision and allowances but are less likely to fail if they have greater capital (Berger and Bouwman (2013)) and higher liquidity (Berger and Bouwman (2009)).[29] Although these studies are useful in understanding the past crisis, the same activities are unlikely to be a factor in the next crisis. Indeed, our analysis of the types

[28]Although we present results of a linear probability model (OLS-based) due to the presence of industry fixed effects, we note that these results are robust to using a logistic model instead.

[29]Other determinants of bank failure include exposure to commercial real estate investments (Cole and White (2011)) and non-traditional banking activities such as investment banking and asset securitization (DeYoung and Torna (2013)).

of emerging risk factors in the current period (2015) suggest that current concerns about emerging risks differ from those that were elevated during the financial crisis. Thus, our methodology allows for a pro-active risk assessment of bank failure independent of specific bank characteristics, and it is robust to crises having different economic foundations.

C Predicting Monthly Volatility

In this section, we examine whether exposure to emerging risk factors, more generally, can predict a bank's monthly volatility in unconditional tests. In Table VIII, we consider monthly Fama and MacBeth (1973) regressions where the dependent variable is the monthly stock return volatility. The independent variable of interest, *Emerging Risk Exposure*, is the number of emerging risk factors each bank is exposed to measured over the number of quarters specified in the first column: one, two, three or four quarters. We include, but do not display in order to conserve space, controls for bank characteristics, momentum (month t-12 to t-2), log book-to- market ratio, the log market capitalization and a dummy variable for negative book-to-market ratio in each regression.

Our baseline regression, in the first row, lags this key independent variable by just one month. Hence, we test whether ex ante exposure to the number of emerging risk factors computed using the most recent quarter (months t=-2 to t=0) predicts ex post volatility in the following month (this same quarter's exposures are used for months t=1 to t=3). We then apply deeper lags up to 36 months. Table VIII shows that even deeply lagged exposures to emerging risks can predict subsequent monthly stock return volatility for up to 30 months.

Columns three and four illustrate that observing emerging risks over longer ex-ante periods does not improve on predictability. Thus, exposure to emerging risks over one quarter is sufficient to predict subsequent volatility.

Overall, consistent with the time-period specific results presented previously, a financial institution's unconditional exposure to collective emerging risk factors can thus be used to predict future stock volatility even in this unconditional setting. We interpret this to mean that emerging risks impact the volatility of stock prices of individual banks both in the short run and also in the long run when systemic risks are more severe (as was the case in 2008). These results are broadly consistent with Bekaert and Hoerova (2014) who state that stock market volatility "predicts financial instability more strongly than does the variance premium." Our results suggest that ongoing monitoring of emerging risks, and individual financial firm exposures, might improve the ability of researchers and regulators to react to potential crises well before they are fully visible in aggregate financial variables such as VIX or cross-sectional return volatilities.

VII Conclusion

We use computational linguistics to analyze financial institutions' disclosures of risk factors in 10-Ks. We propose an empirical model based upon theories of bank opacity and the production of information by Gorton and Ordonez (2014) to identify emerging risks that may threaten financial stability. Our model satisfies five criteria that we propose an ideal model of systemic risk should have: it should 1) be automated, replicable, and free from user bias 2) identify risks that are clearly interpretable without ambiguity, 3) be dynamic, and capable of identifying new emerging risks not seen in the past, 4) be flexible to permit deeper analysis and 5) be powerful enough to identify risks well before they reach crisis levels.

Our methodology is designed to extract themes from the corpus of financial firm 10-Ks using Latent Dirichlet Allocation (LDA) and Semantic Vector Analysis (SVA) in tandem. The combination provides a framework that is dynamic, flexible, and allows each of the 18 baseline emerging risk factors we detect to be interpretable. We find that the model detects emerging risks that foreshadow the financial crisis of 2008, well before other potential indicators become elevated such as stock return volatility, the VIX, or those based on accounting variables. Many emerging risk themes become prominent as early as late 2005 and include risks associated with credit default, mortgages and real estate, capital requirements and counterparty risk.

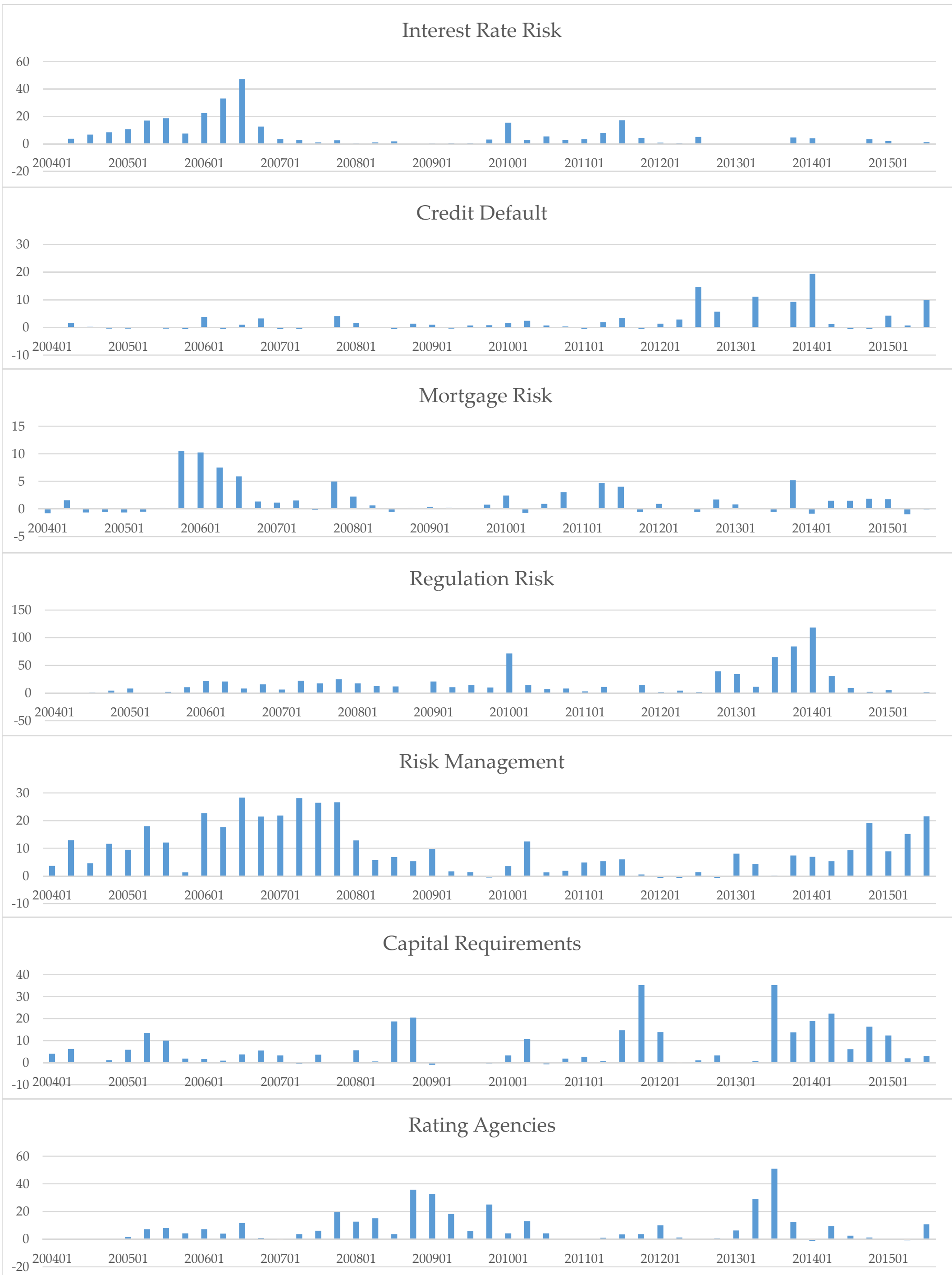
Our model also measures individual bank exposure to emerging risks. We find that banks with greater ex ante exposure to emerging risks experience significantly lower stock returns during the financial crisis. Furthermore, the more a bank is exposed to emerging risks in the period leading up to the crisis, the more likely it is to subsequently fail. In unconditional tests based on Fama-McBeth regressions using the entire sample from 1998 to 2015, we find that deeply lagged exposures generally predict subsequent stock return volatility for as long as 30 months.

