Essays on the Bank Lending Channel

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To Mom, Dad, Mario, Cristina and Kotufa.

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Abstract

This thesis contributes to the understanding of how banks shift their supply of credit when confronted with uncertainty, regulatory supervision and macroprudential policies. The first chapter proposes a new index to detect the idiosyncratic uncertainty banks face at the bank-quarter level. I use machine learning and natural language processing on speeches made by bank management during quarterly earnings conference calls to develop the new measure. I find that higher uncertainty is associated with lower lending the next quarter and higher liquidity, suggesting active management of uncertainty. The second chapter explores how banks respond to supervision by window-dressing their balance sheets. In preparation for Europe's 2014 Asset Quality Review (AQR), reviewed banks decreased their share of riskier securities and loans. After the AQR, banks reloaded riskier securities onto their balance sheets, but not riskier credit. In the third chapter, I study how the introduction of capital controls in Colombia affected domestic credit. The results point to complementarities in credit supply between domestic and foreign credit.

Resumen

Esta tesis estudia los cambios en la oferta de crédito de los bancos cuando se enfrentan a incertidumbre, supervisión regulatoria y políticas macroprudenciales. El primer capítulo propone un nuevo índice para detectar la incertidumbre idiosincrática de los bancos a nivel trimestral. Para desarrollar la nueva medida, utilizo técnicas de aprendizaje de máquinas y procesamiento del lenguaje natural sobre los discursos trimestrales hechos por la gerencia de cada banco. Encuentro que una mayor incertidumbre está asociada con un menor préstamo el próximo trimestre y una mayor liquidez, lo que sugiere un manejo activo de la incertidumbre. El segundo capítulo explora cómo los bancos responden a la supervisión maquillando sus balances. En preparación para la revisión de calidad de activos (AQR) de 2014 en Europa, los bancos revisados redujeron su participación en bonos y préstamos riesgosos. Después del AQR, los bancos volvieron a adquirir bonos más riesgosos en sus balances, pero no créditos más arriesgados. En el tercer capítulo, estudio cómo la introducción de controles de capital en Colombia afectó el crédito doméstico. Los resultados apuntan a complementariedades entre la oferta de crédito domestico y externo.

Preface

Banks provide a range of services to the real economy. Commercial banks focus their activities on consumers and private sector firms, offering checking and savings accounts, mortgages, lines of credit and personal loans. Investment banks help firms with corporate financing, such as going public and issuing corporate bonds, and provide investment management services. Yet, the banking sector's risky behavior can generate lasting effects on the real economy, as seen infamously during the Great Depression and the recent 2007-2008 financial crisis. Recent literature has highlighted differences in banks to non-financial firms, mainly in that their assets are highly complex and opaque, they communicate to both their shareholders and regulators, they are highly leveraged and susceptible to small asset price fluctuations, all the while acting as one of the main providers of lending to the real economy. The goal of this thesis is to shed light on how banks respond, predominantly through lending, when confronted with three different scenarios: uncertainty, regulatory supervision and macroprudential policies.

In the first chapter, I propose a new index to detect the *idiosyncratic uncertainty* banks face at the bank-quarter level. The index uses a recent natural language processing technique, called Skip-gram Model, to discover a novel list of "uncertainty" words based on semantic and syntactic similarities. I use the frequencies of these words in banks quarterly conference calls as a proxy for bank-level uncertainty. The index spikes at the beginning of the 2007-2009 financial crisis and reveals which banks at a given quarter signal more uncertainty about their balance sheets. Higher uncertainty is associated with lower lending the next quarter and higher liquidity, suggesting active management of uncertainty. The active management of uncertainty is more pronounced during periods of higher aggregate volatility and for banks with more skin-in-the-game.

Government regulation requires effective supervision, but regulated entities may window-dress to supervisors. In the second chapter, joint with Puriya Abbassi, Rajkamal Iyer and José-Luis Peydró, I explore how banks shift their balance sheets when confronted with a comprehensive review by regulators of their assets. For empirical identification, we analyze banks exploiting a quasi-natural experiment — ECB's 2014 asset quality review (AQR)— in conjunction with the security and credit registers of Germany. After the AQR announcement, reviewed banks decrease the share of riskier securities and loans, and level of overall securities and credit supply. After AQR compliance, reviewed banks reload riskier securities, but not riskier credit. Effects are stronger for banks with higher trading expertise. Finally, this behavior induces spillovers on asset prices and firm level credit availability. Results suggest banks' window-dressing for supervisory audits, especially on liquid securities that are easier to trade, and hold important implications for supervision.

The effectiveness of capital controls on financial stability relies on understanding the interaction between foreign capital inflows and domestic credit. However, evidence of this interaction remains elusive. In the third chapter of the thesis, joint with Andrea Fabiani, Martha López Piñeros and José-Luis Peydró, I document the efficacy of capital controls and illustrate the impact on domestic credit and non-financial firm activity. For identification, we analyze the introduction of capital controls in Colombia, through the form of a 40% Unremunerated Reserve Requirement (URR), in 2007 using granular data on firm-level debt inflows and the Colombian credit registry. First, we document that the URR successfully reduced foreign debt inflows, with stronger effects for companies relying heavily on this form of external financing. Next, we ask whether these firms were able to switch to domestic lending. We find firms which obtained foreign credit through direct financing abroad were penalized through credit cutbacks and higher interest rates. Firms which sought foreign debt via Colombian financial intermediaries were more able to substitute foreign debt with domestic peso credit. Our results point to complementarities between domestic and foreign credit supply, a channel which has been forgone in both empirical and theoretical applications. Finally, we find that the introduction of capital controls breaks the link between dollarization of domestic credit and loosened global financial conditions as proxied by the VIX.

Given the central role banks play in modern economies, understanding their behavior is imperative for financial stability. This thesis aims to elucidate the banking sector's activities for policymakers and market participants. The new index I develop in the first chapter can be used to predict which banks face high uncertainty and are most likely to cut credit. The second chapter studying bank reactions to a comprehensive supervisory review can help regulators design Asset Quality Reviews for the banking sector. Lastly, the third chapter studying the introduction of capital controls can help policymakers understand externalities associated with shutting down bank debt from abroad.

Table of Contents

Chapter 1

BREAKING THE WORD BANK: EFFECTS OF VERBAL UNCERTAINTY ON BANK BEHAVIOR

I. INTRODUCTION

The 2007-2009 financial crisis shed light on the stark consequences of an opaque banking system. This paper attempts to provide a new measure to elucidate the financial industry through a bank-level uncertainty index and illustrate how banks manage uncertainty through changes in balance sheet composition. The new measure is constructed by applying novel techniques in natural language processing and machine learning to earnings conference call transcripts over the 2002-2015 period. The purpose of this paper is to compliment extant aggregate uncertainty measures with one at the bank-level to allow for cross-sectional heterogeneity.

I start by constructing a proxy for bank-level uncertainty by counting the frequency of uncertainty words in bank conference call transcripts. Many economic and finance papers employing word counts use dictionaries from other papers, which may not be perfectly suited for the set of documents at hand. Rather than relying on word lists from other papers or subjectively choosing words pertaining to uncertainty, I discover a new word list using a more objective machine learning technique known as word embeddings. Word embeddings are vector representations of words where distances preserve syntactic and semantic similarities within the documents. Figure 1 illustrates the two-dimensional projection of the word embeddings from transcripts in my sample. The rightmost region of the map shows words such as “unprecedented", “war", and “fears" alongside “uncertainty", suggesting semantically similar meanings for these words within the context of bank speech. The new uncertainty word list is generated by clustering the words in this region. Bank-level uncertainty is calculated with the frequency of these words in each quarterly conference call. Because the usage of uncertainty words will be related to aggregate conditions, such as the growth in volatility, economic policy uncertainty and the term structure of corporate bond yields, I filter out these variables from the frequency counts. The residual is the new measure I propose in this paper and represents the idiosyncratic uncertainty banks face at a given quarter.

Three results help validate the new measure as a good proxy for uncertainty. First, the time series average of bank uncertainty lines up with events hampering the banking sector during the last business cycle. As seen in Figure 2, the index begins to rise at the onset of the recent financial crisis, in December 2007. Bank-level uncertainty remained high following the collapse of Lehman Brothers in September 2008, increasing shortly after as regulators and banks sought solutions to the ongoing crisis. The index peaks during the first quarter of 2009, when banks questioned whether regulators would force banks to value assets at fire-sale prices. Towards the end of the crisis, uncertainty plummets while at the same time cross-sectionally banks differed largely in their assessment of idiosyncratic uncertainty, as seen by the dashed blue lines representing the 95% confidence intervals. Second, correlations to aggregate measures of the economy help validate the index as a useful macroeconomic variable. Though the measure is not associated with popular uncertainty measures such as the VIX and the Economic Policy Uncertainty index from Baker at al. (2016), the new measure is positively and significantly correlated to changes in the term structure of corporate bond yields. This correlation is reassuring because the slope of the yield curve provides a measure of uncertainty about the economy (Collin-Dufresne et al., 2001). Because bank assets predominantly revolve around credit products, the fact the new measure moves hand in hand with one pertaining to credit uncertainty is encouraging. Third, bank uncertainty is positively associated with post-call volatility, suggesting uncertainty through speech relays some form of risk and new information to market participants.

Encouraged by the evidence that the new measure proxies uncertainty, I next assess how banks actively manage their balance sheets following changes in their idiosyncratic uncertainty. While extant uncertainty measures are restricted to only the time dimension, the new measure allows me to exploit the cross-sectional heterogeneity of bank uncertainty at a given quarter. Furthermore, all analyses can include time fixed effects to control for time variation, such as interest rates, aggregate firm productivity, the stochastic discount factor, and other time varying characteristics related to credit and trading. Bank fixed-effects are also included in all regressions to account for observed and unobserved time invariant characteristics of each bank, such as governance structure and risk appetite. To further account for endogeneity stemming from the bank-time dimension, I also control for a bank's lagged profitability, liquidity, leverage and size. While I do not claim any causality through the regressions, the robust set of controls and fixed effects suggests bank-level uncertainty, proxied through word-counts in earnings calls, helps understand bank balance sheet compositions.

The predominant variable of interest I analyze with the new measure is lending to the real economy. The banks in my sample are responsible for the majority of lending in the United States. I find that a one standard deviation increase in a bank's uncertainty is associated with a 4% drop in lending relative to total assets the following quarter. The drop in lending from idiosyncratic uncertainty is not due to time-varying macroeconomic conditions, the bank's profitability, leverage, liquidity or size, nor time-invariant characteristics of the bank. While banks cut back on credit extensions after speaking about higher uncertainty, their balance sheets the following quarter report larger liquidity.

Next, I allow the coefficient of bank uncertainty to vary depending on the leverage of the bank and the recent growth in aggregate volatility. Higher equity funding is associated with larger "skin-in-the-game", either from the part of shareholders or internally from executives and employees. Board members monitor and threaten bad and incompetent executives to incentivize diligent and conscientious actions. I find that declines in credit from higher idiosyncratic uncertainty are larger for banks with more skin-in-the-game, suggesting bank CEOs actively manage uncertainty more under higher shareholder market discipline. Similarly, during times of high aggregate uncertainty, banks who speak more uncertainly tend to not only reduce credit, but also increase their securities portfolios and load up on liquidity.

I then disentangle the parts of speech to identify topic-specific bank uncertainty. Using a technique in textual analysis and machine learning known as topic modeling, I divide the earnings conference call transcripts based on whether the speech pertains to non-performing assets, interest rates, or housing, and then compute the frequency of uncertainty terms in each section. I find the uncertainty about non-performing assets provides the similar magnitude in the drop in lending observed using the non-topic-specific bank uncertainty. Similarly, uncertainty about interest rates leads to higher exposures of interest rate derivatives, while uncertainty of real estate is significantly associated with lower real estate loans. The results are not only reassuring for the methodology to properly capture topic-specific uncertainty, but also suggestive of how balance sheet compositions are partly driven by active management of uncertainty.

Finally, I provide evidence of the contraction in credit from bank-level uncertainty at the loan level. A criticism of analyses done at the bank-level is that firm-specific demand may be driving both the uncertainty in banks and lower demand for credit by firms, resulting in the observed credit cutbacks. To mitigate these concerns, I use new issuances of loans at the bank-firm-quarter level and include firm-time fixed effects to control for observed and unobserved time varying firm specific characteristics, especially firm demand. The identifying assumption requires one firm at a particular quarter to receive bank credit from two different banks. I find that banks which relay higher idiosyncratic uncertainty provide smaller sized loans to firms, consistent with the results at the bank-level. The loan level data provides further evidence that banks actively manage their uncertainty by reducing lending conditional on the credit demanded at the firm-level.

The paper strings together three branches of literature. First, recent literature emphasizes effects of the financial industry communicating to both regulators and shareholders[1]. This paper attempts to better understand the communication of banks to shareholders by analyzing their quarterly earnings conference calls. The ability for regulators to monitor effectively a bank's balance sheet is hampered by their ability to mask risk and manipulate assets (Abbassi et al., 2017). Their communication to shareholders leads to severe corporate governance problems, resulting in opaque and complex balance sheets (Morgan, 2002; Mehran et al., 2011)[2]. Banks uniquely stand advantageous in providing credit (Kashyap et al., 2002), yet their fragility can

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[1] Healthcare and pharmaceutical companies must also report to regulators and shareholders. For example, Healy et al. (2002) and David et al. (2010) discuss the interaction between regulators and pharmaceutical firms.
[2] Flannery et al. (2004) find opposing results suggesting banks assets are not unusually opaque.

create adverse effects to the real economy through impaired credit markets (Bernanke et al., 1999). When profitable credit opportunities erode, banks shift the composition of their balance sheets in favor of credit rationing, securities or search for yield (Stiglitz and Weiss, 1992, Abbassi et al., 2016). This is one of the first papers, in my review of the literature, to directly relate the communication of bank's uncertainty with credit provisioning and trading. Verbal idiosyncratic uncertainty could provide another layer of transparency to the banking system in relation to banking behavior.

Secondly, this paper adds to the growing literature on measuring uncertainty. Most similar to this paper is Baker et al. (2016) who develop a text based economic policy uncertainty index by counting the frequency of “uncertainty" and “uncertain" in newspapers within certain contexts. Their measure spikes during tight presidential races, military conflicts, and the 2008 failure of Lehman Brothers. The economic policy index is associated with declines in firm investments and output, which coincides with the decline in credit caused by the uncertainty in credit conditions observed in this paper. One import distinction with their measure is that the economic policy index is aggregated as a time series and, when used as a sole regressor cannot be joined with time fixed effects. This paper looks at the cross-section of uncertainty facing banks, allowing me to accurately control for aggregate uncertainty. Jurado et al. (2015) develop another measure of uncertainty which suggests uncertainty episodes, such as those found in Baker et al. (2016), appear more infrequently than suggested while exhibiting high persistence. Baley and Blanco (2015) develop a firm-level uncertainty index caused by a firm's inability to disentangle temporary and permanent uncertainty shocks. Ludvigson et a. (2015) show that higher macro uncertainty is often an endogenous response to the business cycle, while financial uncertainty is found to cause declines in real activity, consistent with the real effects of this paper. Similarly, Berger et al. (2017) find forward-looking measures of uncertainty have no real effects while measures derived from realized stock market volatility lead to contractions.

Lastly, I provide applications of novel natural language processing and machine learning techniques to economic and finance problems. Hassan et al. (2016) and Gissler et al. (2016) are most similar in this regard. Hassan et al. (2016) employ a computational linguistics technique to measure political risk in earnings conference calls while Gissler et al. (2016) measure bank-level regulatory uncertainty using dictionary-based methods and document a decrease in lending following uncertainty from new regulations. Mayew and Venkatachalam (2012) apply voice recognition software to earnings calls to study the effect of vocal cues and emotions on financial variables. Loughran and McDonald (2011) use dictionary-based methods to illustrate the misclassification of word counts in economic and finance applications. Hansen et al. (2014) apply Latent Dirichlet Allocation modeling to Fed transcripts to extract economic related topics as they assess the impact of transparency on monetary policy planning.

The remainder of this paper is organized as follows. Section II provides a summary of earnings conference calls. Section III describes a conceptual framework to develop empirical predictions. Section IV describes the methodology I use to extract *idiosyncratic* bank uncertainty from the conference calls. Section V describes the data sources. I validate the newly created measure in Section VI and describe how banks actively manage uncertainty in Section VII. In Section VIII, I use loan-level data to control for firm demand to demonstrate uncertainty management through lower lending. Lastly, Section IX concludes the paper.

II. CONFERENCE CALLS

In 2000, the Securities and Exchange Commission of the United States passed the Regulation Fair Disclosure Act requiring public companies to disclose material information pertaining to business activities publicly. The commission encouraged public companies to post written transcripts of calls and webcasts on their websites for an appropriate period each quarter. The National Investor Relations Institute reports an increase from 80% to nearly 97% of companies holding calls to discuss their earnings from the mid-90s to 2014. The calls last anywhere between 30 minutes to 60 minutes, depending on the market capitalization of the company, current events and analyst coverage. Earnings conference calls typically begin with the Chief Executive Officer and the Chief Financial Officer providing a summary of the recent quarter, along with guidance of what to expect the following quarter. Following the executive's summary, the line opens for questions by analysts and sometimes shareholders. Conference calls represent a unique opportunity to analyze information executives would like to share with market participants along with information investors demand, providing a setting where new and valuable information is made public (Mayew, 2008).

Earnings call transcripts were downloaded from Factiva. The Regulation Fair Disclosure Act of 2000 mandated all publicly traded companies release material information to all existing and potential investors. Since then, most conference call transcripts have been made public around the date of the call. Factiva amassed one of the largest databases, though the banks in my database are only present from 2002 onward. Nonetheless, the utility of Factiva as opposed to other public transcript databases, such as Seeking Alpha, is the large time series of calls which can be collected. I downloaded the calls for the banks in my sample from 2002Q1 - 2015Q4.

III. CONCEPTUAL FRAMEWORK

In this section, I illustrate reasons a bank would respond to increased idiosyncratic uncertainty by changing their balance sheet composition. I start with a stylized framework, based on Buch et al. (2014), as a useful foundation for establishing testable hypotheses in the following sections. Then, I discuss other possible mechanisms at play.

III.1 Stylized Example

A risk-neutral bank *b* must decide at time *t* the proportion of its assets to invest into lending, α_t, with the remainder $1-\alpha_t$ invested into bonds. Bonds return 1 with zero risk, while the return on lending, r_{t+1}^L , is random. Macroeconomic forecasts suggest a prior over the return on lending such that $r_{t+1}^L \sim N(\mu, \sigma_V^2)$, where σ_V^2 represents aggregate uncertainty. Additionally, the bank guides investors by signaling their own beliefs on the uncertainty of r_{t+1}^L in a conference call, by providing another signal of r_{t+1}^L:

$$r_{t+1}^{L,call} \sim N(\mu, \sigma_B^2)$$

The speech during the conference call provides a new variance on the expected return of lending. σ_B^2 represents the bank-level uncertainty. Importantly, σ_B^2 is composed of an aggregate component and an idiosyncratic component. Because conference calls contain important insights into the profitability of the firm, I assume σ_B^2 is increasing in the idiosyncratic component (Roychowdhury and Sletten, 2012; Mayew, 2008; Hassan et al., 2016). I abstract from strategic communication because the empirical analysis below demonstrates that banks act as if they relay truthful information in σ_B^2.