We also consider whether the model can predict market instability in the current market environment. Using very recent data, we find evidence of significant emerging risks since 2013. In particular, semantic themes related to sources of funding, marketable securities, regulation risk, and credit default are elevated (among others). These topics suggest that the market may be concerned about the impact of a potential rise (or prolonged deflation) in the federal funds rate and the resulting impact on sources of funding. Thus, our risk model offers insights on emerging risk exposure at both the aggregate level and at the individual bank level.

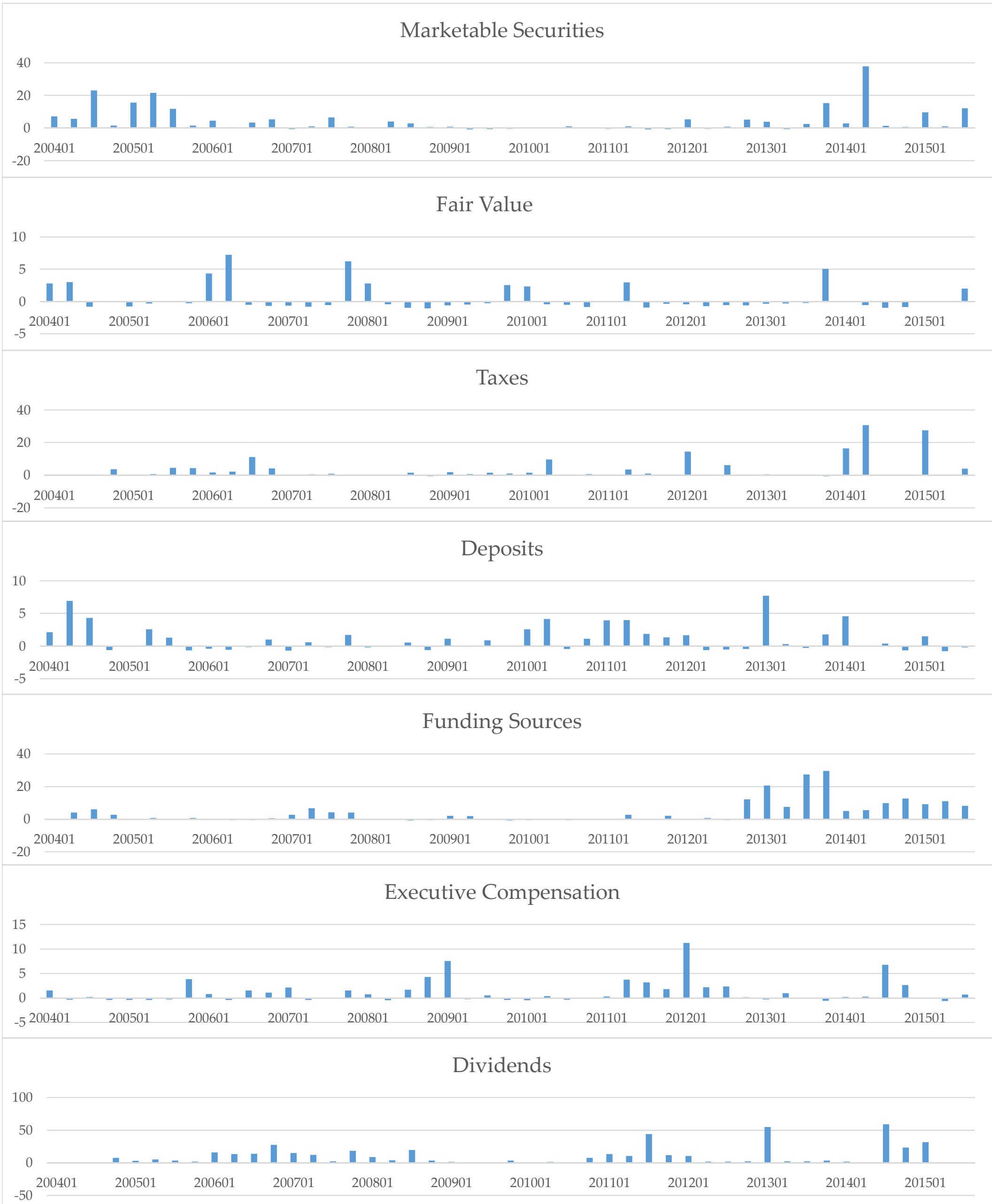
We conclude that not all information about banks should necessarily remain opaque. The disclosure of highly aggregated information, particularly about systemic risks facing financial institutions, can be used as an input to an early warning system that identifies emerging risks before a systemic event. The identification of such risks can spur information production by market participants and regulators at a more granular level to understand the source of the emerging risk. In normal times, we find that the disclosure of such information interferes minimally with optimal bank opacity, suggesting that the current 10-K risk factor disclosure framework likely has few negative externalities. Our findings also point to the need for additional theory that specifically examines the role of aggregated information in banks and how information production might increase conditional on the emergence of systemic risks.

Appendix A: Time Series of Emerging Risks

The figures report the time series of t-statistics of the R^2 from the model in Equation (3) for all 18 semantic theme emerging risks . The results are based on the time series of the contribution of individual semantic themes in explaining pairwise covariance of banks. We define the initial part of our sample (1998 to 2003) as a calibration period, and use this period to compute each semantic themes' R^2 baseline quarterly mean and standard deviation. In each of the subsequent quarters from 2004 to 2015, we compute a t-statistic based on how many standard deviations the current value is from the baseline mean. The figure is a plot of the quarterly t-statistic for each semantic theme.



Appendix A: Time Series of Emerging Risks (continued)



Appendix A: Time Series of Emerging Risks (continued)

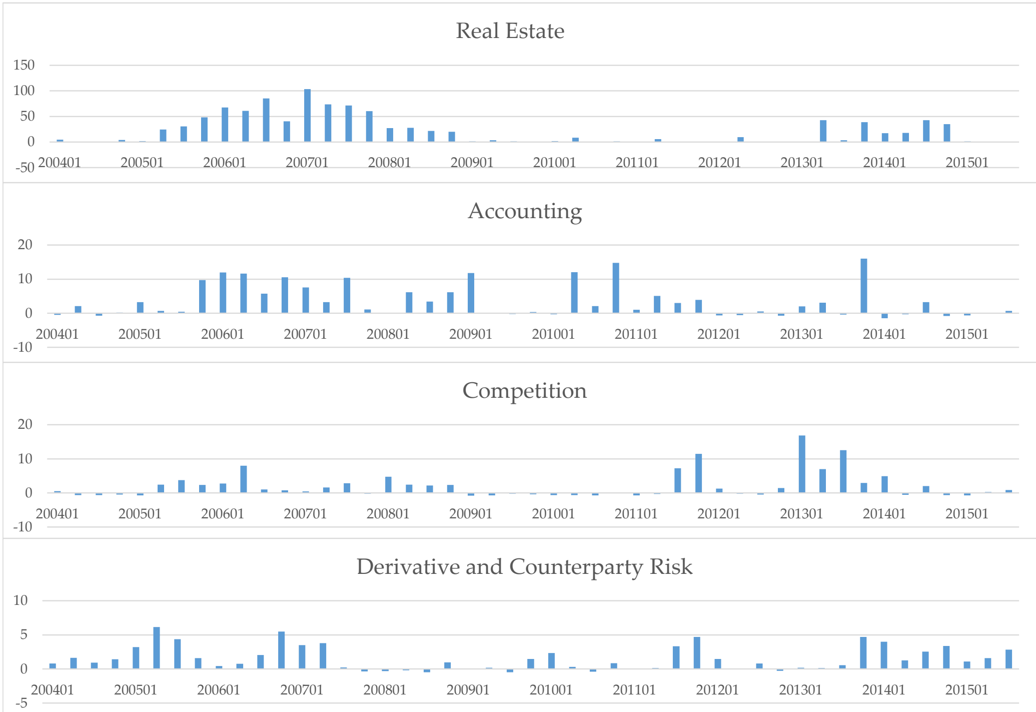


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Figure 1: Aggregate Systemic Risk Measure

Aggregate measure of systemic risk from our dynamic emerging risks model. The measure is the (normalized) adjusted R^2 contribution to pairwise return covariance of bank stocks of all of the 18 semantic themes extracted from 10-K disclosed bank risk factors from 1998 to 2015.