Thus, investors use Bayesian updating to form a posterior of r_{t+1}^L:

$$\tilde{r}_{t+1}^L = r_{t+1}^L | r_{t+1}^{L,call} \sim N(\mu, \tilde{\sigma}^2)$$

with the posterior variance $\tilde{\sigma}^2 = \frac{\sigma_B^2 \sigma_V^2}{\sigma_B^2 + \sigma_V^2}$. The expected shareholder capital, k_{t+1}, can be written as:

$$k_{t+1} = \alpha_t(1 + \tilde{r}_{t+1}^L) + (1-\alpha_t) - d_t = 1 - d_t + \alpha_t \tilde{r}_{t+1}^L = k_t + \alpha_t \tilde{r}_{t+1}^L$$

Banks seek to maximize shareholder capital tomorrow k_{t+1}. As a result, banks want to choose α_t as high as possible. However, a Value-at-Risk (VaR) constraint limits the amount the bank can invest in the risky technology, lending. The VaR constraint can be interpreted as limiting the probability that equity capital tomorrow is negative:

$$\Pr(\tilde{r}_{t+1}^L < -\frac{k_t}{\alpha_t}) = 1 - p$$

Regulators also have information on the distribution of $\tilde{r}_{t+1}^L$, so the constraint can be rewritten as a function of the first and second moments[3]:

$$\Pr(\tilde{r}_{t+1}^L < \mu - \phi \frac{\sigma_B^2 \sigma_v^2}{\sqrt{\sigma_B^2 + \sigma_v^2}}) = 1 - p$$

I assume regulators are more conservative in their estimates of $\tilde{r}_{t+1}^L$, making $-\frac{k_t}{\alpha_t} \leq \mu - \phi \frac{\sigma_B^2 \sigma_v^2}{\sqrt{\sigma_B^2 + \sigma_v^2}}$.

Because the bank wants to set α_t as high as possible, the inequality will bind. Equating the moments and the ratio of capital to lending leads to the optimal level of lending:

$$\alpha_t = \max\left\{0, min\left\{1, \frac{k_t}{\phi \frac{\sigma_B^2 \sigma_v^2}{\sqrt{\sigma_B^2 + \sigma_v^2}} - \mu}\right\}\right\}$$

III.2 Hypotheses

First, I derive how the posterior variance $\tilde{\sigma}^2$ is affected by increases to uncertainty σ_B^2:

$$\frac{d\tilde{\sigma}^2}{d\sigma_B} = \frac{2\sigma_v^4 \sigma_B}{(\sigma_B^2 + \sigma_v^2)^4} > 0$$

Thus, in order to validate a measure of bank-level uncertainty, a positive relationship to post-call volatility would be reassuring as the posterior variance increases in σ_B. Next, I derive how optimal lending α_t changes depending on bank-level uncertainty.

$$\frac{d\alpha}{d\sigma_B} = -\frac{\sigma_v^3 k_t \phi}{\sqrt{\sigma_B^2 + \sigma_v^2}\left(\sigma_B \sigma_v \phi - \mu\sqrt{\sigma_B^2 + \sigma_v^2}\right)^2} < 0$$

As risk increases through a larger variance, banks actively manage their balance sheet compositions in favor of less risky investments in lending. The effects are more severe for

[3] I assume the banks assets are marketable. Note that the banks I study in the empirical analysis are all publicly traded.

banks with higher capital, as seen by differentiating with respect to k_t:

$$\frac{d^2\alpha}{d\sigma_B dk} = -\frac{\sigma_v^3\phi}{\sqrt{\sigma_B^2+\sigma_v^2}\left(\sigma_B\sigma_v\phi - \mu\sqrt{\sigma_B^2+\sigma_v^2}\right)^2} < 0$$

Lastly, active management of bank-level uncertainty is influenced by the level of aggregate uncertainty σ_v.

$$\frac{d^2\alpha}{d\sigma_B d\sigma_v} = -\frac{\sigma_v^2\sigma_B^2 k_t\phi(\sigma_B\sigma_v\phi - 3\mu\sqrt{\sigma_B^2+\sigma_v^2})}{(\sigma_B^2+\sigma_v^2)^{3/2}\left(\mu\sqrt{\sigma_B^2+\sigma_v^2} - \sigma_B\sigma_v\phi\right)^3} < 0$$

The cross-partial derivative will be negative as long as $\frac{\sigma_B\sigma_v}{\sqrt{\sigma_B^2+\sigma_v^2}} < 3\mu$. If the language in the conference call relays significant uncertainty (such that the posterior standard deviation is over 3 times larger than the prior mean), then during times of high macroeconomic uncertainty banks will reduce lending more from responses to idiosyncratic uncertainty.

The empirical predictions of the stylized model are as follows. Any measure of idiosyncratic uncertainty, given a level of investment in lending and equity capital, increases the volatility of the returns. Second, the optimal level of investment in lending is decreasing in a bank's idiosyncratic uncertainty. The decline in lending as a result of higher idiosyncratic uncertainty is more severe for banks with larger equity capital funding and periods in which aggregate uncertainty is high.

III.3 Alternative Explanation

Risk-neutrality serves as a nice benchmark for understanding the decisions of the bank as a whole. However, at the individual level, bank managers may very well exhibit risk aversion, for example through lending to only favorable clients or prioritizing above all else shareholder desire to avoid bankruptcy (Froot and Stein, 1998). As a result, another explanation could be that bank managers reduce lending when their signals of r_{t+1}^L are noisy because of risk-averse preferences. This reduction in lending would reduce cash flows for investors and share price, resulting in higher volatility. While the empirical results in this paper illustrate the effects of higher idiosyncratic uncertainty on balance sheet compositions, I am agnostic of the mechanism and use the hypotheses presented here as guidance for the following empirical section.

IV. MEASURING UNCERTAINTY

The variable σ_B represents the uncertainty communicated by the bank during the conference call. I measure this by counting the number of words pertaining to uncertainty spoken by the bank management during the call. Recent literature relies on counting words of existing dictionaries, most famously that of Loughran and McDonald (2011). They generated their list of uncertainty words by ciphering through 10-K filings of public companies, retaining only words with occurrence in at least 5% of the filings. While this method is useful for many financial contexts, I attempt another useful method better tailored for measuring bank uncertainty. First, Loughran and McDonald use 48 industries while I am only interested in financial companies. Second, restricting the choice of words to those occurring in 5% of filings rules out rare words which are most likely related to uncertainty, such as “war" and “illiquidity". Lastly, to ensure little subjectivity from the part of the researcher, as Loughran and McDonald manually judge whether a word pertains to uncertainty given the context, I rely on recent developments in machine learning and natural language processing to objectively identify a new word list. As robustness I use the list proposed by Loughran and McDonald to count the frequency of uncertainty words in the conference call and obtain similar results. The lists are quite disjoint sets of each other, suggesting “uncertainty" is not restricted to one set of terms. I discuss the comparisons in Section VI and VII once I define my newly discovered list of terms.

IV.1 Word Embeddings

IV.1.1 The Skip-gram Model

Mikolov et al. (2013a) develop the Skip-gram Model to learn vector representations of words, commonly known as word embeddings. The embeddings serve not only as a dimension reduction tool for representing words, but also as a way of preserving the syntactic and semantic relationship in a Euclidean space. For example, the model trained in the original paper from Google famously predicts the relationship: i) vec(“Madrid”) - vec(“Spain”) + vec(“France”) is closest to vec(“Paris”), and ii) vec(“Germany”) + vec(“capital”) is closest to vec(“Berlin”).

The Skip-gram model takes as input a word represented as a one-hot encoded vector[4]. The output is the words in the context of w_i. The context is the M words to the left and M words to

[4] A one-hot encoded vector for word w_i is a vector of length V, the number of unique words across all documents. A value of 1 is placed at the index of w_i and 0 elsewhere.

the right of w_i. Let w_{i+m} represent the word which lies $|m|$ words to the left (right) of word w_i for *m<0* (*m>0)* in the original document.

The transformation of the input to the output happens in two steps. Let x_{w_i} be a one-hot representation of word w_i and *V* the total number of unique words across all documents. First, x_{w_i} is projected onto an *H*-Dimensional space with **U,** an *H*-by-*V* matrix, to create u_{w_i}. Second, u_{w_i} is projected back onto a *V* dimensional space using a *V*-by-*H* matrix **V**. To obtain a probability distribution over all *V* words in the vocabulary, the softmax function[5] is applied to the resulting vector. The neural network, illustrated in the appendix in Figure A1 with a simplified training example, can be summarized by the following equations:

$$\begin{aligned} \text{Input} \quad & x_{w_i} \\ \text{Hidden Layer (Word Embedding)} \quad & u_{w_i} = \mathbf{U}x_{w_i} \\ \text{Output} \quad & x_o = \mathbf{V}u_{w_i} = \begin{bmatrix} v_1' u_{w_i} & v_2' u_{w_i} & \dots & v_V' u_{w_i} \end{bmatrix}' \\ \text{Output Probabilities} \quad & y_o = softmax(x_o) \end{aligned}$$

y_0 will be a distribution over all *V* terms and will be the same output for all *2*M* words in the context of w_i.

The important object of the Skip-gram model is the matrix **U**. **U** provides the word embeddings where each word will be represented as a vector in $\mathbb{R}^H$. Because **U** is an *H*-by-*V* matrix, the word embedding of word w_i will be the column in **U** pertaining to w_i. **V** can also be interpreted as another space of word embeddings, where each row *i* represents the word embedding of word w_i with different valued elements. However, the semantic and syntactic differences across words are still preserved, hence typically only **U** is used for the word embeddings.

The model is trained by finding **U** and **V** such that the average probability of context words is maximized. The objective function to maximize is $\frac{1}{Z}\sum_{i=1}^{Z}\sum_{\substack{-M \le m \le M \\ m \ne 0}} \log(p(w_{i+m}|w_i))$, where *Z* is the total number of words across all documents and $p(w_{i+m}|w_i)$ is the element in y_0 pertaining to word w_{i+m}. Taking just one word w_i, we can change the objective function to a loss function to minimize:

[5] The softmax function maps a vector of *K* elements to a range of [0,1] with elements summing to 1. If z_i is element *i* of vector **z**, the softmax function is given by $softmax(\mathbf{z})_i = \frac{\exp(z_i)}{\sum_{k=1}^{K}\exp(z_k)}$.

$$E = -\sum_{\substack{-M \le m \le M \\ m \neq 0}} log(p(w_{i+m}|w_i)) = -\sum_{\substack{-M \le m \le M \\ m \neq 0}} log \frac{exp(v'_{w_{i+m}} u_{w_i})}{\sum_{j'=1}^{V} exp(v'_j u_{w_i})}$$

$$= -\sum_{\substack{-M \le m \le M \\ m \neq 0}} v'_{w_{i+m}} u_{w_i} + log(\sum_{j'=1}^{V} exp(v'_j u_{w_i}))$$

where $v_{w_{i+m}}$ is the row of **V** pertaining to w_{i+m}.

Training the model requires obtaining optimal estimates of **U** and **V** through gradient descent. Basically, given some values of **U** and **V**, we observe how ``far off" the current estimates of the probabilities for the words in the context of w_i were. Then, depending on the error we move around the elements of **U** and **V** such that the error improves.

More formally, first, every word in every sentence is fitted with the model to obtain the prediction y_0. Second, we calculate the errors and use the gradient of *E* with respect to **U** and **V** to update the two matrices:

$$\mathbf{V}^{new} = \mathbf{V}^{old} - \alpha \frac{\partial E}{\partial \mathbf{V}^{old}}$$
$$\mathbf{U}^{new} = \mathbf{U}^{old} - \alpha \frac{\partial E}{\partial \mathbf{U}^{old}}$$

While normal gradient descent could be applied to discover optimal parameters, Mikolov et al. (2013b) discuss significant improvements to training with respect to sampling for parameter updates. I follow the suggestions in their paper to estimate the word embeddings in my sample. The appendix provides a brief overview of their improvements.

IV.1.2 Output

The Skip-gram model was estimated with a hidden layer dimension of *H*=100 and context window size *M*=5. These are typical default values recommended by various programming modules which estimate Skip-gram models. I estimated the model with 2,385 earnings conference call transcripts which contained 56,820 unique words. Thus, the word embedding matrix **U** is 100-by-56,820, where each column w_i is a 100-by-1 vector representing the word embedding of w_i.

The high-dimensionality of the output leads to difficulties in interpreting the word embeddings. However, a recent paper by Maaten and Hinton (2008) develops a new methodology to visualize high dimensional data in lower dimensions, known as t-Distributed Stochastic Neighbor Embedding (t-SNE). Economics has often resorted to other dimensionality reduction tools, predominantly principal component analysis (PCA). PCA minimizes squared errors between distances, thereby preserving large distances between the high dimension space and the low dimension space since they are highly penalized. t-SNE, on the other hand, preserves the local distances in the high dimensional space in the low-dimensional mapping. The appendix provides further details by summarizing the contribution of Maaten and Hinton (2008).

Figure 1 illustrates the two-dimensional projection of the 100-dimensional word embeddings using t-SNE. Each point represents a unique word in the vocabulary across all 2,385 conference calls. The Euclidean proximity of two points proxies the similarity both semantically and syntactically of the words.

On the north-west region of the map appear words related to securities, such as "security", "stock", "bond" and "cdo". Due to their strong association with each other, "fannie" (from Fannie Mae) and "freddie" (from Freddie Mac) are shown nearly on top of each. The southern island separated from the mainland of the words represents names, with "jpmorgan" and "suntrust" appearing on the ends. The southeastern region displays words pertaining to the macroeconomy, such as "bust", "boom", "gdp" and "inflation". The northeast section illustrates similarities among forecast nouns such as "estimate", "outlook", and "projection". Lastly, the word embeddings seem to bring together the word uncertainty with "instability", "fear", "war", and "illiquidity".

IV.2 Creating New Dictionary of *Uncertainty* Terms

The previous section generated one H-dimensional word embedding, $\boldsymbol{u}_{w_i}$ for each word w_i. As the distances between word embeddings preserve their semantic and syntactic relationships with one another, I want to find the words nearest to the vector representations of "uncertainty" and "uncertain" as the new list of *uncertain* words .

I turn to the K-means algorithm to cluster the word embeddings into *K* disjoint sets in hopes of finding the cluster containing "uncertainty" and "uncertain". K-means is an unsupervised learning algorithm which takes as input a set of vectors, $\{\boldsymbol{u}_1, \boldsymbol{u}_2, \dots, \boldsymbol{u}_V\}$, and a hyperparameter, *K*, representing the number of clusters. The output are K-disjoint sets, $\{\boldsymbol{S}_1, \boldsymbol{S}_2, \dots, \boldsymbol{S}_K\}$, composed of the input vectors. Training the algorithm works iteratively in two steps. At the onset of training, a set of vectors, $\{c_1, c_2, \dots, c_K\}$ are chosen randomly as cluster centroids. The first step is cluster assignment in which each $\boldsymbol{u}_i$ is assigned to the cluster which minimizes the distance between $\boldsymbol{u}_i$ and the cluster's centroid. In other words, each $\boldsymbol{u}_i$ is assigned to cluster *k* if $k = \underset{k}{\operatorname{argmin}}\, dist(\boldsymbol{u}_i, c_k)$. The second step is updating the cluster centroids, $\{c_1, c_2, \dots, c_K\}$, so that c_k is the average of all points assigned to cluster *k*. These two steps are repeated until the sum of the squared errors is minimized:

$$SSE = \sum_{k=1}^{K} \sum_{\mathbf{u} \in \mathbf{S}_k} dist(\mathbf{u}, c_k)$$

Taking as input the word embedding matrix$\{\boldsymbol{u}_{w_1} \boldsymbol{u}_{w_2}, \dots, \boldsymbol{u}_{w_V}\}$, I first choose the hyperparameter *K*. Setting *K* too small leads to less number of clusters though larger number of words within each cluster and setting *K* too large would lead to sparse words within clusters. In order to set *K* strategically, I run a series of cross-validation tests for various values of *K*[6]. The appendix reports the average score for each value of *K* between 1 and 400. The scores tend to plateau around *K*=150, with little marginal benefit for larger number of clusters. Therefore, I set *K*=150, though it should be noted the results in the paper are quite similar if *K* is set to 175 or 200.

After estimating K-means, I find the clusters containing "uncertainty" and "uncertain" and use the words within the cluster to generate the new *uncertainty* word list. The resulting dictionary, $\boldsymbol{S}_{uncertainty}$, is shown in Table1. The list contains words associated with uncertainty, such as "fears", "unprecedented" and "instability". Similarly, the methodology picks up events which are associated with rises in uncertainty, such as "brexit", "katrina", "terrorism", "war" and "disasters". We also see words which are economic specific that typically lead to uncertainty in financial markets, such as "illiquidity", "recessionary" and "crisis". By inspection, the set appears to accurately resemble words related to uncertainty.

[6] Cross-validation involves running the following experiment multiple times: 1) Splitting a proportion, typically 80%, of the input vectors $\{\boldsymbol{u}_1, \boldsymbol{u}_2, \dots, \boldsymbol{u}_V\}$ as "training", while holding the other 20% as an "out-of-sample" testing set. 2) Obtaining a set of centroids from training using the 80% training sample 3) After training, each vector in the out-of-sample set are allocated to the cluster which has the minimum distance between itself and the cluster centroid. 4) The score, which is the negative of the total distance between each point and the assigned cluster centroid, is then reported.

IV.3 Uncertainty Measures

IV.3.1 Bank-Level Uncertainty

The first measure I use for bank-level uncertainty is the frequency of *uncertainty* words, the cluster $\boldsymbol{S}_{uncertainty}$ defined in the previous section, in banks conference calls. Formally, I define bank-level uncertainty as:

$$\sigma_B = \frac{\sum_{w \in W} \mathbb{1}(w \in \mathbf{S}_{\mathbf{uncertainty}})}{|W|} \tag{1}$$

where W is the set of all words in the earnings conference call[7][8].

The uncertainty measure is computed at the bank-quarter frequency, as earnings conference calls occur once per quarter per bank. It is useful, however, to look at examples for individual responses, for example how executive officers answer particular questions during the call. Table 4 shows the most uncertain expressions used in 2008. The top result from Capital One Financial discusses *cyclical economic headwinds and uncertainties* the bank faces. Other highly uncertain responses include *challenging, softening*, *unprecedented* and *severely* as descriptors of the economy during that year.