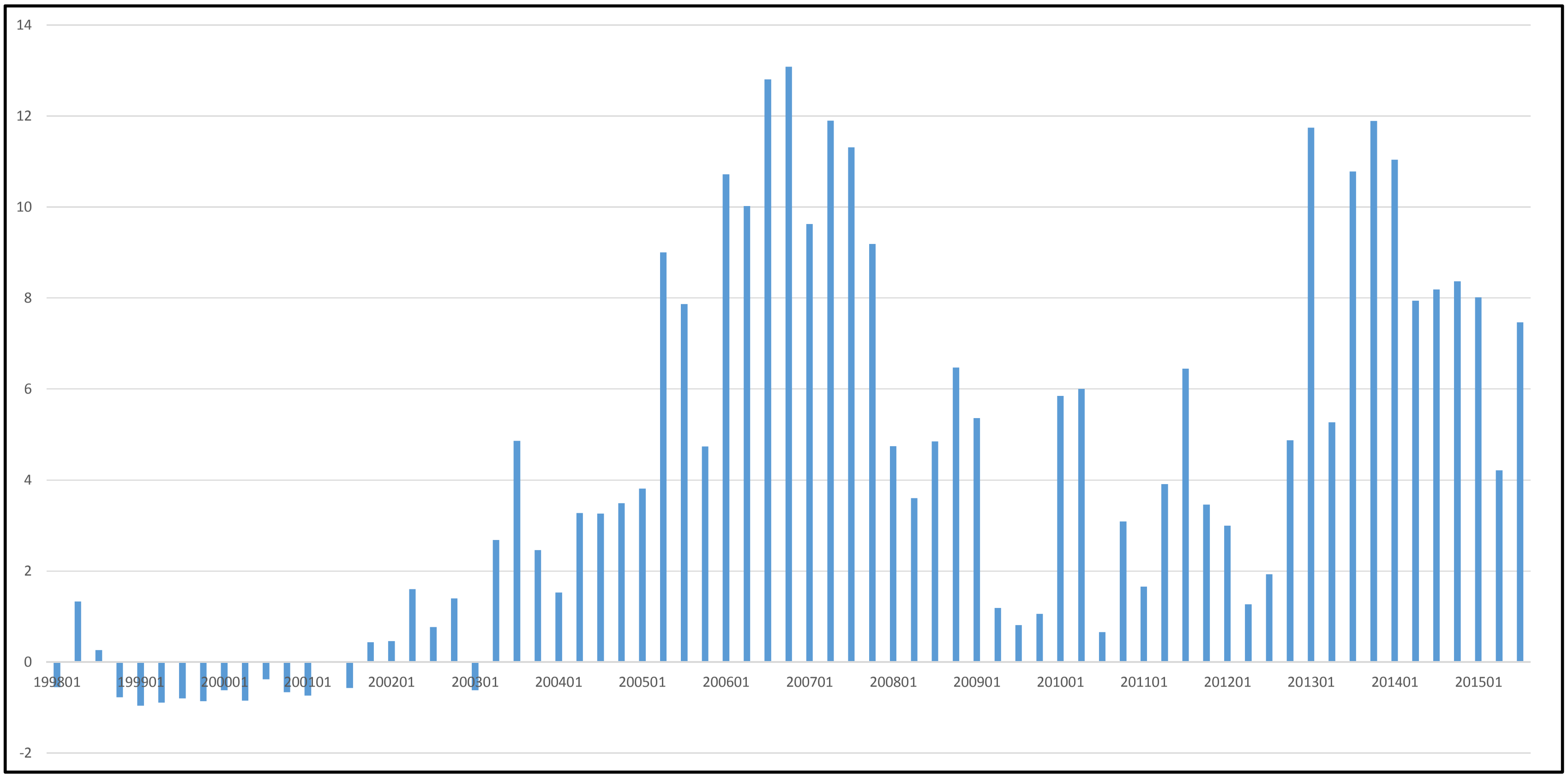

Figure 2: Emerging Risks Using LDA with 25 Topics

Overview of the 25 risk factors detected by metaHeuristica from the corpus of bank risk factors disclosed in fiscal years ending in 2006.

Figure 3: Sample of Banks from 1997 to 2014

Number of banks in our study's sample from 1997 to 2014. There are 9,046 banks total. To be included, a bank must be in the CRSP and Compustat databases, must have a SIC code in the range 6000 to 6199, and must be in the meta-Heuristica database of 10-Ks with a non-zero number of paragraphs residing in a section of the 10-K that discusses risks.

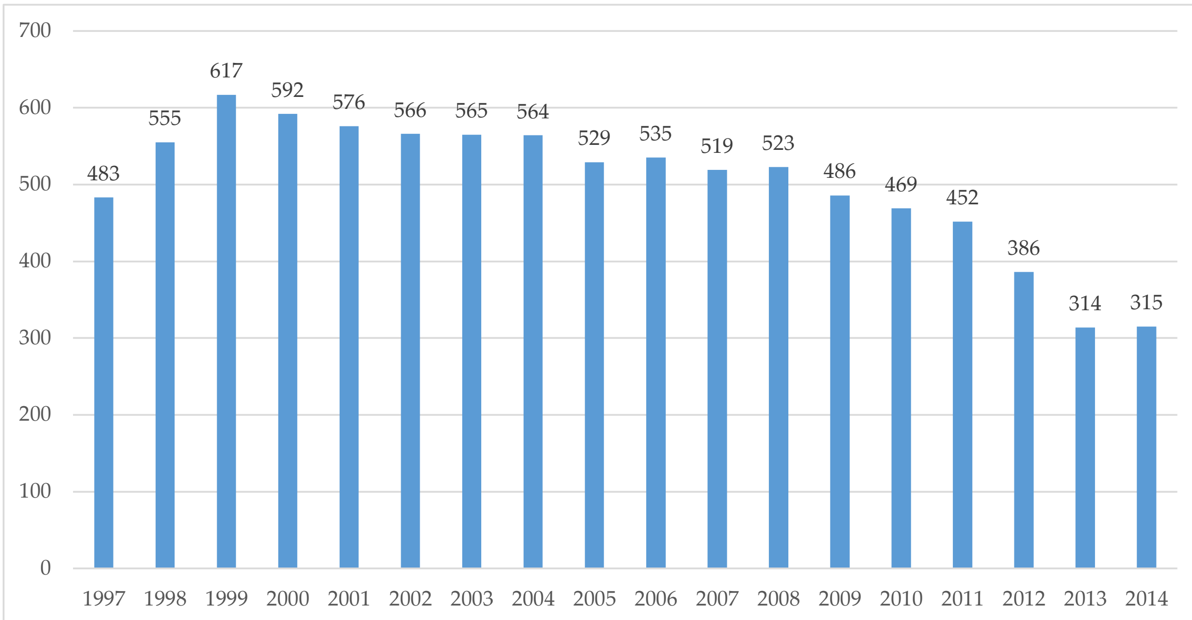

Figure 4: Emerging Risks Comparison

Time series of t-statistics for semantic theme emerging risk variables. We define the initial part of our sample (1998 to 2003) as a calibration period, and use this period to compute each variable's baseline quarterly mean and standard deviation. In each of the subsequent quarters from 2004 to 2015, we compute a t-statistic based on how many standard deviations the current value is from the baseline mean. The figure is a plot of each variable's quarterly t-statistics. Panel A displays the time series of t-statistics for the VIX index, and the quarterly average pairwise covariance among bank-pairs. We also report t-statistics for the average quarterly standard deviation of monthly returns across all stocks in the CRSP database and for financial firms only (SIC codes from 6000 to 6199). Panel B reports t-statistics for the R^2 of the accounting and text variables created by our covariance emerging risk model.