As σ_B is given assuming σ_V is known, I am interested in the uncertainty which is idiosyncratic to the bank independent of aggregate volatility. The bank may experience large uncertainty merely as a result of an increase in aggregate uncertainty, therefore it is important to filter out the components of σ_B explained by aggregate measures. I do this through the following regression:

$$(\sigma_B)_{b,t} = \beta_1 \Delta EPU_t + \beta_2 \Delta \mathrm{VIX}_t + \beta_2 \Delta \mathrm{CorpSpread}_t + \gamma_b + \epsilon_{b,t} \tag{2}$$

The residuals, $\epsilon_{b,t}$, capture the component of bank uncertainty, σ_B unexplained by aggregate uncertainty. Thus, the idiosyncratic uncertainty is represented by the residual,

$$BankUncertainty_{b,t} = \widehat{\epsilon_{b,t}} \tag{3}$$

[7] As commonly done in textual analysis, I remove frequent words from the earnings conference calls. These include English pronouns, auxiliary verbs, and articles.

[8] It should be noted that as robustness, I also compute σ_B using the words from Loughran and McDonald 2011. 7 words overlap both of our lists: “instability”, “turbulence”, “uncertain”, “uncertainty”, “unpredictable”, “unsettled”, and “varying”.

IV.3.2 Topic Specific Uncertainty

While $BankUncertainty$ represents the idiosyncratic uncertainty facing the bank over the entire conference call, I am also interested in topic-specific sections of the call to better understand the uncertainty related to interest rates, non-performing loans and real estate. In order to extract the responses of the bank dealing with specific topics, I implement a Latent Dirichlet Allocation (LDA) model. Introduced by Blei et al. (2003), LDA is an unsupervised algorithm which takes as input a set of documents and a hyperparameter K, the number of topics, and outputs two objects: 1) A document-topic matrix revealing the distribution over topics of each document 2) a term-topic matrix showing a distribution over all words in the corpus for each topic. Similar to principal component analysis, the topics themselves do not have any objective meaning but rather are given by the researcher's interpretation of the output. LDA models have recently been used in the economic literature to gain insight into speech data, as in Hansen et al. (2014).

I ran three chains of a K=50 topic model. For each chain, I allowed a burn-in period of the Gibbs sampling of 3,000 iterations. Then, 40 samples were taken every 50 iterations until 2,000 iterations have elapsed. The token-topic and document-topic matrices were then averaged across samples. I use a perplexity score to assess the goodness of fit for each chain, where a low perplexity score implies a good fit. The scores are reported in the appendix. Minimizing perplexities leads me to choose chain 2 to perform all subsequent analyses.

The topic descriptions are reported in Table 3. While only the top 5 words for each topic are reported, the results suggest coherent topics. For example, Topic 9 is related to interest rates with words such as *interest*, *net*, *income*, *margin* among the top descriptors. Topic 49 seems to be a topic of non-performing loans, with top words *asset*, *non*, *perform*, *past*, *day*, *level.*

Some topics together seem to be part of similar broader topics. For example, topic 25 and topic 40 seem to be generally about housing: topic 25 has top words *commercial, real, portfolio* while topic 40 has top words *mortgag, portfolio, origin*. To group topics together, I use a hierarchical clustering algorithm. The input to the algorithm are vectors and the output is a hierarchy of structures. In my case, the input are distributions over words (one for each topic), and the output is a hierarchy such that topic 40 and topic 25 are one cluster, where these two topics together create another cluster joined with topic 32; then these three topics together create another cluster and so on. Generally, for every term-topic distribution, β_i, I compute the average distance between all pairs:

$$dist_{avg}(G,H) = \frac{1}{n_G n_H} \sum_{\beta_{i'} \in G} \sum_{\beta_i \in H} dist_{\beta_{i'},\beta_i}$$

where n_G is the number of topics in cluster *G* and n_H the number of topics in cluster *H*. The algorithm works by assuming each *K* term-topic distribution is an independent group. At each step, the two most similar groups are merged until there is a single group left containing the entire dataset. I inspect the words within each group to identify those most related to the relevant topics of interest: interest rates, non-performing loans and real estate.

The output is displayed in Figure 3. Topic 49, with words "non", "past", and "delinqu" appears within the branch containing topic 38, which has top words "loss", "charge", and "prov". Figure 4 shows the word clouds next to each other, which I label the problem loans topic. The interest rate topic (Topic 9) and the topics with top words "point" and "basis" (Topic 23) and "rate" and "yield" (Topic 41) appear to be in one branch of Figure 4 spanning Topic 41 and Topic 29 along the x-axis. Putting these topics next to each other in the form of word clouds in Figure 5 creates an interest rate topic. Figure 6 groups together words I assume relate to real estate. Using these broader categories of topics, I keep only responses predominantly related to either problem loans, interest rates, or housing. For each of these three broader topics, I count the frequency of words from $\boldsymbol{S}_{uncertainty}$ and recalculate $BankUncertainty$ for each conference call using (3). Thus, for each conference call I generate three new variables: idiosyncratic uncertainty about problem loans, interest rates and housing.

Table 4 displays the top responses by bank management for the three topics analyzed. Reviewing the top responses for each topic helps validate that the topic modeling is able to objectively, and in an automated manner, select the portions of the earnings call transcripts specific to each topic.

V. DATA

V.1 Data Sources

The dataset I use combines three different sources. For bank-level balance sheet data I use the Federal Reserve Y-9C forms, which is required for banks with more than 1 billion dollars in consolidated assets. I retrieve the following balance sheet characteristics: total loans (*BHCK2122*), trading assets (*BHCK1773+BHCK1754*), liquidity (*BHCK0081+BHCK0395 +BHCK0397+BHCK0383*), loans secured by real estate (*BHCK1410*), interest rate exposure (*BHCK8757*), profitability (*BHCK4340*), equity (*BHCP3210*) and total assets (*BHCK2170*). I compute all balance sheets variables relative to total assets for the summary statistics and levels for the regression analysis. The measures I use for aggregate uncertainty are the Economic Policy Uncertainty dataset from Baker et al. 2016, which can be accessed at www.policyuncertainty .com, the CBOE volatility index VIX, and corporate bond yields from the United States Treasury. Lastly, I use the uncertainty measures calculated from earnings conference calls as described above.

V.2 Final Dataset

I merge the FR Y-9C database with the bank uncertainty measures generated from the earnings conference calls manually using the names of the institutions. In the event of a merger, I used the largest banking group at a consolidated basis. The resulting dataset is joined to the aggregate uncertainty variables. The sample covers the years 2002 - 2015, encompassing an entire business cycle. While not all quarterly transcripts could be found on Factiva for every bank, I restrict the sample to banks with at least two thirds of the quarters represented. The threshold was chosen so as to maintain a high cross-section of banks, but results are robust if I only keep banks for which I have data for every quarter. After the merge I am left with 51 banks and 2,385 bank-quarter observations.

Table 5 provides the summary statistics. In total, I analyze 51 banks over Q1 2002 until Q4 2015. The average size of the banks is roughly 27.5 billion dollars with an average equity ratio of 10.1%. Applying (1), the average percentage of uncertain words used in each call is 1.08%. The average lending is about 63.25%, trading assets account for 19.88%, and liquidity represents 7.37% of total assets on average.

While the summary statistics report the nominal values, in all subsequent analyses, I demean the variables so the coefficients in regressions can be interpreted as a percentage change in the dependent variable in response to a one standard deviation increase in the independent variable. Unless otherwise noted, standard errors are clustered at the bank and quarter level.

VI. Validation

VI.1 Relation to Aggregate Variables

To begin understanding the interpretation of $BankUncertainty_{b,t-1}$, I start by reviewing how balance sheets and aggregate uncertainty variables differ depending on the value of idiosyncratic uncertainty. In Table 6, I separate the sample into banks displaying high uncertainty and banks with low uncertainty using the median value of 1.00% as the threshold. Unconditionally, banks exhibiting low uncertainty report 2.6% more loans than banks with high uncertainty. In contrast, liquidity is higher among those with high $BankUncertainty_{b,t-1}$, suggesting banks compensate the reduction in credit with more liquid assets. The bank-quarter observations exhibiting high uncertainty correlate to a 5.6% larger slope of the yield curve for corporate bonds, suggesting my bank uncertainty measure is associated with frictions in the corporate lending market. The correlations are reassuring as uncertainty signaled by banks should be associated with their primary market: credit.

In (2), I filtered out the components of σ_B driven by aggregate factors driving uncertainty to obtain $BankUncertainty_{b,t-1}$. The second point of validation is the results of the regression in (2). Table 7 summarizes the results, where the dependent variable is either total lending, liquidity or σ_B. Without bank fixed effects, lending is not related to any of the aggregate uncertainty measures. Once included, in column (2) we see when the EPU index increases, lending decreases. In contrast, liquidity moves counter-cyclical to aggregate uncertainty changes according to the VIX. σ_B is statistically and positively related to the growth in the term structure of corporate bond yields. As the financial sector is largely responsible for allocating capital to the real economy through corporate lending, the positive relationship suggests uncertainty in the corporate bond market propagates to bank's speeches.

With the residuals of each regression, I retain the portion of the bank balance sheet variables not explained by aggregate uncertainty conditions.

Third, I plot the time series of the average idiosyncratic uncertainty and observe well-known events hampering the banking sector and bank uncertainty over the last business cycle. Figure 2 plots $BankUncertainty_{b,t-1}$, averaged at each quarter. As the recent financial crisis began to unravel, in December 2007, banks begin to exhibit larger idiosyncratic uncertainty. Bank-level uncertainty remained high following the collapse of Lehman Brothers in September 2008, peaking the following quarter as the bailout of the financial system was announced. The dashed blue lines show the 95% confidence intervals of the uncertainty of the banks at a given quarter. Cross-sectionally, the boom period between 2004-2007 showed moderate disparities in uncertainty, while the beginning of the crisis in December 2007 suggests banks shared similar beliefs of uncertainty with small confidence intervals. The interval rose subsequently during the end of the recession and remained wide thereafter. Figure 7 displays $BankUncertainty_{b,t-1}$ averaged each quarter alongside two similarly constructed measures. Rather than using my newly constructed dictionary, I use the dictionary from Loughran and McDonald (2011) and another composed of just the words “uncertain" and “uncertainty". The correlation of my index with Loughran/McDonald and only using “uncertain" and “uncertainty" at the bank-quarter level is less than 0.2. These correlations are reassuring as it suggests my newly discovered set of words has the benefit of needing no manual reading of transcripts, as in Loughran/McDonald, yet achieving similar dynamics and different variation.

VI.2 Relation to Volatility

To ensure my measurement of idiosyncratic uncertainty pertains to some form of risk, I assess how the measure associates to post-call volatility. First, I analyze the effect of idiosyncratic uncertainty on volatility 7 days after the call in columns (1)-(4) of Table 8. Column (1) illustrates how the average idiosyncratic uncertainty, which varies only at the quarter-level, is positively and significantly associated with post-call volatility. Even when running the regression with uncertainty at the bank-quarter level, the positive association between idiosyncratic uncertainty and short-run volatility remains statistically significant, as evident from columns (2) and (3). By including the most stringent specification with both bank and quarter fixed effects, the impact of a 1 standard deviation increase in idiosyncratic uncertainty on post-call 7-day volatility drops to nearly 3%, remaining statistically significant. The coefficients are reassuring for suggesting that the content of the earnings call provides new information not previously priced into the banks market value.

Columns (5)-(8) repeat the exercise with a longer horizon of 60 day post-call volatility. The coefficients are smaller and remain statistically significant, except for column (8) which includes both quarter and bank fixed effects. The results suggest idiosyncratic uncertainty through speech is not largely associated with long-run volatility conditional on the current time period.

Table A2 in the appendix displays similar regressions, though with the dependent variable as the cumulative absolute returns 7 days and 60 days after the call. In the strictest regressions with full fixed effects, neither short term or long term returns are associated with *BankUncertainty*. Because *BankUncertainty* is more associated to volatility than prices, which represent discounted future cash flows, the results of Table A2 suggest that "uncertainty" is not a euphemism for future losses and justifies using *BankUncertainty* as a proxy for the bank's uncertainty.

VII. Managing Uncertainty

VII.1 Balance Sheet Responses

Do banks cutback more on lending, or increase trading and liquidity, when they emit higher uncertainty to the market? To answer this question, I regress lending and liquidity on $BankUncertainty_{b,t-1}$ as calculated in the previous section:

$$YResid_{b,t} = \beta_1 BankUncertainty_{b,t-1} + controls_{b,t-1} + \gamma_b + \delta_t + \epsilon_{b,t}$$

(4)

YResid and $BankUncertainty_{b,t-1}$ are the residuals from (2), where the dependent variables are lending and liquidity. I include time-fixed effects to control for observed and unobserved time varying characteristics. This allows me to control for all aggregate variables related to credit, such as market pricing, the stochastic discount factor and aggregate firm productivity. The coefficient β_1 reports the change in $YResid_{b,t}$ as a response to a one standard deviation increase in bank uncertainty through speech in the earnings conference calls. Time fixed effects allow β_1 to represent the change in $YResid_{b,t}$ at a given quarter relative to other banks, as the time dimension is muted. Furthermore, $controls_{b,t-1}$ addresses potential endogeneity stemming from the fact that the relationship between what banks speak about at *t-1* and $YResid_{b,t}$ is confounded by bank specific characteristics last quarter. Lastly, γ_b, bank fixed effects, control for time-invariant bank characteristics such as corporate governance structures and risk appetites.

Results are reported in Table 9. Higher $BankUncertainty_{b,t-1}$ is associated with lower lending and more liquidity. Given a quarter, a bank speaking more uncertainly by one standard deviation decrease their lending next quarter by nearly 0.03 standard deviations. The effects on liquidity is not significantly significant, though as shown below depends on the level of equity and aggregate volatility. A one standard deviation increase in $BankUncertainty_{b,t-1}$ leads to a 0.03 standard deviation increase in liquidity.

VII.2 Heterogeneous Effects

To better assess the impact of uncertainty on next period credit and securities holding, I analyze the impact with two more sources of variation: aggregate uncertainty and leverage. I run the following specification in Table 10:

$$YResid_{b,t} = \beta_1 BankUncertainty_{b,t-1} + \beta_2 BankUncertainty_{b,t-1} * X_{b,t-1} \quad (5)$$

$$+controls_{b,t-1} + \gamma_b + \delta_t + \epsilon_{b,t}$$

First, I use $X_{b,t-1}$ equal to the equity of bank *b* at quarter *t-1*. By exploiting the variation of leverage at the time of giving the conference call, this regression allows me to assess whether banks with more skin-in-the-game, that is higher equity, align their actions more with their words. A bank with more equity that speaks more uncertainly has more incentive to not confuse investors, therefore enabling the bank to respond appropriately to higher uncertainty with less credit extensions and preemptive liquidity hoarding. Columns (1) and (3) suggest banks with higher equity reduce more their lending and increase liquidity when they emit a noisier signal through speech.

Next, I use $X_{b,t-1}$ equal to an increase in the VIX as an exogenous variation to see if alignments match more when aggregate volatility is high. $HighAggVol_{t-1}$ is a dummy variable equal to 1 when quarter *t-1* experiences an above average increase in the growth of the VIX and 0 otherwise. The sign of β_2 is unclear. On one hand, when aggregate volatility is high, banks which are extremely uncertain may themselves be on the verge of insolvency, thus next period they may reach for yield by increasing lending to riskier borrowers. Thus β_2 could be positive. On the other hand, banks could be frank in their assessment of uncertainty and reduce credit more drastically when speaking with high uncertainty, leading to a negative coefficient. Columns (2) and (4) show effects of $BankUncertainty_{b,t-1}$ on bank behavior are stronger during times of high aggregate uncertainty. Banks that speak with one standard deviation more uncertainty during times of high volatility growth reduce credit more than the average bank. The contrary is true for liquidity as seen by the positive and significant coefficient in column (4).

VII.3 Topic Specific Uncertainty

Table 11 shows the relationships of these variables to specific balance sheet characteristics with (4). A bank speaking more uncertainly of problematic loans reduces lending nearly 0.01 and increases trading nearly 0.03 standard deviations. The magnitude of the reduction in credit is similar to the bank uncertainty measure using the entire call, indicating the reduction in credit could be attributed to responses relaying uncertainty in credit conditions. Similarly, higher uncertainty of interest rates increases the exposure of banks reporting interest rate positions, suggesting hedging activities or speculation. Lastly, the uncertainty in real estate responses is associated with reductions in loans secured by real estate. These results suggest topic specific uncertainty may allow for a better lens to understand specific avenues of bank behavior.

VII.4 Robustness

Table 12 reports the effect of idiosyncratic uncertainty on balance sheet outcomes using only banks with non-missing quarters. While the coefficients are no longer significant, from larger standard errors with only 11 banks in the cross-section, the similar magnitudes are reassuring that results are not driven by sample selection.

Similarly, while the dictionary produced using the word embeddings could lead to ambiguous words possibly unrelated to uncertainty, I analyze the relationship using the dictionary proposed by Loughran and McDonald (2011) to count the frequency of uncertainty terms in conference calls. Columns (4)-(6) illustrate similar results with statistically significant coefficients. While Loughran and McDonald's dictionary was produced using human read 10-K filings for 48 industries, the approach presented in this paper is easily automated, industry-specific, and preserving of semantic and syntactic similarities to the word “uncertainty”. Nonetheless, the fact Loughran and McDonald's dictionary, which incorporates human affirmation of semantic and syntactic similarity, leads to similar results bolsters my confidence that choosing words based on machine learning natural language processing techniques could provide for a more scientific approach to dictionary-based textual analysis.

Another cause for concern with the regressions is the level of clustering in the credit and liquidity regressions. In the appendix, I rerun the main tables with quarter-level clustering in A.3 and bank-level clustering in A.4. The coefficients are in fact stronger with more relaxed clustering and the estimates provided in the main table serve as the most conservative estimates available.

Lastly, defining σ_B as the frequency of uncertainty words throughout a conference call could be contaminated by over-weighting common and rare *uncertainty* words. The term frequency-inverse document frequency (tfidf) approach accounts for how important an uncertainty word is in the call relative to the collection of all calls. Rather than providing each uncertainty word with an equal weight, tfidf gives each uncertainty word its own weight in each document. The tfidf weight of uncertainty word *i* in conference call *d* is given by:

$$w_{i,d}^{tfidf} = tf_{i,d} * idf_i = \frac{F_{i,d}}{N_d} * log\frac{N}{N_i}$$

where $F_{i,d}$ is the number of times uncertainty word *i* shows up in call *d*, N_d is the total words in call *d*, *N* is the total number of calls, and N_i is the total number of calls containing word *i*. Intuitively, $w_{i,d}^{tfidf}$ increases proportionally to the number of times an uncertainty word appears in the call but is offset by the frequency of the word in the entire set of calls. Table A5 displays the results using σ_B estimated with tfidf weights for each uncertainty word. The new variable, $BankUncertainty_{b,t-1}^{tfidf}$, is similarly associated negatively with next period lending and positively with next period liquidity. Additionally, the heterogeneous effects exhibit similar magnitudes and signs as before, suggesting the tfidf weights could provide a more conservative estimate of calculating bank-level uncertainty through speech.

VIII. MANAGING UNCERTAINTY AT THE LOAN LEVEL

The results in Section VII suggest bank-level uncertainty reduces credit the following quarter. However, data at the bank-level cannot rule out the reverse causality that banks are uncertain precisely because they know firms' demand for credit will be low, resulting in a negative relationship between bank uncertainty and lending.

In order to mitigate this concern, I use loan level data from Dealscan. The data contains new issuances of large, syndicated, commercial loans in the United States from 2002-2013 at a quarterly frequency. The previous analysis using the Federal Reserve Y-9C form incorporated not only commercial lending, but also loans to agriculture, consumers and foreign firms. While the type of lending in Dealscan is only a subset of bank lending, two features of the data help provide evidence of active management of uncertainty through credit cutbacks. First, the Federal Reserve Y-9C gives the stock of all bank lending while Dealscan gives new loan issuances. Second, and perhaps more importantly, Dealscan and loan-level data allows for the inclusion firm-time fixed effects, which control for observed and unobserved characteristics at the firm level each quarter. The identifying assumption in firm-time fixed effects regression is each firm at each time period must receive new loans from two different banks. Each firm included in the estimation can be assumed to have a positive demand for credit during the quarter, allowing for a better estimation of the effect of bank-level uncertainty on the amount of the new loan. At the same time, the merge with Dealscan and the identifying assumption reduces the cross-section of banks in the sample to 9 banks and 168 firms using the sample from 2002-2013. The average size of the loans is $883 million, and the median was $400 million.

I run the following specification in Table 13:

$$Log(Loan)_{f,b,t} = \beta_1 BankUncertainty_{b,t-1} + controls_{b,t-1} + \gamma_b + \delta_{f,t} + \epsilon_{f,b,t} \tag{6}$$

where $Log(Loan)_{f,b,t}$ is the log loan amount of *b* to firm *f* at time *t* and $\delta_{f,t}$ is firm-time fixed effects to control for firm demand at time *t*. Column (1) excludes all forms of fixed-effects and shows a negative relationship between bank uncertainty and the amount of the loan. The next two columns (2) and (3) include bank fixed effects along with fixed effects to control for yearly trends while still maintaining a significantly negative coefficient. Column (4) adds firm fixed-effects to control for unobserved firm characteristics affecting demand for credit such as time invariant risk-appetite and corporate structure. Lastly, Column (5) illustrates the strictest regression including firm-time fixed effects. The coefficient drops in magnitude to -0.0176, suggesting a one standard deviation increase in bank level uncertainty is associated with nearly a 2% drop in the loan amount of new credit issuances. Table 13 demonstrates the importance of firm-level fixed effects to account for demand, as the first columns without such controls overestimated the cutbacks in credit associated with larger uncertainty. In fact, the increase in the coefficients between columns (3) and (4) where firm-fixed effects are included suggests *BankUncertainty* is not orthogonal to observed and unobserved characteristics of the firm, considerably firm-demand (Altonji et al., 2005). Thus, while firm-demand tomorrow plays an important role in determining banks uncertainty today, the negative coefficient suggests even after controlling for firm-demand, *BankUncertainty* still predicts lending at the loan-level.

The Dealscan data has been practical for understanding the drop in lending during the financial crisis of 2007-2009. Ivashina and Scharfstein (2010) provide evidence that banks with connections to Lehman Brothers, the investment bank that failed September 15, 2008, was positively related to credit cutbacks. The mechanism proposed is that a bank with larger syndications with Lehman produced more uncertainty of that bank, as their assets could be tightly linked and similar in quality. In Table 14, I run (5) during a smaller window of time to incorporate the financial crisis, 2004-2009. I interact the bank-uncertainty measure with $LehmanConnection_b$, the percentage of loans bank *b* syndicated with Lehman Brothers before the crisis during 2004-2007, and also a dummy variable for the crisis in years 2008 and 2009. The reduction in credit from higher bank uncertainty is larger during the crisis for banks with tighter connections to Lehman Brothers, as seen from the significantly negative coefficient on the triple interaction term. Furthermore, the negative coefficient on *LehmanConnection*Crisis* is consistent with the findings of Ivashina and Scharfstein, as larger connections to Lehman resulted in lower credit extensions. Column (3) provides the strictest specification with firm and time fixed effects. The coefficient of $BankUncertainty_{b,t-1}$ remains similar in magnitude to that found in Table 13, and yet, the reduction in credit from higher uncertainty during the crisis is larger as seen from the negative coefficient on $BankUncertainty_{b,t-1} * Crisis_t$.

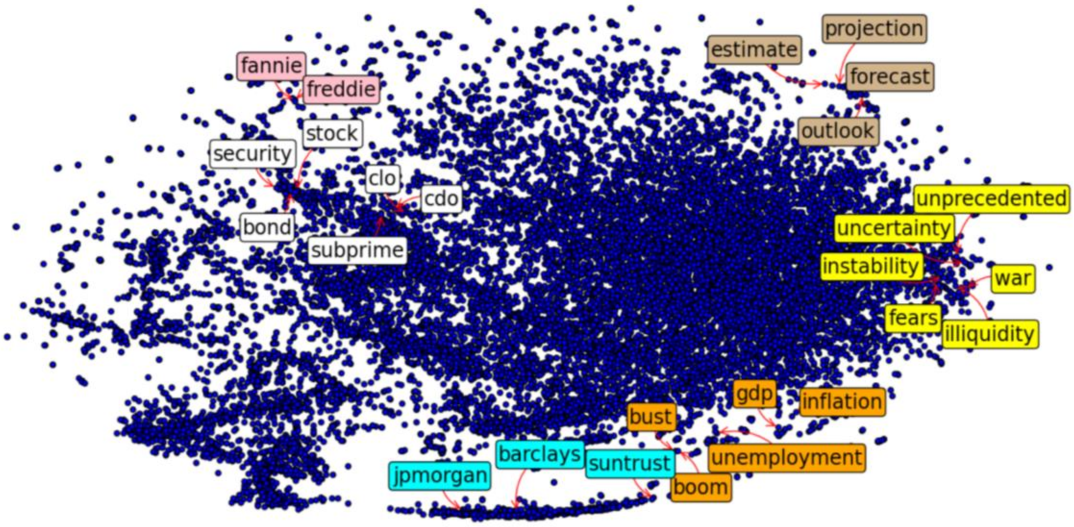
In general, Dealscan allows for an analysis at the loan-level while controlling for firm demand and new issuances. While this exercise includes only a subset of banks and firms, the loan-level evidence remains suggestive of active bank management of uncertainty through lower amounts of new loan issuances.

IX. Conclusions

In this paper I propose a complimentary measure to existing uncertainty variables by using speech to quantify bank-level uncertainty. Using bank earnings call transcripts, I first generate a new list of uncertainty terms not based on existing dictionaries, but rather generated from the transcripts themselves to better capture semantic and syntactic similarities to the word "uncertainty". The measure of bank uncertainty counts the frequency of uncertainty terms within a given conference call, filtering out aggregate uncertainty such as growth in the term structure of corporate bond yields, VIX and the economic policy uncertainty index. Banks communicating larger uncertainty decrease future lending, while simultaneously increasing their trading assets and liquidity. By developing a measure at the bank-level, my analyses include not only bank fixed effects and important lagged variables, but also time fixed effects to control for observed and unobserved time varying characteristics. The results suggest this new measure proxies well the idiosyncratic uncertainty facing a bank.

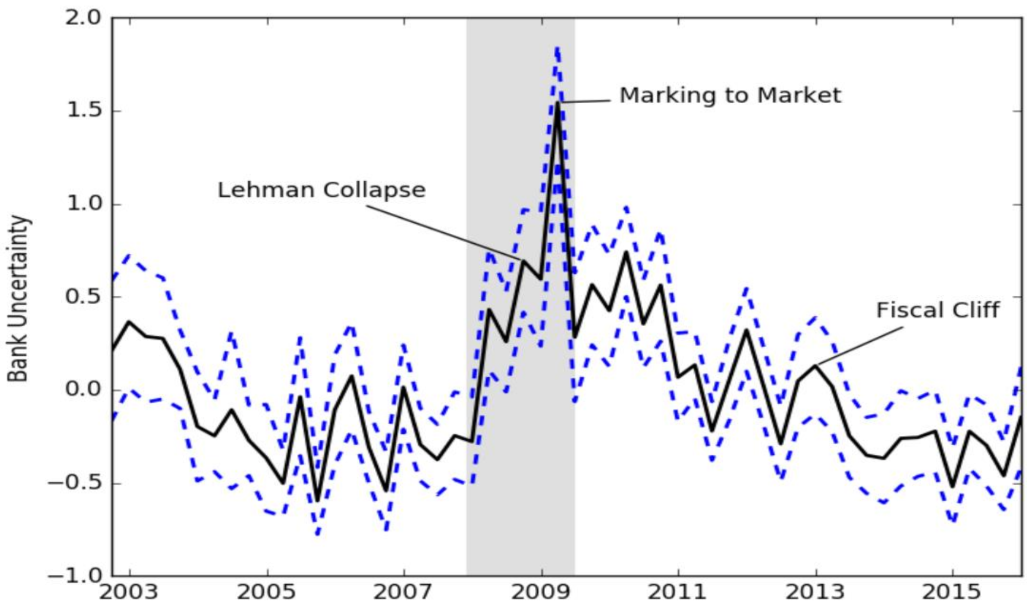
It is my hope that this new measure can be used to track the flow of credit to the real economy by identifying banks most likely to cutback credit during the business cycle and deviate to trading or liquidity hoarding. The new bank-level measure could shine light on an otherwise opaque financial industry.

FIGURE 1: WORD EMBEDDINGS OF BANK EARNINGS CONFERENCE CALL TRANSCRIPTS



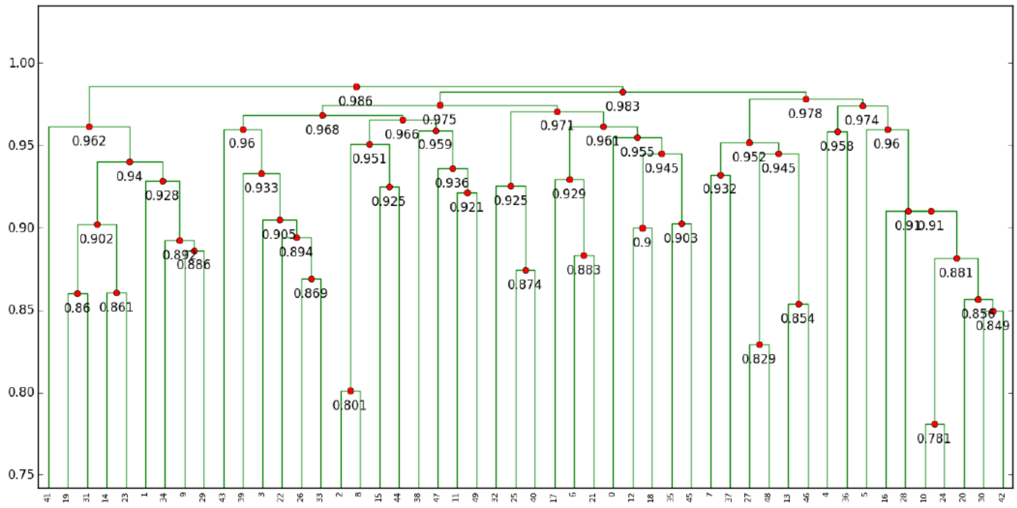
This figure illustrates the vector representations of words, known as word embeddings, from bank earnings conference calls estimated using the Skip-gram model. The word vectors, initially at 100 dimensions, are projected onto two dimensions using the t-Distributed Stochastic Neighbor Embedding algorithm described in the appendix.

FIGURE 2: BANK UNCERTAINTY



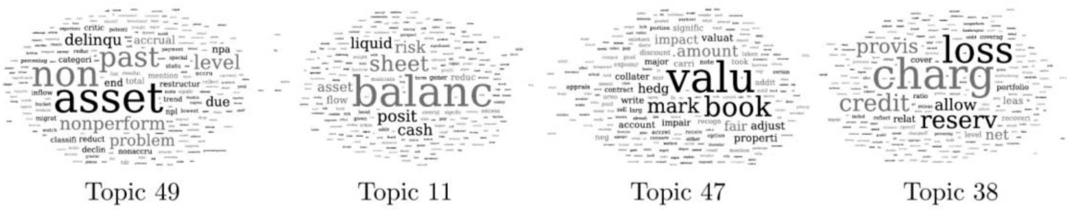
This figure plots the time series average of the bank uncertainty variable, $BankUncertainty_{b,t-1}$ I construct in this paper. "Bank Uncertainty" is the count of uncertainty terms from management responses of banks quarterly earnings conference call after filtering out aggregate uncertainty measures, calculated at the bank-quarter level. 95% confidence intervals are shown in blue.

FIGURE 3: TOPIC CLUSTERING



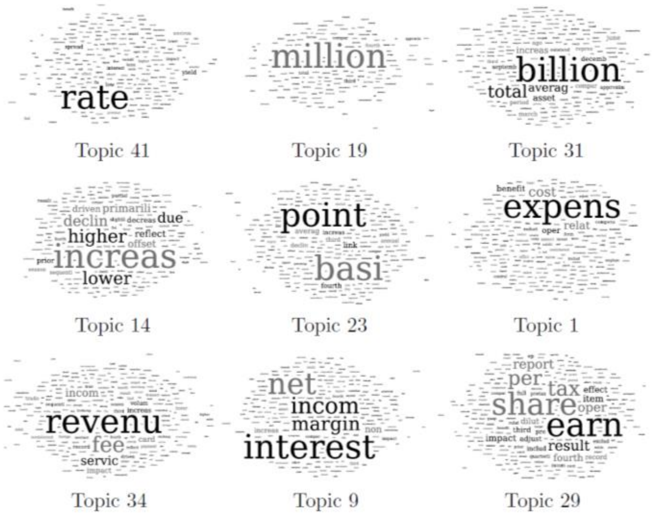
This figure displays the hierarchical clustering of the term-topic matrix generated from the latent Dirichlet allocation model. The linkages were constructed using a Nearest Point Algorithm.

FIGURE 4: PROBLEM LOANS TOPIC



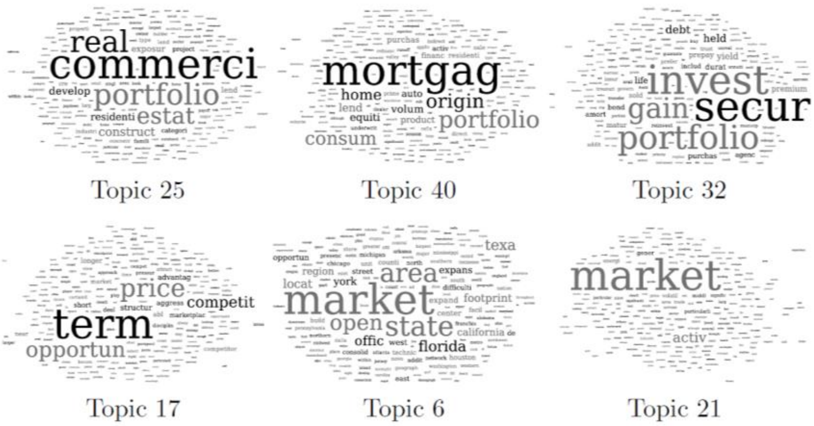
This figure displays the topics I use to distinguish responses pertaining to *problem loans*. The topics were identified using the branches of the hierarchical clustering described in Section IV.3.

FIGURE 5: INTEREST RATES TOPIC



This figure displays the topics I use to distinguish responses pertaining to *interest rates*. The topics were identified using the branches of the hierarchical clustering described in Section IV.3.

FIGURE 6: HOUSING TOPIC



This figure displays the topics I use to distinguish responses pertaining to *housing*. The topics were identified using the branches of the hierarchical clustering described in Section IV.3.

FIGURE 7: BANK UNCERTAINTY

This figure plots the bank uncertainty measure $BankUncertainty_{b,t-1}$, , I construct in this paper along with two similarly constructed measures. Instead of constructing $BankUncertainty_{b,t-1}$ with $S_{uncertainty}$, ``Loughran/McDonald" uses the dictionary Loughran and McDonald 2011 and "Uncertain + Uncertainty" only uses those two words as the dictionary.

TABLE 1: UNCERTAINTY WORDS FROM WORD EMBEDDINGS: $S_{uncertainty}$

adverse, affecting, amid, amidst, anemic, backdrop, brexit, bust, challenged, challenges, challenging, climate, concerns, conditions, confronting, crisis, cycles, cyclical, depressed, depression, deteriorating, developments, difficulties, disasters, dislocation, dislocations, disruption, disruptions, distress, divergence, downturn, downturns, economic, economy, election, elections, emerged, emerging, encountered, environment, environmental, environments, eurozone, existed, extreme, face, faced, faces, facing, fears, fiscal, forces, fragile, fundraising, geopolitical, governmental, hawaiian, headwinds, heightened, hurricane, hurricanes, illiquidity, immune, industrywide, instability, iraq, katrina, lackluster, landscape, legislative, light, lingering, looming, macro, macroeconomic, malaise, midst, monetary, multitude, navigate, navigated, persist, persistent, persistently, persists, political, poor, posed, presidential, pressured, pressures, prevailing, prolonged, protracted, realities, recession, recessionary, recovery, reforms, resiliency, severe, severely, slowdowns, sluggish, softening, spite, storm, storms, strain, stressed, stressful, struggles, subdued, surrounding, tepid, terrorism, threat, tragic, tumultuous, turbulence, turbulent, turmoil, uncertain, uncertainty, uneven, unfolded, unforeseen, unprecedented, unpredictable, unsettled, unstable, upheaval, varying, vc, war, weak, weaken, weakened, weakening, weakness, weaknesses, weather, weathering, withstand, worsening, worst

This table reports the new word list I generate by clustering words close to the word embeddings of "uncertainty" and "uncertain" using the K-means algorithm.

TABLE 2: TOP UNCERTAINTY RESPONSES FROM 2008

Capital One Financial Q3 2008	Like all banks, we **face** increasing **cyclical economic headwinds** and market **uncertainties**. We remain well positioned to **navigate** the near term **challenges** and to realize value-creating opportunities when the time is right. Now Gary and I will answer your questions. Jeff?
Valley National Q1 2008	Today's operating **environment** remains **challenging**, as the economy appears on the fringe of a **recession** and **dislocation** within the capital markets **persist**. The manner in which Valley has operated, and continues to operate, becomes even more paramount to our future success.
Capital One Financial Q2 2008	I will conclude tonight on slide 16. **Despite** continuing **economic headwinds**, Capital One continues to deliver profits, generate capital and build resilience. As a result we remain well positioned to **navigate** the current **economic cycle**.
First Horizon Q1 2008	Let's begin with asset quality. Which is being **severely** impact by the **softening economy**, falling home prices, and limited credit availability. In light of these **unprecedented** real estate market conditions, we are actively identifying and addressing problem loans. Resulting in increased reserves.
Bank of America Q3 2008	Going forward into '09, let me reiterate that there's considerable **uncertainty** about the **economic environment** and it does appear that the market **disruptions**, housing situation and rising unemployment are starting to take their toll on the economy.

This table reports the responses with the highest BankUncertainty during 2008.