Figure 5: Crisis Period Emerging Risks

Time series of t-statistics of the R^2 from the model in Equation (3) for the most prominent emerging risk in 2008 (Appendix A presents all 18 semantic theme emerging risks). The results are based on the time series of the contribution of individual semantic themes in explaining pairwise covariance of banks. We define the initial part of our sample (1998 to 2003) as a calibration period, and use this period to compute each semantic themes' R^2 baseline quarterly mean and standard deviation. In each of the subsequent quarters from 2004 to 2015, we compute a t-statistic based on how many standard deviations the current value is from the baseline mean. The figure is a plot of the quarterly t-statistic for each semantic theme.

Figure 6: Current Period Emerging Risks

Time series of t-statistics of the R^2 from the model in Equation (3) for the most prominent emerging risk in 2015 (Appendix A presents all 18 semantic theme emerging risks). The results are based on the time series of the contribution of individual semantic themes in explaining pairwise covariance of banks. We define the initial part of our sample (1998 to 2003) as a calibration period, and use this period to compute each semantic themes' R^2 baseline quarterly mean and standard deviation. In each of the subsequent quarters from 2004 to 2015, we compute a t-statistic based on how many standard deviations the current value is from the baseline mean. The figure is a plot of the quarterly t-statistic for each semantic theme.

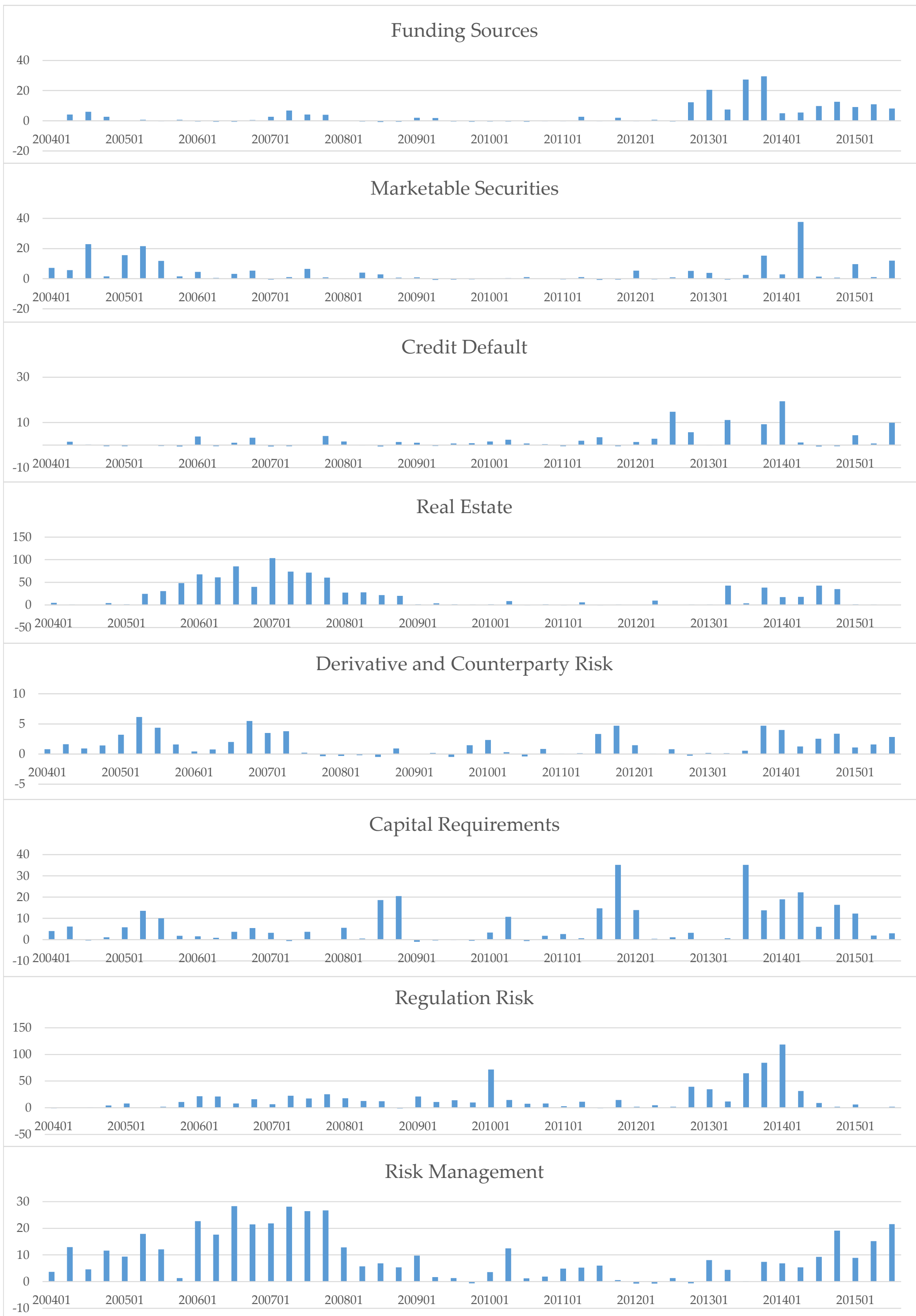

Figure 7: Sub-Theme Emerging Risks

Time series of t-statistics for sub-themes related to the semantic theme "Marketable Securities." We define the initial part of our sample (1998 to 2003) as a calibration period, and use this period to compute each semantic sub-themes' R^2 baseline quarterly mean and standard deviation. In each of the subsequent quarters from 2004 to 2015, we compute a t-statistic based on how many standard deviations the current value is from the baseline mean. The figure is a plot of the quarterly t-statistic for each semantic theme.

Table I: Examples of Semantic Vectors

Focal word and phrase lists for six of the 18 semantic themes derived from Latent Dirichlet Allocation on the risk factor discussion of publicly traded banks (those having SIC codes in the range 6000 to 6199). The title of each theme is the short one to two word phrase noted in the column headers. For each of the six themes, we include two columns. The first is the list of specific words or phrases identified by the Semantic Vector module in metaHeuristica as being highly similar to the theme's title. The second is each word's cosine similarity to the theme's title.

	Mortgage Risk		Capital Requirements		Derivative & Counterparty Risk		Fair Value		Deposit Risk		Competition	
Row	Word	Cosine Dist	Word	Cosine Dist	Word	Cosine Dist	Word	Cosine Dist	Word	Cosine Dist	Word	Cosine Dist
1	mortgages	1	capital	0.789	counterparty	1	fair	0.961	deposits	1	competition	1
2	mortgage	0.7974	requirements	0.789	counterparties	0.8916	value	0.961	deposit	0.8211	compete	0.7932
3	impac alt	0.7148	meet	0.5369	counterparty's	0.8009	values	0.6277	brokered deposits	0.759	intense competition	0.7822
4	residential mortgage	0.7085	regulatory	0.4508	netting	0.7556	valuation techniques	0.5068	brokered certificates	0.7406	highly competitive	0.7798
5	originated	0.6939	additional	0.4422	counterparty nonperforman	0.6873	estimated	0.4865	noninterest bearing	0.7382	competing	0.7504
6	residential mortgages	0.6922	capital expenditure	0.4404	nonperformance	0.6869	valuation methodologies	0.4857	bearing checking	0.7213	extremely competitive	0.7454
7	adjustable rate	0.6726	minimum	0.4278	master netting	0.6704	valuation	0.4823	bearing deposits	0.7175	competes	0.7327
8	collateralizing	0.6372	expenditures	0.4273	anticipate nonperformance	0.6604	carrying	0.4749	passbook	0.671	competitors	0.7297
9	originations	0.6363	requirement	0.4228	netting arrangements	0.6278	discounted	0.4666	checking accounts	0.6655	face intense	0.7266
10	fhlmc	0.6303	iubfsb	0.4166	parental guarantees	0.5735	quoted	0.4645	cdars	0.6372	faces competition	0.7141
11	fnma	0.6271	fund	0.4096	swap	0.5659	asc 820	0.4569	jumbo certificates	0.6316	face competition	0.7138
12	fannie mae	0.6231	liquidity	0.407	collateral postings	0.5643	valuation technique	0.4551	brokered	0.6274	competitive	0.7123
13	single family	0.6174	comply	0.4004	counterparty owes	0.5615	naturaldrive contingent	0.4507	passbook savings	0.6181	intense	0.7117
14	freddie mac	0.6156	ratios	0.3963	isda	0.5571	measuring	0.4485	mmda	0.611	intensify	0.6999
15	mbs	0.6142	regulations	0.3939	swaps	0.5568	underlying	0.4403	sweep accounts	0.5862	compete effectively	0.6993
16	originate	0.6095	satisfy	0.39	creditworthy counterparti	0.5529	pricing models	0.4349	cdars program	0.5836	entrants	0.6973
17	newly originated	0.6069	required	0.3864	association isda	0.5517	valuing	0.4334	borrowed funds	0.5818	faces intense	0.6799
18	association fnma	0.606	guidelines	0.3836	isda master	0.546	115 aaccounting	0.427	checking savings	0.5724	intensely competitive	0.6721
19	mortgage backed	0.6052	regulators	0.3798	exposure	0.5252	measured	0.4223	brokered cds	0.5678	compete successfully	0.6644
20	loan originations	0.6049	needs	0.3781	margining	0.5242	determined	0.4217	cdars deposits	0.5526	low barriers	0.6563