TABLE 3: TOPIC DESCRIPTIONS

Topic 0	bank,compani,nation,corpor,hold	Topic 25	commerci,real,portfolio,estat,construct
Topic 1	expens,cost,relat,benefit,oper	Topic 26	continu,posit,focu,oper,strategi
Topic 2	look,base,forward,futur,expect	Topic 27	thank,call,today,confer,good
Topic 3	environ,continu,econom,economi,industri	Topic 28	move,part,start,come,earli
Topic 4	last,month,time,period,ago	Topic 29	earn,share,tax,per,result
Topic 5	chang,right,use,time,may	Topic 30	lot,thing,realli,peopl,got
Topic 6	market,branch,state,area,open	Topic 31	billion,end,total,averag,increas
Topic 7	slide,turn,result,provid,detail	Topic 32	secur,invest,sale,portfolio,gain
Topic 8	forward,statement,look,result,may	Topic 33	credit,continu,improv,qualiti,remain
Topic 9	interest,net,incom,margin,non	Topic 34	revenu,fee,servic,incom,card
Topic 10	can,want,tri,sure,time	Topic 35	compani,team,work,great,peopl
Topic 11	balanc,sheet,risk,posit,cash	Topic 36	acquisit,close,transact,complet,announc
Topic 12	busi,line,small,grow,across	Topic 37	talk,comment,let,give,ye
Topic 13	next,come,question,line,pleas	Topic 38	charg,loss,reserv,credit,provis
Topic 14	increas,higher,lower,declin,due	Topic 39	expect,level,rang,guidanc,half
Topic 15	capit,ratio,return,equiti,common	Topic 40	mortgag,portfolio,origin,consum,home
Topic 16	number,look,percent,actual,dollar	Topic 41	rate,yield,spread,low,environ
Topic 17	term,price,opportun,competit,structur	Topic 42	littl,bit,probabl,mayb,ye
Topic 18	manag,client,invest,asset,busi	Topic 43	deposit,fund,account,core,cost
Topic 19	million,fourth,third,total,compar	Topic 44	process,issu,need,regul,regulatori
Topic 20	good,realli,pretti,feel,much	Topic 45	custom,product,relationship,servic,exist
Topic 21	market,activ,gener,energi,volatil	Topic 46	question,time,answer,pleas,turn
Topic 22	growth,strong,continu,grow,pipelin	Topic 47	valu,book,mark,amount,fair
Topic 23	basi,point,link,averag,fourth	Topic 48	call,financi,offic,chief,investor
Topic 24	know,realli,can,happen,tell	Topic 49	asset,non,perform,past,day

This table displays the top 5 tokens pertaining to each topic of the Latent Dirichlet Allocation model with the lowest perplexity score. Tokens were stemmed prior to the estimation and are reported as such.

Table 4: Top Topic Specific Uncertainty Responses from 2008

Problem Loans	
First Horizon Q3 2008	We believe our capital position is sufficient to **withstand** significantly higher credit losses should the current **economic downturn** continue to worsen. We are also improving our liquidity position in a **challenging environment**. We reduced assets on our balance sheet, allowing us to decrease our dependence on unsecured wholesale funding and retire maturing debt.
Valley National Q1 2008	Future period loan-loss provisions will continue to reflect the actual and expected delinquency rates, net charge-offs, as well as **economic conditions** in the marketplace.
Interest Rates	
Mercantile Bank Q2 2008	But that is short-term thinking. Certainly, with the **economics struggles**, not only just local and regional, but certainly national, obviously an increase in the prime rate would put additional **pressures** on our borrowers, so that might tip the asset quality scale a little bit.
Silicon Valley Bank Q3 2008	While we are positive about the near term, we expect it to be **challenging**. If interest rates remain low or fall further, it will cause our net interest margin to further decline. If valuation **pressures** and a lack of exit opportunities **persist**, it will challenge our clients and suppress returns from warrants and our investment funds management business.
Housing	
Bank of the Ozarks Q2 2008	Mortgage lending income for the second quarter reflected the effects of higher mortgage rates and generally **weak** housing market **conditions**. While mortgage lending income in the second quarter was down slightly from the first quarter results, there were actually more changes in the mortgage activity than the numbers suggest on their **face**.
U.S. Bancorp Q2 2008	Sure. I'll go with the last part first. For us, this really began in the Michigan and Ohio region and that's still an **extremely stressed** area for us. then you look to California, Nevada, Arizona, very **stressed** markets, especially as you move out from the major metropolitan areas. also Florida, we don't have a lot of exposure in Florida but that's obviously an **extremely stressed** market.

This table reports the responses with the highest BankUncertainty in the problem loans, interest rates and housing topics during 2008.

TABLE 5: SUMMARY STATISTICS

	Mean	SD	Min	P25	Median	P75	Max
Dependent Variables							
Total Loans	63.25	16.19	4.65	59.40	67.43	73.48	96.21
Liquidity	24.70	13.01	1.85	16.49	21.60	28.50	78.92
Independent Variables and Controls							
σ_B	1.08	0.54	0.00	0.71	1.00	1.35	5.16
CorpBond Growth	4.21	29.25	-57.14	-11.48	-0.70	11.32	122.22
EPU Growth	2.84	24.26	-41.40	-14.61	2.92	17.18	98.55
VIX Growth	2.96	28.39	-39.21	-12.66	-3.67	9.68	133.75
LogAssets	17.13	1.85	12.88	15.89	16.72	18.33	21.67
Equity	10.10	2.19	4.56	8.57	10.01	11.33	18.27
Profitability	0.56	0.62	-0.62	0.29	0.55	0.88	3.10

This table reports the summary statistics of the variables used throughout the paper. Balance sheet variables are retrieved from the FR Y-9C forms from the Federal Reserve Board. Lending is total quarterly commercial and industrial, agricultural, consumer, and foreign loans over total assets. Liquidity is the interest and non-interest bearing balances, available-for-sale, and hold-until-maturity portfolios over total assets. Log Assets is the logarithm of total assets measured in thousands. Equity is total equity capital over total assets. Profitability is net income over total assets. CorpBond Growth is the growth in the 10-year less 2-year corporate bond rate. VIX Growth is the percentage change in the CBOE VIX index. EPU Growth is the percentage change of the Economic Policy Uncertainty index from Baker, Bloom and Davis 2016. σ_B is the count of uncertainty terms of a banks quarterly earnings conference call.

TABLE 6: HIGH AND LOW BANK UNCERTAINTY

	Low Uncertainty (N=1192)		High Uncertainty (N=1192)		
	Mean	SD	Mean	SD	
σ_B	0.684	0.233	1.475	0.453	
Dependent Variables					
Total Loans	64.576	15.266	61.929	16.97	-2.647***
Trading Securities	23.72	12.10	25.68	13.80	1.95***
Independent Variables and Controls					
CorpBond Growth	1.42	23.152	7.002	34.064	5.583***
EPU Growth	2.866	22.487	2.813	25.916	-0.053
VIX Growth	3.475	24.882	2.451	31.518	-1.025

This table divides observations in the sample between above and below the median bank uncertainty level. The rightmost column reports the differences in the mean. σ_B is the count of uncertainty terms of a banks quarterly earnings conference call. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7: FILTERING OUT AGGREGATE MARKET CONDITIONS

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$Lending_{b.t}$		$Liquidity_{b.t}$		$(\sigma_B)_{b.t}$	
EPU_t	-2.0026	-4.3893***	-9.2783	-12.0475***	-0.0000	-0.0001
	(15.25)	(1.42)	(17.33)	(1.97)	(0.00)	(0.00)
VIX_t	-3.4003	11.1626***	-15.2652	-1.8718	-0.0002	-0.0002
	(13.18)	(1.80)	(14.99)	(2.59)	(0.00)	(0.00)
$CorpBond_t$	5.2241	8.3392***	-0.3571	-2.8567	0.0024***	0.0025***
	(12.22)	(2.04)	(13.89)	(3.23)	(0.00)	(0.00)
Constant	1661.4013***		1562.3309***		0.0107***	
	(3.60)		(4.09)		(0.00)	
Bank FE	N	Y	N	Y	N	Y
N	2,385	2,385	2,385	2,385	2,385	2,385
R^2	0.00	0.96	0.00	0.94	0.02	0.21

This table reports regression results of bank characteristics on aggregate measures. Lending is total quarterly commercial and industrial, agricultural, consumer, and foreign loans. Liquidity is the interest and non-interest bearing balances, available-for-sale, and hold-until-maturity portfolios. $CorpBond_t$ is the growth in the 10-year less 2-year corporate bond rate. VIX_t is the percentage change in the CBOE VIX index. EPU_t is the percentage change of the Economic Policy Uncertainty index from Baker, Bloom and Davis 2016. σ_B is the count of uncertainty terms of a banks quarterly earnings conference call. * p < 0.10, ** p < 0.05, *** p < 0.01.

TABLE 8: BANK-LEVEL UNCERTAINTY AND POST CALL VOLATILITY

	Short Term Volatility (7 days)				Long Term Volatility (60 days)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{BankUncertainty_t}$	0.3444***				0.2984***			
	(0.03)				(0.02)			
$BankUncertainty_{b,t-1}$		0.1310***	0.1320***	0.0320**		0.0730***	0.0778**	0.0066
		(0.02)	(0.03)	(0.01)		(0.01)	(0.03)	(0.01)
Previous Volatilit	0.4326***	0.6056***	0.5940***	0.1971***	0.5788***	0.8053***	0.7839***	0.5248***
	(0.04)	(0.04)	(0.06)	(0.03)	(0.03)	(0.03)	(0.10)	(0.04)
VIX_t	0.0386***				0.2259***			
	(0.02)				(0.01)			
Constant	-0.0059	-0.0014			-0.0035	-0.0006		
	(0.01)	(0.01)			(0.01)	(0.01)		
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	N	Y	Y	Y	N	Y	Y
Quarter FE	N	N	N	Y	N	N	N	Y
N	2,385	2,385	2,385	2,385	2,385	2,385	2,385	2,385
R^2	0.5900	0.4974	0.5304	0.6707	0.8242	0.7313	0.7391	0.8961

The estimations report the effect of bank uncertainty on post-call volatility. Columns (1)-(4) show results where volatility is the standard deviation of returns for t+1 to t+8 days after the conference call, while columns (5)- (8) is t+1 to t+61 days after the conference call. $\overline{BankUncertainty_t}$ is the average value of $BankUncertainty_{b,t-1}$at quarter t. Previous Volatility is the volatility 7 days prior to the earnings call for columns (1)-(4) and 90 days prior for columns (5)-(8). $BankUncertainty_{b,t-1}$ is the count of uncertainty terms of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes. Standard errors clustered at the bank and quarter level reported in parentheses.

TABLE 9: BANK-LEVEL UNCERTAINTY AND BALANCE SHEET VARIABLES

	(1)	(2)	(3)	(4)
Dependent Variable:	Lending		Liquidity	
$BankUncertainty_{b,t-1}$	-0.0290**	-0.0234**	0.0332*	0.0287
	(0.01)	(0.01)	(0.02)	(0.02)
Bank FE	Y	Y	Y	Y
Quarter FE	N	Y	N	Y
Bank Controls	Y	Y	Y	Y
N	2,385	2,385	2,385	2,385
R^2	0.9094	0.9226	0.6924	0.7130

The estimations report the effect of bank uncertainty on bank balance sheet variables. Lending is total quarterly commercial and industrial, agricultural, consumer, and foreign loans. Liquidity is the interest and non-interest bearing balances, available-for-sale, and hold-until-maturity portfolios. $BankUncertainty_{b,t-1}$ is the count of uncertainty terms of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes. Standard errors clustered at the bank and quarter level reported in parentheses.

TABLE 10: BANK-LEVEL UNCERTAINTY: HETEROGENEOUS EFFECTS

	(1)	(2)	(3)	(4)
Dependent Variable:	Lending		Liquidity	
$BankUncertainty_{b,t-1}$	-0.0268***	-0.0276**	0.0302	0.0324
	(0.01)	(0.01)	(0.02)	(0.02)
$BankUncertainty_{b,t-1}*Equity_{b,t-1}$	-0.0207***		0.0312**	
	(0.01)		(0.01)	
$BankUncertainty_{b,t-1}*HighAggVol_{t-1}$		-0.0177**		0.0325**
		(0.01)		(0.02)
Bank FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y
N	2,385	2,385	2,385	2,385
R^2	0.9216	0.9213	0.7253	0.7250

The estimations report the effect of bank uncertainty on bank balance sheet variables. Lending is total quarterly commercial and industrial, agricultural, consumer, and foreign loans. Liquidity is the interest and non-interest bearing balances, available-for-sale, and hold-until-maturity portfolios. $BankUncertainty_{b,t-1}$ is the count of uncertainty terms of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes. Equity is total equity capital over total assets. $HighAggVol_{t-1}$ is a dummy variable equal to 1 when the growth in the VIX index is above average and 0 otherwise. Standard errors clustered at the bank and quarter level reported in parentheses.

TABLE 11: BANK-LEVEL UNCERTAINTY: TOPIC SPECIFIC

Dependent Variable:	(1) Problem Loans Topic Lending	(2) Problem Loans Topic Liquidity	(3) Interest Rate Topic Interest Exposure	(4) Real Estate Topic Real Estate
$BankUncertainty_{b,t-1}$	-0.0112**	0.0293***	0.0270***	-0.0221**
	(0.00)	(0.00)	(0.01)	(0.01)
Bank FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y
N	2,385	2,385	2,385	2,385
R^2	0.9497	0.7343	0.1377	0.7015

The estimations report the effect of topic specific bank uncertainty on bank balance sheet variables. Lending is total quarterly commercial and industrial, agricultural, consumer, and foreign loans. Liquidity is the interest and non-interest bearing balances, available-for-sale, and hold-until-maturity portfolios. Interest Exposure is total interest rate exposure over total assets. Real Estate is total loans secured by real estate. $BankUncertainty_{b,t-1}$ is the count of uncertainty terms of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes. Columns (1) and (2) calculate $BankUncertainty_{b,t-1}$ only for responses during the earnings call pertaining to the problematic loans topics of Figure 4; Column (3) of the interest rate cloud of Figure 5; (4) of the real estate cloud of Figure 6. Standard errors clustered at the bank and quarter level reported in parentheses.

TABLE 12: BANK-LEVEL UNCERTAINTY AND BALANCE SHEET VARIABLES

Dependent Variable:	Complete Banks Only		Loughran & McDonald 2011	
	Lending	Liquidity	Lending	Liquidity
	(1)	(2)	(3)	(4)
$BankUncertainty_{b,t-1}$	-0.0224	0.0244	-0.0308***	0.0534**
	(0.02)	(0.03)	(0.01)	(0.02)
Bank FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y
N	596	596	2,385	2,385
R^2	0.9210	0.7202	0.9393	0.9051

The estimations report the effect of bank uncertainty on bank balance sheet variables. Columns (1)-(3) include only banks with non-missing quarters while columns (4)-(6) use the dictionary provided by Loughran & McDonald 2011. Standard errors clustered at the bank and quarter level reported in parentheses.

TABLE 13: BANK-LEVEL UNCERTAINTY AND LOAN-LEVEL DATA

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:			Loan Issuance Amount		
$BankUncertainty_{b,t-1}$	-0.0727**	-0.0902***	-0.0858**	-0.0247*	-0.0165**
	(0.02)	(0.02)	(0.04)	(0.01)	(0.01)
Bank FE	N	Y	Y	Y	Y
Firm FE	N	N	N	Y	-
Year FE	N	N	Y	Y	-
Firm*Quarter FE	N	N	N	N	Y
Dealscan Controls	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y
N	544	544	544	544	544
R^2	0.1068	0.1483	0.3157	0.8108	0.8188

The estimations report the effect of bank uncertainty on corporate loans from 2002-2013. The dependent variable is new loan issuances of commercial loans from Dealscan at the bank-firm-quarter level. $BankUncertainty_{b,t-1}$ is the count of uncertainty terms of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes. Dealscan Controls include indicators for secured or unsecured loans; indicators for lead arranger credit. Standard errors clustered at the bank level are reported in parentheses.

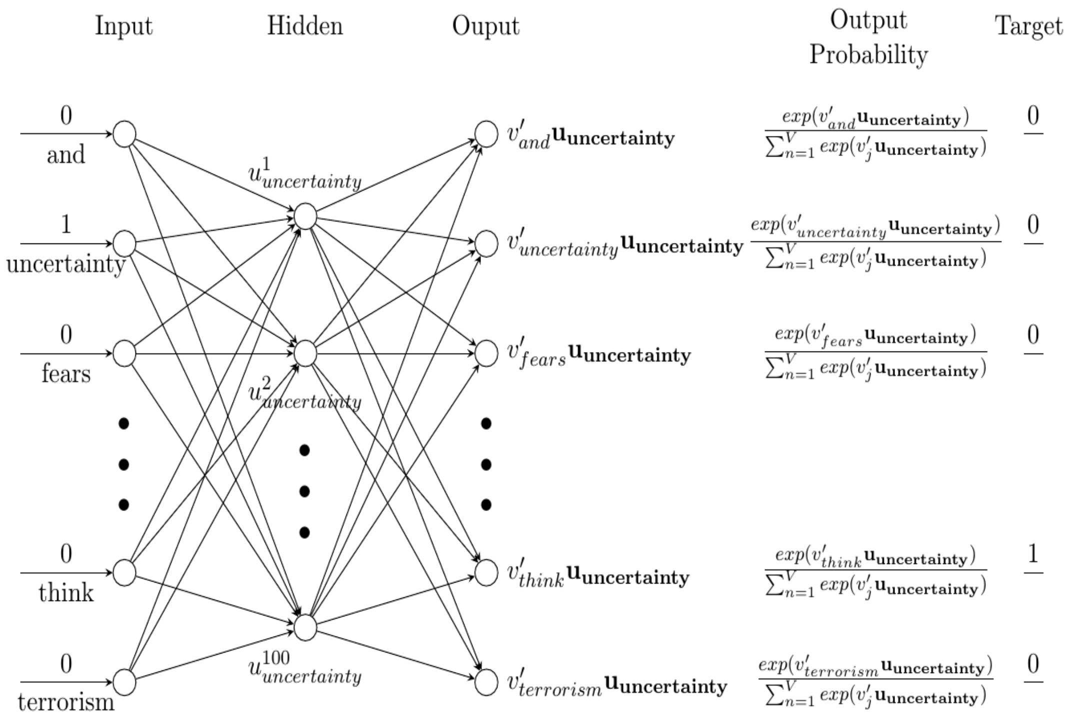
TABLE 14: BANK-LEVEL UNCERTAINTY DURING THE FINANCIAL CRISIS

	(1)	(2)	(3)
Dependent Variable:	Loan Issuance Amount		
$BankUncertainty_{b,t-1}$*$LehmanConnection_b$*$Crisis_t$	-0.2024**	-0.2107*	-0.2266**
	(0.09)	(0.09)	(0.09)
$LehmanConnection_b$*$Crisis_t$	-0.0996	-0.1004	-0.1118
	(0.08)	(0.06)	(0.06)
$BankUncertainty_{b,t-1}$*$Crisis_t$	-0.1603***	-0.1303**	-0.1248
	(0.04)	(0.05)	(0.07)
$BankUncertainty_{b,t-1}$*$LehmanConnection_b$	0.0331	0.0409	0.0568**
	(0.03)	(0.03)	(0.02)
$Crisis_t$	-0.6305***		
	(0.06)		
$BankUncertainty_{b,t-1}$	0.0218	-0.0078	-0.0133
	(0.06)	(0.07)	(0.09)
$LehmanConnection_b$	0.0269	0.0276	0.0390
	(0.05)	(0.04)	(0.04)
Firm FE	Y	Y	Y
Year FE	N	Y	Y
Quarter of Year FE	N	N	Y
N	121	121	121
R^2	0.9478	0.9529	0.9609

The estimations report the effect of bank uncertainty on corporate loans from 2004-2009. The dependent variable is new loan issuances of commercial loans from Dealscan at the bank-firm-quarter level. $BankUncertainty_{b,t-1}$ is the count of uncertainty terms of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes. $LehmanConnection_b$ is the percentage of loans b had syndicated with Lehman Brothers before the financial crisis during 2004-2007. $Crisis_t$ is a dummy variable for the years 2008 and 2009. Standard errors clustered at the bank level are reported in parentheses.

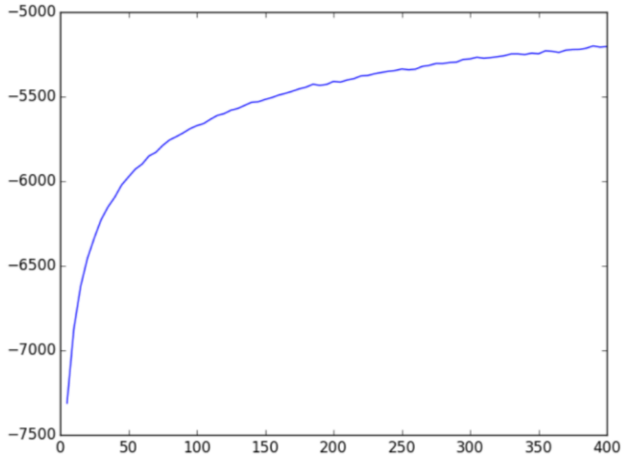
APPENDIX

FIGURE A1: SKIP-GRAM MODEL



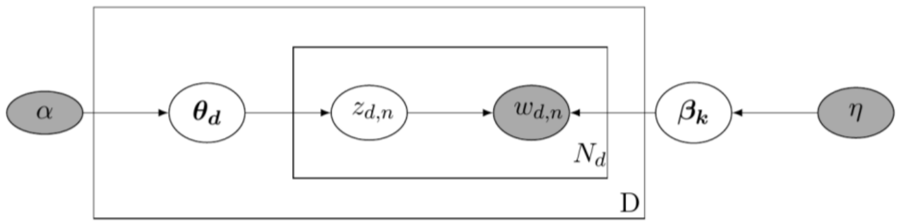
This figure illustrates the Skip-gram model proposed by Mikolov et al. (2013a) using one training example: (*uncertainty*, *think*). The Input Layer is a one-hot encoded vector of length *V*, the number of unique words across all documents. A one is placed at the index of word *uncertainty* and a zero elsewhere. Using an *H*-by-*V* matrix, **U**, the Input is transformed into an *H* dimension vector in the Hidden Layer, $\boldsymbol{u_{uncertainty}}$. Lastly, $\boldsymbol{u_{uncertainty}}$ is transformed back into a vector of length *V* using a *V*-by-*H* matrix **V**. The output vector is normalized using the softmax function to create y_o. The errors, the difference between y_o and the one-hot encoded vector of the target words in the context, are then used to update the weight matrices **U** and **V** using gradient descent.

FIGURE A2: CROSS-VALIDATION SCORE



This chart plots the scores of different values of K for the K-means algorithm used on the word embeddings from the earnings call transcripts.

FIGURE A3: LATENT DIRICHLET ALLOCATION



This figure sketches out the generative story of the Latent Dirichlet Allocation model proposed by Blei et al. (2003). Using the hyperparameter of a Dirichlet process, α, a multinomial distribution, θ_d, is generated for *D* documents. Each word within the document is then assigned to a topic, $z_{d,n}$ using θ_d. The topic assignment, along with the multinomial distribution over words within the topic, β_k, which is generated by a Dirichlet process with hyperparameter η, generates the observed words $w_{d,n}$ within each document. The Latent Dirichlet Allocation process is used in this paper to find the distribution over words, β_k, which can then be used to uncover documents pertaining to problematic assets, interest rates and housing.

TABLE A1: PERPLEXITIES

Chain	Iteration 4,350	Iteration 4,400	Iteration 4,450	Iteration 5,000
0	561.79	561.93	561.99	561.79
1	562.89	562.94	562.85	562.82
2	559.24	559.44	559.49	559.46

This table reports perplexity scores from three chains of topic model estimation using Gibbs sampling. A 3,000 burn-in sample was used in each chain. Subsequently, 40 samples were taken every 50 iterations out of the remaining 2,000. The last 4 scores are reported.

TABLE A2: BANK-LEVEL UNCERTAINTY AND POST CALL RETURNS

	Short Term Returns (7 days)				Long Term Returns (60 days)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{BankUncertainty_t}$	-0.0985**				-0.1372***			
	(0.04)				(0.04)			
$BankUncertainty_{b,t-1}$		-0.0184	-0.0157	0.010		-0.0342	-0.0354	0.0019
		(0.02)	(0.02)	(0.02)		(0.03)	(0.04)	(0.02)
Previous Volatility	-0.0379	-0.1062**	-0.1155*	-0.0280	0.1109**	0.0210	0.0253	-0.3049***
	(0.05)	(0.04)	(0.06)	(0.08)	(0.05)	(0.04)	(0.15)	(0.10)
VIX_t	-0.1216***				-0.0542*			
	(0.03)				(0.03)			
Constant	-0.0054	-0.0001			0.0024	0.0006		
	(0.02)	(0.02)			(0.02)	(0.02)		
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	N	Y	Y	Y	N	Y	Y
Quarter FE	N	N	N	Y	N	N	N	Y
N	2,385	2,385	2,385	2,385	2,385	2,385	2,385	2,385
R^2	0.0521	0.0146	0.0345	0.1376	0.0179	0.0016	0.0064	0.4858

The estimations report the effect of bank uncertainty on post-call returns. Columns (1)-(4) show results where the dependent variable is cumulative absolute returns for t+1 to t+8 days after the conference call, while columns (5)- (8) is t+1 to t+61 days after the conference call. $\overline{BankUncertainty_t}$ is the average value of $BankUncertainty_{b,t-1}$at quarter t. Previous Volatility is the volatility 7 days prior to the earnings call for columns (1)-(4) and 90 days prior for columns (5)-(8). $BankUncertainty_{b,t-1}$ is the count of uncertainty terms of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes.

TABLE A3: BANK-LEVEL UNCERTAINTY: QUARTER-LEVEL CLUSTERING

Dependent Variable:	(1)	(2) Lending	(3)	(4)	(5) Liquidity	(6)
$BankUncertainty_{b,t-1}$	-0.0234***	-0.0253***	-0.0261***	0.0287**	0.0318**	0.0340**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$BankUncertainty_{b,t-1}*Equity_{b,t-1}$		-0.0208***			0.0322***	
		(0.00)			(0.01)	
$BankUncertainty_{b,t-1}*HighAggVol_{t-1}$			-0.0174***			0.0330**
			(0.01)			(0.01)
Bank FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y
N	2,385	2,385	2,385	2,385	2,385	2,385
R^2	0.9226	0.9231	0.9229	0.7130	0.7142	0.7139

The estimations report the effect of bank uncertainty on bank balance sheet variables. Lending is total quarterly commercial and industrial, agricultural, consumer, and foreign loans. Liquidity is the interest and non-interest bearing balances, available-for-sale, and hold-until-maturity portfolios. $BankUncertainty_{b,t-1}$ is the count of uncertainty terms of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes. Equity is total equity capital over total assets. $HighAggVol_{t-1}$ is a dummy variable equal to 1 when the growth in the VIX index is above average and 0 otherwise.

TABLE A4: BANK-LEVEL UNCERTAINTY: BANK-LEVEL CLUSTERING

Dependent Variable:	(1)	(2) Lending	(3)	(4)	(5) Liquidity	(6)
$BankUncertainty_{b,t-1}$	-0.0234**	-0.0253***	-0.0261**	0.0287	0.0318*	0.0340*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
$BankUncertainty_{b,t-1}*Equity_{b,t-1}$		-0.0208***			0.0322**	
		(0.01)			(0.01)	
$BankUncertainty_{b,t-1}*HighAggVol_{t-1}$			-0.0174**			0.0330**
			(0.01)			(0.01)
Bank FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y
N	2,385	2,385	2,385	2,385	2,385	2,385
R^2	0.9226	0.9231	0.9229	0.7130	0.7142	0.7139

The estimations report the effect of bank uncertainty on bank balance sheet variables. Lending is total quarterly commercial and industrial, agricultural, consumer, and foreign loans. Liquidity is the interest and non-interest bearing balances, available-for-sale, and hold-until-maturity portfolios. $BankUncertainty_{b,t-1}$ is the count of uncertainty terms of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes. Equity is total equity capital over total assets. $HighAggVol_{t-1}$ is a dummy variable equal to 1 when the growth in the VIX index is above average and 0 otherwise.

TABLE A5: BANK-LEVEL UNCERTAINTY: TFIDF WEIGHTS

Dependent Variable:	(1)	(2) Lending	(3)	(4)	(5) Liquidity	(6)
$BankUncertainty^{tfidf}_{b,t-1}$	-0.0160	-0.0155*	-0.0178*	0.0184	0.0138	0.0177
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
$BankUncertainty^{tfidf}_{b,t-1} * Equity_{b,t-1}$		-0.0198***			0.0379**	
		(0.01)			(0.01)	
$BankUncertainty^{tfidf}_{b,t-1} * HighAggVol_{t-1}$			-0.0182**			0.0304**
			(0.01)			(0.01)
Bank FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y
N	2,385	2,385	2,385	2,385	2,385	2,385
R^2	0.9218	0.9223	0.9221	0.7116	0.7132	0.7123

The estimations report the effect of bank uncertainty on bank balance sheet variables. Lending is total quarterly commercial and industrial, agricultural, consumer, and foreign loans. Liquidity is the interest and non-interest bearing balances, available-for-sale, and hold-until-maturity portfolios. $BankUncertainty_{b,t-1}$ is the count of uncertainty terms, multiplied by the Term Frequency-Inverse Document Frequency (tfidf) weight, of a banks quarterly earnings conference call after filtering out the effects of aggregate uncertainty changes. Equity is total equity capital over total assets. $HighAggVol_{t-1}$ is a dummy variable equal to 1 when the growth in the VIX index is above average and 0 otherwise.

ESTIMATION OF THE SKIP-GRAM MODEL (MIKOLOV ET AL. 2013B)

Training the network requires cycling through every word in every earnings call, all the while updating **U** and **V**. In my sample of 2,385 earnings calls, there are 19,506,829 total words and 56,820 unique words. I use the default settings of M=5 and H=100 recommended. This would require updating over 10 million weights in both matrices for each iteration over the 19,506,829 tokens. Mikolov et al. 2013b address the computational complexity of using basic gradient descent by describing two techniques known as *negative sampling* and *subsampling of frequent words*.

For each training example, the output will be a sparse vector with 1 only at the index of the context word and 0 in the tens of thousands of indices which are not in the context. *Negative sampling* means only updating the weights of a sample of the words (columns) in **V** which should output a 0, or negative sample[9]. The positive word, the target word in the context whose output should be 1, is also updated in **V**. The sampling distribution for the negative words is given by:

$$P(w_i) = \frac{f(w_i)^{3/4}}{\sum_{v=0}^{V} f(w_v)^{3/4}}$$

where $f(w_i)$ is the frequency of word w_i. Mikolov et al. suggest choosing 5-20 negative samples so only 0.04% of the millions of weights need to be updated for each training example.

Another improvement to the computational speed of estimating the neural network is *subsampling of frequent words.* The Skip-gram model can learn much from the co-occurrence of words such as *terrorism* and *uncertainty*, as these are relatively infrequent. However, words such as *the* are relatively uninformative as a multitude of words can precede or follow them. Thus, each input word in the training set are kept with probability $P(w_i) = \sqrt{\frac{t}{f(w_i)}}$, where t is a chosen threshold, typically 0.001[10].

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[9] Note the update in **U** will only be the word embedding of the input word w_i. This is evident when looking at the update function of $\boldsymbol{U}^{new}: \frac{dE}{d\boldsymbol{U}^{old}} = \boldsymbol{V}^T[x^o \circ \sigma']x^h x^{iT}$. The input vector x^{iT} is a sparse vector with a 1 only at the index of word w_i.

[10] This functional form was chosen by Mikolov et al. because it attributes higher probabilities to more frequent words while preserving the ranking of the frequencies. The *C*-code for estimation provided by

T-DISTRIBUTED STOCHASTIC NEIGHBOR EMBEDDING (MAATEN /HINTON 2008)

The goal of t-SNE is to map a set of V vectors, $X = \boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_V$, from $\mathbb{R}^M$ into another set of vectors, $Y = \boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_V$, from $\mathbb{R}^N$ such that $N<M$. First, distances are measured between each vector in X as probabilities. This is done by centering a Gaussian distribution at each vector, $\boldsymbol{x}_i$, to compute a probability for every other vector in X. That is, the probability/distance measure is calculated as follows:

$$p_{ij} = \frac{p_{j|i} + p_{i|j}}{2V} \qquad \text{where} \qquad p_{j|i} = \frac{exp(-||x_i - x_j||^2/2\sigma_i^2)}{\sum_{j' \neq i} exp(-||x_i - x_{j'}||^2/2\sigma_i^2)}$$

Each p_{ij} provides a measure of probability between points which is proportional to their similarity. If two points are close together in $\mathbb{R}^M$, then the probability is high. t-SNE seeks to find the set Y whose distances are similar to all p_{ij}s. The distances in $\mathbb{R}^N$ are calculated similarly, except the t-distribution density is used.

$$q_{ij} = \frac{q_{j|i} + q_{i|j}}{2V} \qquad \text{where} \qquad q_{j|i} = \frac{(1 + ||y_i - y_j||^2)^{-1}}{\sum_k \sum_{l' \neq k} (1 + ||y_l - y_k||^2)^{-1}}$$

Ideally, the p_{ij}s and q_{ij}s will be similar to each other. If so, then distances in the high-dimensional space would be preserved in the low-dimensional space. As a result, the objective function to minimize is the divergence between the p and q distributions, which is commonly computed as the Kullback-Leibler divergence:

$$KL(P||Q) = \sum i \sum j \neq i p_{ij} log \frac{p_{ij}}{q_{ij}}$$

The Kullback-Leibler divergence is well suited for this task as large penalties are produced when p_{ij} is large and q_{ij} is small. Thus, it will aim to associate large ps with large qs, hence the difference between PCA and t-SNE. t-SNE will seek to preserve vectors close together (high ps), while PCA preserves vectors further apart.

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the authors, however, uses $P(w_i) = (\sqrt{\frac{f(w_i)}{t}} + 1)\frac{t}{f(w_i)}$, which is a slightly more convex form of the initial suggestion.

t-SNE is then estimated via gradient descent. The points in Y will move around until the Kullback-Leibler is sufficiently small. Maaten and Hinton 2008 provides more details about the estimation and algorithm for optimal performance.

TOPIC MODELLING (BLEI ET AL. 2003)

Consider a set $D = \{d_1, d_2, \ldots, d_D\}$ of documents whose total vocabulary is a set $V = \{v_1, v_2, \ldots, v_D\}$ of words or tokens. The goal is to create a distribution over K topics for each document d, $\theta_d \in \Delta^K$, and a distribution of each topic over words, $\beta_k \in \Delta^V$. Figure 3 illustrates the generative process of LDA. First, document d is associated with a lottery over topics, θ_d, which is chosen from a Dirichlet distribution with hyperparameter α. Each word within the document, $w_{d,n}$ is assumed to be generated from two components i) the topic assignment of the word, $z_{d,n}$ which is chosen from the multinomial distribution θ_d, and ii) the distribution over words for topic $z_{d,n}$, represented as $\beta_{z_{d,n}}$. Thus, the probability of $w_{d,n}$ appearing in the document increases if the rest of the document is about topic $z_{d,n}$, and word $w_{d,n}$ represents largely topic $z_{d,n}$.

The likelihood of the model is:

$$L(\theta, \beta) = \sum_{d \in D} \sum_{v \in V} x_{d,v} log(\sum_{k \in K} \theta_{d,k} \beta_{k,v})$$

However, estimating θ_d and β_k by maximizing the log-likelihood is intractable. A better estimation technique is using Gibbs sampling. Goodness of fit is determined by a perplexity score, such as $-\exp(\frac{L(\theta,\beta)}{V})$.

Chapter 2

DRESSING UP FOR THE REGULATORS: EVIDENCE FROM THE LARGEST-EVER SUPERVISORY REVIEW

Joint with Puriya Abbassi, Rajkamal Iyer and José-Luis Peydró

"*Identifying regulatory arbitrage [...] likely a reflection of incentives that banks have to "window-dress" their balance sheets at period*-ends by downsizing their balance sheets, or *improving their composition."* William Coen, Secretary General of the Basel Committee on Banking Supervision, London, May 2017

X. INTRODUCTION

Government regulation is widespread in modern societies, with governments prevalently intervening throughout the marketplace (Stigler, 1971; Tirole, 2014; White House, 2015). However, effective supervision is challenging, as it requires a policy framework that does not allow regulated entities to behave differently from what supervisors aim for (Laffont and Tirole, 1993). From the perspective of designing effective supervisory practices, it is important to understand window-dressing behavior by regulated entities to supervisors.

In this paper we analyze window-dressing behavior to supervisors in the banking sector. Analyzing this question in the context of the banking sector not only helps us with empirical identification, but it is also important given the difficulties associated with banking supervision. Supervision of banks is substantially more challenging than that of other industries (Dewatripont and Tirole, 1994), not only due to assets of banks being more opaque (Morgan, 2002), but also because banks hold a sizeable part of their portfolio in liquid assets, the riskiness of which can be changed quickly (Myers and Rajan, 1998). The financial crisis highlighted the difficulty in supervision as banks, despite existing stringent regulatory supervision, took excessive risk, thus deviating from the supervisor's original intention to build a resilient financial system. From a financial stability perspective, understanding the effectiveness of supervisory practices to regulate the banking system is therefore of crucial importance.

We focus on an important new policy tool that has emerged as a major component of the supervisory toolkit —stress testing (see e.g. Bernanke, 2013). For stress testing to be effective, a correct risk assessment of the assets of banks is a necessary condition —an asset quality review (ECB, 2013). There is however considerable debate as to whether banks choose assets that perform well in the test and then quickly liquidate them after passing (see e.g., Tarullo, 2014; Goldstein and Sapra, 2014; Coen, 2017). For example, there have been several instances of banks that have passed the stress tests and then failed within a short period time thereafter.[11]

We analyze whether banks dress up for the regulators by changing the risk composition of their portfolio before the largest-ever supervisory exercise, i.e. the European Central Bank (ECB)'s 2014 comprehensive bank assessment including an asset quality review (AQR), where EUR 22 trillion bank assets were reviewed. Moreover, we examine whether banks undo this change in the risk composition of their portfolio after the culmination of the asset quality review. In doing so, we also analyze whether banks alter specific type of assets (e.g., liquid securities versus illiquid loans) and whether banks also change their overall level of assets (securities holdings and the supply of credit to the real sector), i.e. whether banks overall downsize.