Table II: Pearson Correlation Coefficients (Semantic Themes)

Pearson correlation coefficients for the 18 semantic themes derived from Latent Dirichlet Allocation on the risk factor discussion of publicly traded banks (those having SIC codes in the range 6000 to 6199).

Variable	Interest Rate Risk	Credit Default	Mortgage Risk	Regul. Risk	Risk Mgmt	Capital Req.	Rating Agen.	Mkt Secur.	Fair Value	Taxes	Deposits	Funding Sources	Exec. Comp.	Dividends	Real Estate	Accounting	Competition
Credit Default	-0.287																
Mortgage Risk	0.005	0.237															
Regulation Risk	-0.274	0.061	0.139														
Risk Management	0.268	0.174	0.006	0.025													
Capital Req.	-0.265	0.173	0.090	0.667	0.131												
Rating Agencies	-0.101	0.149	0.070	0.143	0.177	0.196											
Marketable Sec.	0.134	0.009	0.220	0.124	0.233	0.388	0.110										
Fair Value	0.332	0.017	0.166	-0.063	0.268	0.125	0.006	0.547									
Taxes	0.395	-0.125	0.113	0.071	0.147	0.179	0.027	0.452	0.522								
Deposits	0.172	0.016	0.179	0.352	0.108	0.375	-0.002	0.355	0.239	0.281							
Funding Sources	-0.006	0.220	0.139	0.392	0.286	0.632	0.199	0.394	0.091	0.142	0.384						
Executive Comp.	-0.025	-0.003	0.115	0.202	0.177	0.303	0.075	0.353	0.392	0.397	0.220	0.166					
Dividends	-0.186	0.010	0.074	0.520	0.015	0.693	0.068	0.392	0.263	0.310	0.343	0.389	0.456				
Real Estate	-0.232	0.315	0.430	0.331	-0.051	0.233	0.025	0.029	-0.040	-0.010	0.203	0.162	0.065	0.210			
Accounting	-0.151	0.114	0.085	0.166	0.191	0.329	0.049	0.443	0.575	0.420	0.174	0.159	0.475	0.406	0.019		
Competition	-0.206	0.084	0.086	0.674	0.037	0.423	0.078	-0.003	-0.152	-0.045	0.273	0.369	0.098	0.378	0.321	0.035	
Deriv+Counterparty	0.236	0.269	-0.042	-0.275	0.491	-0.118	0.110	0.064	0.254	-0.038	-0.192	0.006	-0.066	-0.188	-0.188	0.084	-0.245

Table III: Summary Statistics

Summary statistics for our sample of 9,046 bank-year observations from 1998 to December 2015. Panel A reports summary statistics based on bank-pair-quarter observations (55.4 million observations). The bank-pair daily covariance is the quarterly covariance of daily stock returns for a pair of banks. Bank-pair SIC variables are dummy variables equal to one if the pair of banks is in the same 2, 3 or 4 digit SIC-based industry, zero otherwise. The TNIC similarity for a pair of banks is from Hoberg and Phillips (2010). The bank-level variables in Panel B is based on Compustat data and includes *Ln(Assets)* and *Ln(Bank Age)*, the time since the first appearance in CRSP. Panel C is based on Call Reports and includes it Cash/Assets, *Loans/Assets*, *Loan Loss Prov & Allow*, the sum of loan loss provision and allowances, *Capital*, the ratio of equity to assets, *Neg. Earnings Dummy* an indicator variable equal to one if net income is negative, zero otherwise, *Bank Holding Co. Dummy*, an indicator variable equal to one if the bank has a parent, zero otherwise, *Non-Performing Assets*, the sum of loans that are 30 days and 90 days past due, and *CatFat/Assets* from Berger and Bouwman (2009). Panel D reports statistics for key time series variables. There are 72 quarterly observations in our database from 1998 to 2015. The average pair covariance is the quarterly average pairwise covariance among bank-pairs. We also report the average quarterly standard deviation of monthly returns across all stocks in the CRSP database and for financial firms only (SIC codes from 6000 to 6199). The accounting variable adjusted R^2 is the quarterly adjusted R^2 from a regression of bank-pairwise correlation on the bank characteristics and industry variables. The text variable adjusted R^2 is the incremental improvement to R^2 when verbal factors are also included in the pairwise covariance regression. Daily covariance figures are multiplied by 10,000 for ease of viewing.

Variable	Mean	Std. Dev.	Minimum	Median	Maximum	# Obs.
			Panel A: Bank-pair level data			
Bank-Pair Daily Covariance	0.913	3.557	-225.51	0.373	329.975	55,412,642
Bank-Pair Same 2-digit SIC	0.872	0.333	0.000	1.000	1.000	55,412,642
Bank-Pair Same 3-digit SIC	0.499	0.499	0.000	0.484	1.000	55,412,642
Bank-Pair Same 4-digit SIC	0.468	0.498	0.000	0.178	1.000	55,412,642
Bank-Pair TNIC Similarity	0.090	0.077	0.000	0.088	0.755	55,412,642
			Panel B: Bank-level data (Compustat)			
Ln(Assets)	7.308	1.616	1.584	7.007	14.598	9,046
Ln(Bank Age)	2.118	0.897	0.000	2.303	3.970	9,046
			Panel C: Bank-level data (Call Reports)			
Cash/Assets	0.042	0.035	0.000	0.033	0.336	7,169
Loans/Assets	0.496	0.178	0.000	0.503	0.907	7,169
Loss Prov & Allow/Assets	0.002	0.004	-0.004	0.001	0.057	7,169
Capital	0.100	0.041	0.008	0.093	1.000	7,169
Negative Earnings Dummy	0.050	0.218	0.000	0.000	1.000	7,168
Bank Holding Co. Dummy	0.850	0.357	0.000	1.000	1.000	7,169
Non-Performing Assets/Assets	0.005	0.007	0.000	0.003	0.056	7,169
CatFat/Assets	6.908	366.698	-0.546	0.389	25965.9	7,169
			Panel D: Time-series data			
VIX Index	21.227	7.594	11.190	20.425	51.723	72
Avg Pair Covariance	1.074	2.069	0.150	0.437	12.704	72
Avg Std Dev Monthly Returns	0.155	0.050	0.095	0.134	0.307	72
Avg Std Dev Monthly Returns (Financials Only)	0.091	0.032	0.050	0.083	0.171	72
Accounting Variable Adj R^2	0.078	0.061	0.005	0.054	0.237	72
Text Variable Adj R^2	0.009	0.007	0.000	0.008	0.025	72

Table IV: Pearson Correlation Coefficients (Time Series Variables)

Pearson Correlation Coefficients are reported for our key time series variables. There are 72 quarterly observations in our database from 1998 to 2015. The average pair covariance is the quarterly average pairwise covariance among bank-pairs. We also report the average quarterly standard deviation of monthly returns across all stocks in the CRSP database and for financial firms only (SIC codes from 6000 to 6199). The accounting variable adjusted R^2 is the quarterly adjusted R^2 from a regression of bank-pairwise correlation on the bank characteristics and industry variables. The text variable adjusted R^2 is the incremental improvement to R^2 when verbal factors are also included in the pairwise covariance regression.

Row	Variable	Accounting Variable Adj R^2	Text Variable Adj R^2	VIX Index	Avg Pairwise Covariance	Avg Std Dev Returns
(1)	Text Variable Adj R^2	0.526				
(2)	VIX Index	0.292	-0.359			
(3)	Avg Pair Covariance	0.504	0.101	0.728		
(4)	Avg Std Dev Monthly Returns	-0.158	-0.605	0.556	0.194	
(5)	Avg Std Dev Monthly Returns (Financials Only)	-0.049	-0.578	0.780	0.488	0.880

Table V: Baseline Semantic Themes and Bank Characteristics

Determinants of the 18 semantic themes using OLS regression using bank characteristics. The dependent variable in Panel A is a bank's loading on the given theme, and the independent variables include bank characteristics *Ln(Assets) Loans/Assets*, *Loan Loss Prov*, the sum of loan loss provision and allowances, *Capital*, the ratio of equity to assets, *Neg. Earnings Dummy* an indicator variable equal to one if net income is negative, zero otherwise, *Non-Performing Assets*, the sum of loans that are 30 days and 90 days past due, and *CatFat/Assets* from Berger and Bouwman (2009). Panel B lists four additional sub-themes related to marketable securities. t-statistics are in parentheses. All RHS variables, and each dependent variable, are standardized to have unit standard deviation prior to running the regression to ensure a relative interpretation in terms of magnitudes.

Row	Semantic Theme	Log Assets	Loans/ Assets	Loss Prov/ Assets	Cap- ital	Neg. Earn.	CatFat/ Assets	NPA/ Assets	Adj R^2
				Panel A: Baseline Semantic Model					
0	Unexp. Topic Content	0.037 (1.98)	-0.039 (-2.19)	0.002 (0.18)	0.019 (1.26)	-0.025 (-2.18)	-0.004 (-0.81)	-0.019 (-1.66)	0.156
1	Interest Rate Risk	-0.014 (-0.67)	0.030 (1.39)	-0.023 (-1.48)	0.026 (1.43)	-0.021 (-1.60)	-0.015 (-2.24)	-0.060 (-3.86)	0.199
2	Credit Default	-0.061 (-2.61)	-0.013 (-0.54)	0.027 (1.51)	-0.060 (-3.36)	-0.021 (-1.68)	0.015 (2.00)	0.038 (1.75)	0.023
3	Mortgage Risk	0.003 (0.13)	0.115 (5.11)	-0.040 (-2.41)	0.043 (1.80)	0.026 (1.87)	-0.019 (-2.46)	-0.019 (-1.22)	0.072
4	Regulation Risk	0.013 (0.80)	-0.018 (-1.28)	0.002 (0.11)	-0.003 (-0.23)	0.026 (1.86)	0.008 (1.54)	0.029 (1.83)	0.420
5	Risk Management	0.097 (4.17)	-0.069 (-3.07)	0.026 (1.40)	-0.045 (-2.26)	-0.023 (-1.60)	0.022 (3.16)	0.026 (1.62)	0.109
6	Capital Req.	0.062 (3.73)	-0.046 (-2.92)	0.041 (2.71)	0.005 (0.42)	0.019 (1.32)	0.008 (1.63)	0.032 (2.66)	0.446
7	Rating Agencies	0.043 (3.09)	-0.032 (-2.86)	0.024 (1.03)	0.004 (0.29)	-0.018 (-0.97)	-0.001 (-0.38)	0.005 (0.26)	0.149
8	Marketable Sec.	0.102 (4.28)	-0.000 (-0.01)	-0.042 (-2.09)	0.018 (0.91)	0.070 (4.18)	-0.004 (-0.67)	0.050 (2.70)	0.129
9	Fair Value	-0.124 (-7.39)	0.025 (1.50)	-0.003 (-0.24)	-0.008 (-0.54)	-0.025 (-2.11)	-0.002 (-0.49)	-0.016 (-1.16)	0.308
10	Taxes	-0.019 (-0.70)	0.007 (0.27)	-0.046 (-2.47)	0.031 (1.31)	0.024 (1.24)	-0.013 (-1.50)	-0.042 (-2.32)	0.029
11	Deposits	0.012 (0.66)	-0.000 (-0.01)	0.023 (1.37)	0.021 (1.52)	0.044 (3.50)	0.003 (0.55)	0.040 (2.60)	0.193
12	Funding Sources	0.029 (1.74)	-0.034 (-2.17)	0.034 (2.36)	0.046 (3.31)	-0.011 (-0.91)	-0.011 (-2.04)	0.022 (1.59)	0.210
13	Executive Comp.	0.110 (5.00)	-0.022 (-1.32)	-0.005 (-0.33)	0.025 (1.54)	0.024 (1.89)	-0.002 (-0.24)	0.017 (1.22)	0.177
14	Dividends	-0.016 (-0.89)	0.017 (0.90)	0.036 (1.87)	0.025 (1.38)	0.046 (2.53)	-0.006 (-1.09)	0.016 (0.91)	0.240
15	Real Estate	-0.077 (-3.36)	0.071 (3.45)	0.021 (1.24)	0.039 (1.69)	-0.004 (-0.31)	-0.014 (-2.06)	-0.024 (-1.58)	0.085
16	Accounting	-0.025 (-1.21)	-0.022 (-1.07)	-0.029 (-1.73)	-0.049 (-2.61)	0.000 (0.00)	0.013 (2.22)	0.026 (1.64)	0.048
17	Competiton	-0.011 (-0.60)	-0.042 (-2.32)	0.003 (0.19)	0.010 (0.63)	-0.000 (-0.00)	-0.004 (-0.94)	-0.017 (-1.10)	0.215
18	Deriv+Counterparty	0.181 (8.77)	-0.003 (-0.19)	-0.015 (-1.07)	0.004 (0.32)	0.009 (0.73)	0.006 (0.81)	-0.014 (-1.29)	0.180
				Panel B: Marketable Security Sub-Themes					
19	Municipal Bonds	0.104 (5.64)	0.076 (3.68)	-0.096 (-6.96)	-0.002 (-0.11)	0.045 (4.66)	-0.001 (-0.17)	0.028 (2.83)	0.222
20	Mortgage Backed Sec.	0.029 (1.10)	0.098 (3.93)	-0.061 (-3.47)	0.044 (1.80)	0.036 (2.27)	-0.017 (-2.33)	-0.019 (-1.09)	0.039
21	Commercial Paper	-0.005 (-0.46)	-0.048 (-3.95)	0.074 (5.56)	-0.004 (-0.39)	-0.018 (-1.94)	0.003 (0.82)	0.005 (0.54)	0.348
22	Cash	0.095 (5.62)	0.003 (0.15)	-0.020 (-1.24)	0.018 (1.07)	0.031 (2.26)	-0.009 (-1.53)	0.011 (0.95)	0.327

Table VI: Crisis and Current Period Return Regressions

Cross-sectional regressions predicting individual bank outcomes during and after the financial crisis and under current economic conditions . For the crisis period in Panel A, the dependent variable is the bank's stock return from September 2008 to December 2012. For the current period in Panel B, the dependent variable is the bank's stock return from December of 2015 to February 2016. The independent variable of interest, *Emerging Risk Exposure*, is the quarterly predicted covariance based on Equation 3. We note that all regressions use ex-ante data and are predictive when noted as such in the *Predictive Timing* column. We include, but do not display in order to conserve space, controls for bank characteristics, momentum, log book to market and the log market capitalization in each regression. We also include industry fixed effects based on four-digit SIC codes. t-statistics are reported in parentheses.