[11] For example Dexia, the Franco-Belgian bank passed the European Banking Authority (EBA)'s stress tests in the summer of 2011 (it came 12th out of 91 banks scrutinized by the EBA), but three months later, in October, required a bail-out from the government ("Dexia poses setback for EBA stress tests", *Financial Times*, 5th October 2011).

The ECB announced on October 23rd 2013 that it would undertake an asset quality review,[12] where bank assets were going to be reviewed in the form of a point-in-time assessment — December 31, 2013— for a pre-identified list of 130 (reviewed) banks within the Euro Area. These banks had to report their assets, in particular loans and securities.[13] Note that —for reviewed banks— the assets held as on *December 31, 2013*, played an important role as they were assessed by the Eurosystem. After a period of compliance (between January and June 2014), which was used by supervisors to consult reviewed banks to give them an opportunity to provide comments, the AQR was concluded in July 2014, and the subsequent stress tests based on each bank's AQR were presented in October 2014 (ECB, 2013 and 2014).

In consequence, the announcement of the AQR with a pre-determined reference date for the asset quality review presents a quasi-natural experiment to examine whether banks try to game the supervisory exercise, and in turn reduce the effectiveness of stress tests as a regulatory tool. Furthermore, we also shed light on whether —as a side-effect of the asset quality review— there is a reduction in the supply of credit to the firms in the real sector, as well as a reduction in overall securities holdings. That is, we analyze Coen (2017)'s conjecture that –to minimize regulatory constraints– banks have incentives to window-dress their balance sheets at period-ends by downsizing their balance sheets or improving their risk composition.

We exploit a unique proprietary dataset from the Bundesbank, which is –together with the German federal financial supervisory authority 'BaFin'– the macroprudential and microprudential bank supervisor in Germany. The supervisory data provides detailed, granular information at the security-level (at monthly frequency) and at the loan-level (at quarterly frequency) for each bank in Germany —a bank dominated economy— covering the period before and after the ECB's AQR.

We match each security that a bank holds with security-level information on rating, issuer, yield and maturity. The exhaustive detail on security-level holdings of each bank allows us to examine the risk characteristics of the securities traded by banks and also the timing of the trades. Importantly, not only do we have the security-level holdings of each bank, but also the credit register containing information on the individual loans made by banks, including the ex-

[12] https://www.ecb.europa.eu/press/pr/date/2013/html/pr131023.en.html.
[13] "*An asset quality review, as elaborated below, examining the asset side of bank balance sheets as at 31 December 2013. This assessment will be broad and inclusive, comprising credit and market exposures.*" (See ECB, 2013).

ante risk of each loan. The security and credit registers are matched with comprehensive bank balance sheet information.[14]

Under the hypothesis that banks try to window-dress during the supervisory exercise, the main testable hypotheses that we examine are: (i) between the ECB's announcement of the supervisory exercise (23rd October 2013) and the day that banks have to report their securities and loans to the ECB (31st December 2013), banks will accumulate safer assets, especially those that the ECB considers to be of highest quality (e.g. securities with ratings from AAA to AA- or loans with low risk weights, see ECB (2005; 2014));[15] (ii) after the asset quality review is concluded (July 2014), banks will liquidate these safer assets and will invest back in assets with a relatively higher risk.

To test these hypotheses, we first analyze the securities holdings and the loans of banks before and after the AQR announcement. We exploit the fact that the ECB required banks to report their assets as on December 31, 2013 (point-in-time assessment) and examine the evolution of security holdings and loans of reviewed and non-reviewed banks based on this cut-off date. In particular, we examine whether reviewed banks increase their holdings of safe assets during this period (as well as reduce the overall security holdings and supply of credit). Second, we analyze whether, after the AQR is concluded in July 2014, the reviewed banks increase their risk back to the level similar to that before the ECB announcement in October 2013.

To study the heterogeneity in risk behavior across different securities and across different loans, and to identify our main hypotheses, we analyze securities holdings at the *bank-security-month* level and loans at the *bank-firm(borrower)-quarter* level. For our two main hypotheses, in a difference-in-difference setting, we analyze *before* and *after* each main event (either the ECB announcement in October 2013, or the conclusion of the AQR in July 2014) whether, for the *same* security or for the *same* firm (for lending), *reviewed* versus *non-reviewed* banks change their holdings depending on the ex-ante security or firm (loan) *risk*.[16]

[14] Abbassi, Iyer, Peydró and Tous (2016) describe in detail the security and credit registers, as well as the bank level data (see also Section 3). As far as we know, only Germany, Portugal and Italy contain security and credit registers for all banks.
[15] See also for example https://www.eba.europa.eu/documents/10180/16166/4+Ausust+2006_Mapping.pdf and https://www.bankingsupervision.europa.eu/ecb/pub/pdf/assetqualityreviewphase2manual201403en.pdf. According to the standardized approach of capital adequacy under Basel II and III, this rating bucket has the lowest risk weight (http://www.bis.org/bcbs/publ/d347.pdf).
[16] We similarly analyze overall changes in security holdings and credit supply. In a difference-in-difference setting, we analyze before and after each main event whether, for the same security or for the same firm, reviewed versus non-reviewed banks change their securities holdings or lending.

As the size of a bank in Germany primarily determines whether or not a given institution is being reviewed, (i) for the comparison group of non-reviewed banks, we either analyze all of the non-reviewed banks or only the largest (with respect to their size) non-reviewed banks; (ii) we analyze whether reviewed or non-reviewed banks differ in other end-of-year periods (placebo tests); (iii) we only analyze very few reviewed and non-reviewed banks with very similar size (around the EUR 30 billion cut-off to be reviewed); (iv) we analyze unconditionally the behavior of only reviewed banks before and after each of the two main events; (v) we control for heterogeneity across banks with different sets of bank (or even bank-security and bank-firm) fixed effects.

We find that, after the announcement of the AQR, reviewed banks differentially increase the share of their safe securities, which are the bonds with the top-tier credit rating for the ECB and thus lowest regulatory risk weights. For reviewed banks, unconditionally (without any controls), the share of safe securities increases during the short-time period of the AQR relative to the period before the announcement. More formally, using a regression framework with controls, we find that between September and December 2013, reviewed banks as compared to non-reviewed banks buy on average between 2.4% and 3.4% more of the securities with top-tier rating.[17]

The results are robust to the inclusion of controls for security fixed effects to analyze the same security before and after the AQR and for bank-security fixed effects to account for unobserved matching between characteristics of banks and securities. We also find similar results when we limit the sample of reviewed and non-reviewed banks to those with more comparable sizes, or when we run the estimation *within* the subset of only reviewed banks examining the risk differences in security holdings before and after the announcement among reviewed banks.

We also examine how reviewed banks respond to the AQR in terms of their lending behavior. Comparing the period after the announcement of the AQR versus before, and within the same firm and bank, we find that reviewed banks increase their share of supply of credit to safer firms relative to non-reviewed banks (where safer firm is classified as those with below

[17] We find similar results if we analyze other risk measures as securities with high yield, from GIIPS-country headquartered borrowers, long-term maturity or long-term maturity non-safe securities, or find similar results if we do not saturate the econometric model with any fixed effect (though identification in this case is weaker).

average firm risk based on ex-ante probabilities of defaults).[18] We perform similar robustness tests as in the case of securities and find similar results, with an increase between 1.7% and 4.5% of the supply of safer loans for reviewed banks after the ECB announcement.

Interestingly, reviewed banks also cut the overall supply of credit to firms in the real sector and reduce their overall level of security holdings (irrespectively of risk). That is, not only do reviewed banks increase their share of safer loans and securities, but also overall they downsize their balance sheets by reducing their supply of credit and security holdings.

Economically, the average increase in safe securities corresponds to EUR 11.80 billion for all reviewed banks and the average increase in the share of credit exposures to safe firms amounts to EUR 42.02 billion for all reviewed banks after the announcement of the AQR as compared to non-reviewed banks. This increase of EUR 53.82 billion worth of safe assets is economically large given the very short period of time (basically two months between announcement and compliance) and accounts for 29% of reviewed banks' overall equity. Importantly, the results are not due to a general end-of-year effect, but only related to the 2013 last quarter's ECB supervisory audit, as we do not find (neither statistical nor economic) significant effects in the last quarter of 2012 or of 2014 (which we use as placebo tests). Finally, we find that this behavior induces spillovers on asset prices and firm level credit availability.

The results above suggest that banks actively shift their portfolio to safer assets in response to the AQR announcement. However, an important question that arises (our second testable hypothesis) is whether this shift is temporary or permanent. Thus, to understand the effectiveness of the supervisory exercise, it is necessary to also examine the response of banks in the post-AQR period. In the post-AQR period (after July 2014), we find that reviewed banks (as compared to non-reviewed banks) partly reload their risk back to the pre-ECB announcement levels. In particular, reviewed banks fully reload on riskier securities; however, this is not the case for riskier credit.

[18] The median default rate within this group of firms equals 0.2%, which corresponds to default rates observed for investment-grade firms worldwide (see e.g., Standard and Poor's Ratings Services, 2012). This coincides also with the Eurosystem's credit quality requirements as laid down in Article 108 (a) (ECB/2014/60) and the mapping exercise carried out by the Joint Committee of the European Supervisory Authorities (2014). Our results are robust to altering the cut-offs of the ex-ante default rate and to using the ex-ante continuous default rate.

We further examine heterogeneous effects across reviewed banks in their dialing up and down into safer securities and credit. In particular, we examine whether there are differences in the investment behavior based on other key bank characteristics. We find that in general results on dialing up and down are stronger for reviewed banks with higher trading expertise (trading banks). In particular, trading banks that are reviewed reduce risk as the others in securities after the ECB announcement of AQR, but increase it more than other banks during the post-AQR period, whereas in lending, trading banks stay at the same level during the post-AQR period than before.[19]

In sum, on the first hypothesis, our results suggest that, after the announcement of the AQR, reviewed banks relatively increase their share in safer securities and reduce riskier loans. Moreover, reviewed banks not only change their risk composition of their assets but also downsize their securities holdings and credit supply. For our second hypothesis, in the period after the AQR, we find that reviewed banks reduce their share of safer securities. With respect to their lending behavior, however, we find that reviewed banks do not increase their riskier lending back to the pre-ECB announcement level. Results are overall more pronounced for banks with higher trading expertise. Our results suggest that banks window-dress in supervisory exercises, especially in terms of altering the risk composition of their liquid assets that are easy to trade. Loans tend to be more illiquid and banks need lending opportunities to occur (it is more difficult to dial up risk on the credit portfolio), while it is easier to change the riskiness of the securities portfolio due to its tradability.

The results hold important policy implications for stress-testing in particular, and for supervision in general. These results suggest that banks change the composition of their assets before a supervisory exercise in favor of safer assets. However, they partly undo this after the supervisory exercise, primarily in their securities portfolio. The results suggest that pre-defining the timing and structure of a supervisory exercise might increase gaming behavior of banks. Thus, it might be necessary to have an element of surprise in the stress testing exercise, both in the timing of the audits (either more continuous or random in time) and also in the transparency of the specific risks assessed.[20] The results also indicate that it is easier for banks

[19] In addition, we do not find any further heterogeneity in investment behavior among reviewed banks based on size, equity capitalization or regulatory capital ratio.

[20] For example, a daily average of bank risks rather than point-in-time estimates such as Bank of England wants to pursue (see e.g. "BoE sticks with anti "window dressing" rule for bank leverage ratio", *Reuters*, December 7, 2015), or not-fully transparent stress tests, as the Federal Reserve currently follows (Bernanke, 2013; Tarullo, 2014), which however may be eliminated by Donald Trump's then nominee to head the Federal Reserve's

to change the composition of liquid assets (securities trading) than illiquid assets (loans to firms). Thus, the results also point to the notion that regulation of banks with substantial volume of tradable assets poses significant problems to supervision and to financial stability.[21]

The paper contributes to the theoretical literature that examines the optimal form of regulation (Stigler, 1971; Posner, 1975; Glaeser and Shleifer, 2001; Becker and Opp, 2013). The paper also contributes to window-dressing in banking (Allen and Saunders, 1992; Kotomin and Winters, 2006) by analyzing window-dressing to bank supervisors and by using supervisory securities and credit registers rather than aggregate bank-level data.[22] Goldstein and Sapra (2014) analyze the optimal public disclosure of stress test results, and also discuss the potential incentives of window-dressing by banks. The results also contribute to the growing literature that examines the incentives of banks to arbitrage regulation, where the bulk of the empirical work focuses on bank liabilities (Hellwig, 2010; Demirguc-Kunt et al., 2013; Acharya et al., 2014), whereas we analyze the asset side. Finally, the paper also relates to the theoretical work that examines the risk-taking incentives associated with liquid assets (Myers and Rajan, 1998). The evidence we find is consistent with the notion that it is easier to change riskiness of a banks' portfolio by changing the composition of liquid assets (securities) in contrast to illiquid assets (loans).

The remainder of the paper is structured as follows. In section XI, we elaborate on the ECB's asset quality review. In Section XII, we present our data. Section XIII presents our empirical strategy and results, and Section XIV concludes.

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regulatory wing (see e.g. "Fed banking watchdog nominee plans more 'transparency' in stress tests", *Financial Times*, July 27, 2017).

[21] Securities holdings are around 20% of bank assets in the US and Europe, and recent policy initiatives aim at limiting security trading by banks (US' Volker Rule in Dodd-Frank, EU's Likaanen Report and UK's Vickers' Report).

[22] Papers that analyze window-dressing in banking, differently from us, do not analyze supervision and regulation and use bank-level rather than security and credit register data. Allen and Saunders (1992) analyzing bank-level data argues about window-dressing of total assets, where money market instruments are the key liabilities facilitating temporary upward movements in total assets. However, results in Kotomin and Winters (2006) using bank-level data suggest that window dressing is customer- rather than bank-driven. Both studies focus on the rationales behind window dressing of total assets, whereas Owens and Wu (2015) analyze specifically possible window dressing channels in the liability accounts that afford banks the most discretion, such as repo and federal funds. In non-banks, there is evidence that fund managers and institutional investors dress up their quarter-end or year-end portfolio holdings by selling losing stocks and buying winning stocks (e.g., Lakonishok et al., 1991; Musto, 1999; He et al., 2004; Ng and Wang, 2004). However, banks suffer substantially more regulation and supervision (the question of our paper) than non-banks.

XI. ECB'S ASSET QUALITY REVIEW

On October 23rd, 2013, the European Central Bank (ECB) officially announced Europe's most comprehensive asset quality review (AQR) of the banking sector in order "to foster transparency, to repair and to build confidence". The timing and the criteria of the AQR came by surprise;[23] banks were informed that the central bank, along with national competent authorities (NCAs) responsible for banking supervision, would review the carrying value of assets on the banks' balance sheets as of December 31, 2013.[24] The AQR was thus a point-in-time assessment.

The banks that were selected to participate in this exercise ('reviewed banks', hereafter) were identified based on the following criteria: (i) total value of the bank's assets exceeded EUR 30 billion, (ii) the ratio of the bank's total assets to GDP of its country of establishment exceeded 20%, unless the total value of their assets was below EUR 5 billion, and (iii) the institution was among the three largest credit institutions in a participating member state, regardless of size. A bank was included if any of these criteria applied. In the end, the ECB identified a list of 130 credit institutions (25 of which were German banks), financial holding companies or mixed financial holding companies from 18 European Union member states that had total assets of
around EUR 22 trillion.[25]

The detailed asset-level review covered all types of assets including securities and credit

[23] The surprise in the content of the announcement is reflected in the stock market reaction on the day of the AQR announcement, as bank share prices fell after the ECB unveiled its plans ("ECB unveils checks in step to banking union; Eurozone crisis", *Financial Times*, October 23, 2013; "Eurozone bank shares sink after ECB outlines health check plan", *Financial Times*, October 23, 2013; "European shares snap winning run as banks hit by ECB review", *Reuters*, October 23, 2013). For instance, Italian bank stocks fell by as much as 3 per cent in early trading and most other leading banks in Spain, France and Germany saw share prices fall about 2 per cent (see e.g., "Draghi says bank tests need failures for credibility; ECB probe", *Financial Times*, October 24, 2013). Moreover, as of September, 24, 2013, it was unclear when the process would start or how long it would take, although it would be completed before the ECB took over full supervisory responsibility in October 2014 ("Consultants who praised defunct bank to advise on ECB review", *Financial Times*, September 24, 2013). On October 15, 2013, the ECB had yet to give banks guidance on how assets will be examined, whether half or full-year results will matter, and what types of loans will be examined ("AQR and stress tests could threaten European banks", *Reuters*, October 15, 2013).

[24] The execution of this exercise involved several parties. While NCAs were responsible for all national project management activities, NCAs appointed so-called NCA bank teams comprising of NCA staff and external auditors, property appraisers and valuation advisors providing their expertise, know-how and independence. In total, the complete exercise spanned over 6,000 experts.

[25] It should be noted that while these banks are the biggest banks in the euro area, they are not the same 'significant credit institutions' that are currently supervised by the ECB's single supervisory mechanism (SSM). The list of the reviewed banks can be found in Table 11 of the final report
https://www.ecb.europa.eu/pub/pdf/other/aggregatereportonthecomprehensiveassessment201410.en.pdf.

exposures.[26] The review, in general though, intended to check the most risky portfolios on banks' balance sheets; therefore, for banks with large trading books, reviewers paid stronger attention.[27] After banks' reporting ("bottom-up") as of December 31, 2013, NCAs drew on the provided data and executed the AQR following the ECB's AQR manuals and guidance. In a next step, NCAs and the ECB engaged in quality assurances until the summer of 2014 to ensure the reported data was consistent and accurate. While the final report of the entire comprehensive assessment was published on October 26, 2014, the ECB published the bank-level disclosure template on July 17, 2014 comprising detailed AQR results (identical to the EBA's disclosure template),[28] and the subsequent stress tests based on each bank's AQR were presented in October 2014 (ECB, 2013 and 2014).

Figure 1 illustrates the timeline of the ECB's AQR, which highlights its four key periods. The period before October 2013 denotes the period before the AQR-announcement ("pre-AQR"), while October, November and December 2013 are the months in the run-up to the AQR reporting due-date as of December 31, 2013, which is why we refer to it as the "AQR" period. We define the period between January 2014 and June 2014 as the "AQR-compliance" period, which was used by supervisors to consult reviewed banks so as to give them an opportunity to provide comments and suggestions. The period from July 2014 onwards describes the "post-AQR" period. Our analysis ends just before the results on the stress tests were released and the European single supervisory mechanism became effective. To ensure a symmetry around the AQR, we choose our sample in such a way that we have nine months before the AQR announcement and nine months after the AQR due date, yielding a sample of 21 months from January 2013 through September 2014. As explained in detail in the empirical strategy, we also analyze the data only around the AQR announcement in October 2013, comparing the AQR reporting due-date as of December 31, 2013 to just before the AQR announcement.