		Panel A: Crisis Period					*Panel B: Current Period*		
Row	Quarter	Emerging Risk Exposure	Obs	Predictive Timing		Quarter	Emerging Risk Exposure	Obs	Predictive Timing
(1)	2004 1Q	-1.493 (-1.16)	412	Predictive	—	2010 1Q	-0.861 (-7.67)	357	Predictive
(2)	2004 2Q	-3.609 (-3.19)	393	Predictive	—	2010 2Q	-0.658 (-2.93)	338	Predictive
(3)	2004 3Q	-2.848 (-1.26)	393	Predictive	—	2010 3Q	-0.760 (-3.96)	338	Predictive
(4)	2004 4Q	-0.420 (-0.26)	393	Predictive	—	2010 4Q	-0.867 (-2.68)	338	Predictive
(5)	2005 1Q	1.014 (0.50)	454	Predictive	—	2011 1Q	-1.592 (-2.24)	360	Predictive
(6)	2005 2Q	0.653 (0.40)	444	Predictive	—	2011 2Q	-1.843 (-2.98)	353	Predictive
(7)	2005 3Q	0.659 (0.44)	444	Predictive	—	2011 3Q	-1.729 (-2.50)	353	Predictive
(8)	2005 4Q	1.291 (0.85)	444	Predictive	—	2011 4Q	-1.169 (-1.94)	352	Predictive
(9)	2006 1Q	0.337 (0.47)	488	Predictive	—	2012 1Q	-0.566 (-1.51)	369	Predictive
(10)	2006 2Q	-4.107 (-3.04)	462	Predictive	—	2012 2Q	-0.424 (-2.94)	360	Predictive
(11)	2006 3Q	-4.809 (-3.54)	462	Predictive	—	2012 3Q	-0.559 (-3.81)	360	Predictive
(12)	2006 4Q	-4.863 (-3.03)	462	Predictive	—	2012 4Q	-0.341 (-1.23)	360	Predictive
(13)	2007 1Q	-7.441 (-3.56)	517	Predictive	—	2013 1Q	-0.603 (-2.88)	372	Predictive
(14)	2007 2Q	-7.169 (-4.03)	508	Predictive	—	2013 2Q	-0.888 (-3.58)	337	Predictive
(15)	2007 3Q	-8.040 (-4.51)	507	Predictive	—	2013 3Q	-0.704 (-2.78)	337	Predictive
(16)	2007 4Q	-8.332 (-3.85)	507	Predictive	—	2013 4Q	-0.649 (-2.53)	337	Predictive
(17)	2008 1Q	-6.780 (-1.83)	545	Predictive	—	2014 1Q	-0.950 (-3.11)	346	Predictive
(18)	2008 2Q	-6.788 (-1.93)	512	Predictive	—	2014 2Q	-0.758 (-1.55)	294	Predictive
(19)	2008 3Q	-8.761 (-3.38)	512	Non-Predictive	—	2014 3Q	-1.522 (-3.88)	294	Predictive
(20)	2008 4Q	-7.503 (-3.60)	512	Non-Predictive	—	2014 4Q	-1.706 (-6.22)	294	Predictive
(21)	2009 1Q	-8.710 (-7.13)	563	Non-Predictive	—	2015 1Q	-1.327 (-3.25)	297	Predictive
(22)	2009 2Q	-9.591 (-7.92)	521	Non-Predictive	—	2015 2Q	-1.738 (-5.31)	295	Predictive
(23)	2009 3Q	-7.084 (-4.81)	520	Non-Predictive	—	2015 3Q	-1.806 (-7.17)	295	Predictive
(24)	2009 4Q	-5.767 (-2.96)	519	Non-Predictive	—	2015 4Q	-1.373 (-3.25)	295	Non-Predictive

Table VII: Bank Failure Regressions

Cross-sectional regressions predicting which banks fail during the period after the Lehman bankruptcy in late 2008. The dependent variable is a dummy variable equal to one if a bank was assisted or failed during the crisis period, zero otherwise as indicated on the FDIC website. This sample of failed banks includes only publicly traded banks, with the first failures occurring in November of 2008, and the last in June of 2012. There are 41 such failures, with {2,12,19,6,2} occurring in the years {2008,2009,2010,2011,2012}, respectively. The independent variable of interest, *Emerging Risk Exposure*, is the quarterly predicted covariance based on Equation 3. We note that all regressions use ex-ante data and are predictive when noted as such in the *Predictive Timing* column. We include as independent variables bank characteristics such as *Ln(Assets) Loans/Assets*, *Loan Loss Prov & Allow*, the sum of loan loss provision and allowances, *Capital*, the ratio of equity to assets, *Neg. Earnings Dummy* an indicator variable equal to one if net income is negative, zero otherwise, *Non-Performing Assets*, the sum of loans that are 30 days and 90 days past due, and *CatFat/Assets* from Berger and Bouwman (2009). We include industry fixed effects based on four-digit SIC codes. t-statistics are reported in parentheses.

Row	Quarter	Emerging Risk Exposure	Log Assets	Loans Assets	Loss/ Assets	Cap-ital	Neg Earn.	CatFat Assets	NPA Assets	Obs	Predictive Timing
(1)	2004 1Q	-0.005 (-2.14)	-0.006 (-0.94)	0.039 (112.21)	0.012 (10.12)	-0.016 (-2.14)	0.010 (0.78)	-0.003 (-7.12)	-0.009 (-9.36)	638	Predictive
(2)	2004 2Q	0.002 (0.85)	-0.004 (-0.58)	0.043 (21.54)	0.007 (3.11)	-0.014 (-1.13)	0.005 (0.53)	-0.010 (-19.10)	0.004 (1.80)	546	Predictive
(3)	2004 3Q	0.003 (1.56)	-0.003 (-0.55)	0.043 (21.37)	0.007 (3.13)	-0.014 (-1.13)	0.005 (0.54)	-0.010 (-20.70)	0.004 (1.82)	546	Predictive
(4)	2004 4Q	0.000 (0.26)	-0.004 (-0.66)	0.043 (22.84)	0.007 (3.09)	-0.014 (-1.15)	0.005 (0.53)	-0.010 (-21.94)	0.004 (1.78)	546	Predictive
(5)	2005 1Q	-0.001 (-0.45)	-0.003 (-0.48)	0.044 (12.09)	0.027 (5.25)	-0.022 (-2.97)	0.005 (0.38)	-0.022 (-16.11)	-0.011 (-13.74)	619	Predictive
(6)	2005 2Q	0.008 (3.59)	0.004 (0.54)	0.048 (11.69)	0.041 (12.16)	-0.026 (-3.86)	0.009 (0.64)	-0.033 (-11.77)	-0.019 (-25.42)	562	Predictive
(7)	2005 3Q	0.009 (6.47)	0.004 (0.62)	0.048 (11.53)	0.041 (12.30)	-0.026 (-3.74)	0.011 (0.75)	-0.033 (-11.43)	-0.019 (-29.80)	559	Predictive
(8)	2005 4Q	0.011 (14.09)	0.004 (0.77)	0.049 (11.68)	0.041 (12.52)	-0.026 (-3.66)	0.013 (0.96)	-0.034 (-11.25)	-0.019 (-37.82)	558	Predictive
(9)	2006 1Q	0.004 (1.66)	-0.002 (-0.29)	0.053 (17.68)	0.042 (9.91)	-0.029 (-6.79)	-0.003 (-0.90)	-0.014 (-2.83)	-0.026 (-26.64)	605	Predictive
(10)	2006 2Q	0.005 (1.12)	-0.005 (-0.48)	0.061 (8.77)	0.034 (5.38)	-0.030 (-5.53)	-0.012 (-4.72)	0.002 (0.20)	-0.025 (-19.55)	525	Predictive
(11)	2006 3Q	0.012 (3.18)	-0.003 (-0.24)	0.061 (8.55)	0.034 (5.30)	-0.030 (-6.07)	-0.012 (-4.38)	0.002 (0.18)	-0.024 (-18.26)	525	Predictive
(12)	2006 4Q	0.018 (5.57)	0.000 (0.03)	0.061 (8.42)	0.033 (5.11)	-0.029 (-6.95)	-0.011 (-4.38)	0.001 (0.09)	-0.024 (-15.14)	524	Predictive
(13)	2007 1Q	0.024 (7.57)	0.003 (0.32)	0.068 (14.24)	0.050 (5.80)	-0.044 (-7.44)	-0.010 (-1.32)	-0.016 (-1.40)	-0.023 (-4.67)	579	Predictive
(14)	2007 2Q	0.025 (4.99)	0.003 (0.32)	0.072 (23.08)	0.055 (6.77)	-0.047 (-4.17)	0.003 (0.90)	-0.023 (-2.47)	-0.031 (-5.32)	532	Predictive
(15)	2007 3Q	0.027 (4.74)	0.003 (0.42)	0.072 (19.06)	0.055 (6.61)	-0.047 (-4.52)	0.005 (1.02)	-0.023 (-2.47)	-0.031 (-5.33)	530	Predictive
(16)	2007 4Q	0.029 (3.98)	0.003 (0.41)	0.072 (18.68)	0.055 (6.74)	-0.046 (-4.48)	0.005 (1.06)	-0.023 (-2.48)	-0.031 (-5.47)	530	Predictive
(17)	2008 1Q	0.025 (4.02)	-0.004 (-0.62)	0.067 (7.70)	0.043 (8.43)	-0.049 (-3.47)	0.015 (1.09)	-0.008 (-1.59)	-0.017 (-3.47)	566	Predictive
(18)	2008 2Q	0.014 (6.41)	-0.016 (-3.48)	0.044 (2.70)	0.013 (1.73)	-0.033 (-2.06)	0.004 (0.20)	-0.002 (-1.46)	0.009 (3.23)	517	Predictive
(19)	2008 3Q	0.016 (5.19)	-0.015 (-3.64)	0.044 (2.78)	0.013 (1.75)	-0.033 (-2.07)	0.004 (0.19)	-0.002 (-1.31)	0.009 (3.02)	515	Predictive
(20)	2008 4Q	0.017 (3.44)	-0.016 (-4.19)	0.044 (2.87)	0.013 (1.78)	-0.033 (-2.09)	0.004 (0.20)	-0.001 (-0.76)	0.009 (2.89)	515	Non-Predictive
(21)	2009 1Q	0.023 (3.07)	-0.015 (-3.39)	0.033 (4.45)	0.037 (5.65)	-0.042 (-2.08)	0.023 (2.40)	-0.015 (-2.00)	0.025 (4.28)	564	Non-Predictive
(22)	2009 2Q	0.011 (4.59)	-0.028 (-3.63)	-0.001 (-0.78)	0.018 (4.88)	-0.023 (-1.49)	0.028 (3.31)	-0.017 (-2.36)	0.055 (8.27)	520	Non-Predictive
(23)	2009 3Q	0.008 (5.26)	-0.029 (-3.61)	-0.001 (-0.38)	0.019 (5.21)	-0.024 (-1.53)	0.028 (3.36)	-0.017 (-2.30)	0.055 (8.26)	519	Non-Predictive
(24)	2009 4Q	0.005 (3.08)	-0.029 (-3.55)	-0.000 (-0.24)	0.019 (5.12)	-0.023 (-1.52)	0.028 (3.41)	-0.017 (-2.28)	0.055 (8.05)	518	Non-‘Predictive

Table VIII: Fama MacBeth Rolling Predictive Volatility Regressions

Fama-McBeth rolling three month cross-sectional regressions where the dependent variable is the bank's monthly volatility of daily stock returns from January 1998 to December 2015 (data from 1997 is needed to compute starting values). The independent variable of interest, *Emerging Risk Exposure*, is the predicted covariance based on Equation 3 measured over the number of quarters specified in the column heading. The number of observations is based on the 1 Quarter Emerging Risk Exposure regression. We include, but do not display in order to conserve space, controls for bank characteristics, momentum (month t-12 to t-2), log book-to- market ratio, the log market capitalization and a dummy variable for negative book-to-market ratio in each regression. We also include industry fixed effects based on four-digit SIC codes. *t*-statistics are reported in parentheses.

Monthly Lag	1 Quarter Emerging Risk Exposure	2 Quarter Emerging Risk Exposure	3 Quarter Emerging Risk Exposure	4 Quarter Emerging Risk Exposure	Obs
1	0.081 (9.53)	0.088 (10.52)	0.084 (9.51)	0.086 (9.40)	110336
2	0.075 (9.22)	0.083 (10.00)	0.080 (9.36)	0.081 (9.13)	109875
3	0.075 (9.24)	0.079 (9.45)	0.079 (9.21)	0.079 (8.77)	109384
4	0.073 (8.98)	0.072 (8.53)	0.076 (8.65)	0.074 (8.42)	108868
5	0.070 (8.69)	0.070 (8.40)	0.071 (8.36)	0.070 (8.07)	107881
6	0.064 (7.68)	0.067 (7.98)	0.067 (7.77)	0.066 (7.43)	106851
7	0.056 (6.35)	0.063 (7.24)	0.062 (7.20)	0.060 (6.95)	105820
8	0.055 (6.27)	0.059 (6.84)	0.059 (6.82)	0.057 (6.55)	104785
9	0.055 (6.42)	0.057 (6.66)	0.057 (6.57)	0.056 (6.48)	103750
10	0.051 (5.92)	0.053 (6.12)	0.054 (6.18)	0.053 (5.95)	102715
11	0.046 (5.36)	0.050 (5.75)	0.051 (5.75)	0.049 (5.43)	101679
12	0.042 (4.90)	0.046 (5.28)	0.049 (5.50)	0.044 (4.97)	100645
13	0.042 (4.95)	0.047 (5.41)	0.047 (5.36)	0.043 (4.84)	99616
14	0.042 (4.90)	0.045 (5.23)	0.044 (5.07)	0.040 (4.59)	98536
15	0.039 (4.40)	0.044 (5.03)	0.039 (4.56)	0.039 (4.45)	97464
16	0.037 (4.33)	0.039 (4.53)	0.036 (4.21)	0.037 (4.34)	96399
17	0.032 (3.75)	0.033 (3.80)	0.031 (3.56)	0.034 (3.86)	95344
18	0.031 (3.62)	0.027 (3.13)	0.028 (3.30)	0.030 (3.52)	94290
19	0.025 (2.94)	0.024 (2.86)	0.027 (3.32)	0.029 (3.52)	93243
20	0.021 (2.39)	0.021 (2.49)	0.025 (3.08)	0.026 (3.29)	92210
21	0.013 (1.58)	0.018 (2.22)	0.022 (2.75)	0.022 (2.79)	91189
22	0.015 (1.73)	0.021 (2.59)	0.023 (2.99)	0.023 (2.96)	90174
23	0.012 (1.41)	0.018 (2.35)	0.022 (2.79)	0.021 (2.66)	89186
24	0.014 (1.84)	0.020 (2.61)	0.021 (2.80)	0.021 (2.64)	88208
25	0.018 (2.35)	0.022 (2.86)	0.022 (2.87)	0.020 (2.59)	87240
26	0.020 (2.62)	0.024 (3.10)	0.022 (2.89)	0.020 (2.53)	86252
27	0.021 (2.75)	0.022 (2.91)	0.021 (2.72)	0.018 (2.35)	85268
28	0.021 (2.87)	0.021 (2.78)	0.019 (2.62)	0.017 (2.39)	84294
29	0.020 (2.69)	0.018 (2.47)	0.017 (2.32)	0.015 (1.99)	83328
30	0.015 (2.08)	0.015 (2.04)	0.014 (1.91)	0.012 (1.59)	82368
31	0.012 (1.57)	0.012 (1.68)	0.012 (1.70)	0.009 (1.27)	81412
32	0.010 (1.30)	0.011 (1.45)	0.009 (1.22)	0.008 (1.11)	80466
33	0.010 (1.25)	0.010 (1.34)	0.008 (1.06)	0.008 (1.04)	79527
34	0.009 (1.23)	0.010 (1.28)	0.006 (0.85)	0.006 (0.72)	78596
35	0.010 (1.32)	0.007 (0.96)	0.007 (0.97)	0.007 (0.91)	77687
36	0.008 (1.09)	0.005 (0.71)	0.007 (0.89)	0.006 (0.77)	76790