XII. DATA

For our analysis, we use proprietary security and credit register data that we obtained from the Deutsche Bundesbank, which –together with the German federal financial supervisory

[26] The assessment was a prudential rather than accounting exercise implying that the outcomes of the review were not necessarily reflected directly in the banks' accounts following the exercise.
[27] The ECB applied a risk-based approach while determining the portfolios that were reviewed in the AQR. That is, for each bank, "at least 50% of credit risk-weighted assets and half of the material portfolios" were selected.
[28] See https://www.bankingsupervision.europa.eu/ecb/pub/pdf/notecomprehensiveassessment201407en.pdf.

authority 'BaFin'– is the macroprudential and microprudential bank supervisor in Germany. We have access to the micro data on securities investments of banks (negotiable bonds and debt securities, equities, and mutual fund shares) at the security-level for each bank in each month. The data comprise of investments of German banks at the security-level on a monthly frequency from January 2013 through September 2014.[29] For each security, banks report the nominal value at the end of each month they hold (stock at the end of each month).[30] We use the unique International Security Identification Number (ISIN) associated with every security to merge the data on security investments with security-level information on rating and yield from FactSet, and on the issuer from the Eurosystem's CSDB.

We also obtain data on individual loans made by banks from the German credit register maintained by the Deutsche Bundesbank. The credit register provides information on the amount of loans outstanding at the borrower level for each bank. In addition, it also provides for selected banks borrower-level information on estimated probability of default (PD) for a loan, and the date of a given default (where applicable).[31] For the credit register banks had to report, on a quarterly frequency, all borrowers whose overall credit exposure exceeds EUR 1.5 million; however, the credit register covered nearly 70% of the total credit volume in Germany.[32]

We append the security and credit register data to confidential supervisory monthly balance-sheet statistics at the bank level. As most securities held by banks are bonds (81 %), and we also analyze loans (the other key component on bank assets), we only analyze bonds within

[29] Note that the reporting requirement specifies that securities holdings, which are passed on or acquired as part of a repo contract, are not double-counted in the securities database. Thus, the transactions we capture in analysis are not a mechanical artifact of repo transactions. For more information, see Amann, Baltzer, and Schrape (2012).

[30] While we know the security holdings of the banks, we do not know whether they are classified as trading book assets, available for sale or held to maturity.

[31] The credit register, however, does not record the maturity and interest rate associated with the loans.

[32] From 2014 onwards though, this threshold was lowered to EUR 1.0 million. Note however, that this does not affect our analysis of our main (first) hypothesis on whether banks window-dress after the AQR announcement as compared to the pre-AQR announcement (a comparison between 31st of December and 23rd of October of 2013). Moreover, on our second hypothesis on risk increase after the AQR compliance, we restrict ourselves to borrowers that were in the credit register at least once also in 2013, i.e., before the reporting level was reduced from EUR 1.5 million to EUR 1.0 million in 2014. This restriction ensures that results are not biased by new borrowers appearing in 2014 as a result of the change in the threshold. However, outstanding credit positions below the 2013's threshold of EUR 1.5 million might still show up in the 2014 data for a given borrower if the exposure exceeds the threshold of EUR 1 million. Moreover, our results (see next section and Table 3, column (4) to (6)) show that there are no statistical differences in results between end of December 2013 and end of July 2014 (not even after the AQR after July); therefore, the credit changes between reviewed and non-reviewed banks before and after the threshold change are not different.

bank securities.[33] In particular, we collect monthly balance sheet items such as each bank's equity, total assets, and total loans. Moreover, we follow the ECB's AQR procedure and focus primarily on credit exposures to non-monetary financial institutions, including large non-financial corporates. Also, we restrict ourselves to banks with a credit exposure to a firm for which we observe a value on its probability of default (PDs). We have this information for 93 distinct banks.[34] Note that this restriction on the availability of borrower PDs reduces the set of banks to those with the most economically meaningful credit portfolios as only those banks provide the PDs for their borrowers. Both restrictions are necessary to explore banks' securities investments and credit supply depending on the ex-ante security and borrower risk type (safer versus riskier).

XIII. EMPIRICAL STRATEGY AND RESULTS

In this section, we will discuss the empirical identification strategy to study the change in the portfolio holdings of reviewed banks, as compared to non-reviewed banks, both before and after the ECB's AQR and the AQR compliance. In particular, we analyze the following testable predictions under the hypothesis that banks try to window-dress before the supervisory exercise: (i) between the ECB announcement of the supervisory exercise (23rd October 2013) and the day that banks have to report their securities and loans (31st December 2013) to the ECB, banks will accumulate safer assets, especially those that the ECB considers to be of high quality; (ii) after the asset quality review is concluded (July 2014), banks will liquidate these safer assets and will
invest back in assets with a relatively higher risk.[35]

To test for these hypotheses, we first analyze the securities holdings and the loans of banks before and after the AQR. We exploit the fact that the ECB required banks to report their assets as on December 31, 2013 (point-in-time assessment) and examine the evolution of security holdings and loans of reviewed banks and non-reviewed banks based on this cut-off date. In particular, we examine whether banks increase their holdings of safe assets during this

[33] For example, if we analyzed the stock of shares, the risk measures would be very different between securities and credit, and moreover, this type of security covers a small share of banks' investments (less than 4% of total assets). Therefore, for the sake of comparison between securities and loans, and for the sake of quantitative importance, we restrict our analysis to bonds.
[34] We replace each borrower's PD with its cross-sectional average PD across all banks that assigned a PD to that borrower. This ensures that the number of bank-borrower observations increases and that a bank's individual PD-reporting does not drive our results.
[35] Our null hypothesis in the regressions is no change, and the alternative is a change (that is, the coefficient is different from 0).

period (as well as reduce the overall security holdings and supply of credit). Second, we analyze whether after July 2014 the reviewed (versus non-reviewed) banks increase their risk back to the levels similar to that before the ECB announcement in October 2013. For the first hypothesis we analyze the period of three months around the ECB announcement, whereas for the second hypothesis we use all the data.

To study heterogeneity in risk behavior across different securities and across different loans, and to identify the two hypotheses, we analyze securities holdings at the *bank-security-month* level and loans at the *bank-firm(borrower)-quarter* level. For our two main hypotheses, in a difference-in-difference setting, we analyze *before* and *after* each main event (either the ECB announcement in October 2013, or the completion of the AQR in July 2014) whether, for the *same* security or for the *same* firm (in the case of lending), *reviewed* versus *non-reviewed* banks change their holdings depending on the ex-ante security or firm (loan) *risk*. As the size of a bank in Germany primarily determines whether or not a given institution is being reviewed, (i) we either analyze all of the non-reviewed banks or only the largest (with respect to their size) non-reviewed banks, for the comparison group of non-reviewed banks;[36] (ii) we analyze whether reviewed or non-reviewed banks differ in other-end-of–year periods (placebo tests); (iii) we only analyze very few reviewed and non-reviewed banks with very similar size (around the cut-off of EUR 30 billion); (iv) we analyze unconditionally the behavior of only reviewed banks before and after each of the two main events;[37] (v) we control for heterogeneity across banks with different sets of bank (or even bank-security and bank-firm) fixed effects. We provide summary statistics on the main variables in the Appendix Table A2, where Table A1 contains the definitions of the variables used in the paper.

XIII.1 DIALING-UP OF SAFE ASSETS IN THE RUN-UP TO THE AQR

The first testable hypothesis, which we examine in this paper, is that –after the announcement

[36] Reviewed banks are larger than non-reviewed institutions (with e.g. differences in bank sizes of EUR 182 billion vs. EUR 2 billion on average), but with rather similar levels of securities holdings (19.48% vs. 21.84% of total assets) and safe credit (77.45% vs. 73.77%), though some differences in the level of credit (44.32% vs. 58.92%) and safe securities (39.36% vs. 26.47%).

[37] Our results are robust to banks close to the EUR 30 billion threshold, though we lose most banks and observations (including the very interesting largest banks) or are robust to only analyzing reviewed banks. Moreover, as our placebo tests presented in the next section show, we do not find a differential effect between reviewed and non-reviewed banks in the last quarter of the year before the AQR (i.e., in 2012) or in the last quarter of the year after the AQR (i.e., in 2014); therefore the differences in changes in securities and credit between the two group of banks are due to the AQR. Note that our sample of reviewed banks close to the EUR 30 billion threshold are also interesting to the extent that they have no foreign subsidiary in Europe (but, our results are also significant in the overall sample if we restrict the sample to these type of banks).

of the supervisory exercise– banks will accumulate safer assets, especially those with a better rating that would perform well in the supervisory test.[38] To examine this statement, we start by studying the securities holdings of reviewed banks versus non-reviewed banks at the *bank-security-month* level using the following econometric model:

$$\text{Log}(securities\ holdings)_{b,s,t} = \beta\left(Safe_{s,t-1} \cdot AQR_t \cdot Reviewed_b\right) + \alpha_b + \alpha_s + \alpha_t + \delta' controls + \varepsilon_{b.s.t} \qquad (1)$$

where the dependent variable is the logarithm of nominal holdings of security *s* by bank *b* at month *t*. Our sample is constructed symmetrically around the AQR announcement, i.e. 3 months before the announcement (i.e., end of July, August, and September 2013) versus 3 months after the announcement (i.e., end of October, November, and December 2013).[39] AQR_t is a (post) dummy variable that equals the value of one during the months following the AQR announcement in October 2013, i.e. during October, November and December 2013, and zero before. We follow the Eurosystem's harmonized rating scale for the definition of safe assets and define a security as safe when the security has a rating between AAA to AA-.[40] That is, 'Safe' is a dummy variable that equals the value of one whenever the security has a rating between AAA and AA-, and zero otherwise. 'Reviewed' is a binary variable that equals the value of one for any bank reviewed under the AQR, and zero otherwise. The estimated coefficient β then measures the differential securities holdings of safe (versus risky) securities by reviewed banks versus non-reviewed banks before versus after the AQR announcement. We cluster standard errors at the bank and security level. For identification, in addition to time fixed effects to control for overall macro shocks, we include controls for security fixed effects to analyze the same security before and after the AQR, bank fixed effects to account for time-invariant heterogeneity in bank characteristics.[41] In some regressions we also include bank*security fixed effects to account for unobserved matching between characteristics of banks and securities. 'Controls' includes all relevant levels and interactions between 'Safe', 'AQR' and 'Reviewed' that are not absorbed by the fixed effects.

[38] We also analyze other risk measures as part of our robustness checks, for example yield, maturity or whether the borrower is headquartered in a GIIPS country. To penalize risk inherent to bank assets, the Eurosystem primarily relies on ratings rather than yields and the origin of issuance (e.g., GIIPS, and there is substantially more penalization in ratings than in maturity (see ECB (2005, 2013 and 2014)). Note also that to judge on the riskiness of loans, we use the ex-ante probability of default, which is comparable to the ex-ante rating in securities, and normally not available in credit registers in other countries (note that we have no information on the credit maturity).

[39] In robustness regressions, we show that comparing end of September to end of December 2013 yields very similar results, see Table A3 of the appendix.

[40] For the standardized approach maps the ECAI's credit assessments to credit quality steps, see for example, https://www.eba.europa.eu/documents/10180/16166/4+Ausust+2006_Mapping.pdf and https://www.bankingsupervision.europa.eu/ecb/pub/pdf/assetqualityreviewphase2manual201403en.pdf. Moreover, according to the standardized approach of capital adequacy under Basel II and III, this rating bucket has the lowest risk weight.

[41] We find similar results if we do not saturate the econometric model with any fixed effect (though identification in this case is weaker).

Based on Figure 2 –unconditionally, before imposing any control such as those in equation (1)– we find that, after the announcement of the AQR, reviewed banks increase the share of their safe securities on average by more than 2% during the short time period of the AQR relative to the period before the announcement. Note that we find similar results if we analyze only the reviewed banks or we compare reviewed versus non-reviewed banks.

More formally, estimating equation (1), we find in column 1 of Table 1 that, after the AQR announcement, reviewed banks increase their share of safe securities by 2.36% as compared to non-reviewed banks. In column 2, we add bank*security fixed effects and find that our main result remains very similar in terms of significance and magnitude, despite that the R2 increases by more than 30 percentage points.[42] Column 3 and 4 replicate the estimation of column 1 and 2 but restrict the sample of non-reviewed banks to the largest ones with respect to total assets to ensure that our results are not affected by the comparison of large reviewed banks and small non-reviewed banks (we use the same number of non-reviewed banks to have an equal set of reviewed and non-reviewed banks). The results remain qualitatively similar, yet stronger in magnitude. We find that reviewed banks increase their safe securities holdings by 3.37% during the AQR period. Economically, this suggests that reviewed banks together increase their safe securities holdings by EUR 11.80 billion in the period after the AQR announcement.[43] Moreover, there is also a significant reduction in the overall security holdings of reviewed banks (as indicated by the coefficient on AQR*Reviewed), i.e. reviewed banks not only relatively cut the riskier securities, but also downsize their level of securities holdings in general.[44]

In a robustness regression, we also restrict the sample of both reviewed and non-reviewed banks to those whose total value of total assets lies within the range of plus/minus EUR 10 billion around the EUR 30 billion threshold, i.e., one of the three criteria used to select the reviewed banks as explained in Section XI (and the only one applied in Germany). Our results remain qualitatively similar but larger in magnitude (see Table A5 of the Appendix). This suggests that our results are neither driven by very large reviewed banks nor by small non-

[42] Following Altonji et al (2005), this implies that our main variable is exogenous to a large set of unobserved security and bank characteristics.
[43] The sum of all safe securities holdings of all reviewed banks amounts to a total of EUR 350 billion as at end of September 2013. Using the estimated coefficient on Safe*AQR*Reviewed from Table 1 column 4, results suggest an increase by EUR 11.80 billion, i.e., 3.37%*EUR 350 billion.
[44] If we just run the double interaction *AQR*Reviewed* without the triple with *Safe*, we also find that overall reviewed (vs. Non-reviewed) banks cut on their assets.

reviewed banks.

In addition, in columns 5 and 6 of Table 1, we restrict ourselves to reviewed banks only. We find that all reviewed banks on average increase their safe securities holdings by 2.25% after the AQR announcement (note that in column 6 we control for security*bank fixed effects). As a robustness check, we also show that comparing end of September to end of December 2013 yields very similar results (see columns 1 to 3 of Table A3 of the appendix).[45] All in all, these results suggest that reviewed banks increase their safe securities holding after the announcement of the AQR.[46]

As credit was a major part of the ECB's AQR, in a next step we examine the response in the lending behavior of banks during the AQR. To that aim, we exploit the data at the *borrower-bank-quarter* level and use the following estimation equation:

$$\text{Log}(credit)_{b,j,t} = \beta\left(Safe_{j,t-1} \cdot AQR_t \cdot Reviewed_b\right) + \alpha_b + \alpha_j + \alpha_t + \delta' controls + \varepsilon_{b,j,t} \quad (2)$$

where the dependent variable is the logarithm of the loan amount by bank *b* to firm *j* during quarter *t*. In analogy to Table 1, we use the same symmetric sample around the AQR announcement, i.e., July, August, and September 2013 vs. October, November, and December 2013.[47] Our binary variables 'AQR' and 'Reviewed' are constructed as before.

To assess the riskiness of a given borrower, we resort to the ex-ante probability of default (PD) that any bank assigns to its borrower. Since only a subset of banks (relatively large banks) provide these PDs, this restricts us to only analyzing those banks and borrowers for which we have a PD. That is, once we observe a PD for a given firm in a given time, we will use this information to assess this firm's riskiness across all of its credit relationships.[48] We then define the binary variable "Safe", which equals the value of one for all borrowers whose

[45] We also show in Table A3 of the Appendix that banks decrease the share of riskier securities measured by (i) high-yield securities (columns 3 and 4), (ii) securities whose issuer is headquartered in GIIPS countries (columns 5 and 6), (iii) long-term securities (columns 7 and 8), and (iv) long-term non-safe securities (columns 9 and 10).
[46] A question that we cannot analyze is who buys the riskier securities sold by the reviewed banks, as our data are securities holdings by each bank, and hence it is not transaction level data with buyer and seller identity.
[47] Recall that our credit data has a quarterly frequency. Therefore, our credit regressions for the sample +/- 3 months around the AQR announcement already compare September 2013, i.e., before the AQR announcement, to December 2013, i.e., the AQR due date.
[48] In case we observe multiple PDs assigned to the same borrower at the same time by different banks, we use the cross-sectional average of all observed PDs for a given borrower and use the average PD to assess this firm's risk profile. Note that the PDs are computed for the default of the given borrower during the next year and thus are independent of the maturity and type of the credit contract at hand.

PD is below the cross-sectional mean, and zero otherwise.[49] The median PD in this group equals 0.2% and corresponds to PDs observed globally for investment-grade firms that have the lowest risk weights (e.g., Standard and Poor's 2012; Joint Committee of the European Supervisory Authorities, 2014).[50] In comparison, the median PD in the group of riskier firms (i.e., when 'Safe' equals the value of zero) is 4.3%, which refers to PDs observed for below-investment-grade firms.

For identification, we include firm fixed effects to control for the borrower characteristics (thus proxying demand as in e.g. Khwaja and Mian, 2008) or firm*bank fixed effects to control for any firm-bank specific match such as geographical distance (Degryse and Ongena, 2005) and relationship lending (Petersen and Rajan, 1995). Thus, we compare the level of credit for the same borrower across reviewed and non-reviewed banks depending on the ex-ante risk of the borrower. We cluster standard errors at the bank and firm level.

In column 1 of Table 2, we find that reviewed banks, as compared to non-reviewed banks, increase their share of supply of credit to safer firms by 2.84% after the AQR announcement. In column 2, we include firm*bank fixed effects and find that our estimated coefficient on Safe*AQR*Reviewed bank remains statistically significant, qualitatively similar but somewhat quantitatively lower. In column 3 and 4, we replicate our security analysis of Table 1 and restrict our sample of non-reviewed banks to the largest institutions in terms of total assets to ensure that our results are not driven by smaller non-reviewed banks.[51] Similar to our security analysis, we find that our results remain qualitatively similar, yet become stronger in magnitude. From column 4, we can see that reviewed banks increase their share of supply of credit to safer firms by 2.68% after the AQR announcement when compared to the largest non-reviewed banks. Economically, this corresponds to an increase of credit supply to safer borrowers in the amount of EUR 42.02 billion in total for all reviewed banks in the period after the AQR announcement.[52] In columns 5 and 6, we restrict ourselves to reviewed banks only and find that on average reviewed banks increased credit to safer firms by 2.81% (with

[49] In Table A4 of the Appendix, we show that our results are robust to the application of different cut-offs to the ex-ante probability of default and to using the ex-ante continuous probability of default.
[50] This credit quality complies with the Eurosystem's credit quality requirements for non-marketable assets as laid down in Article 108 (a) (ECB/2014/60).
[51] Recall that our credit regressions rely already on a subset of non-reviewed banks as not all non-reviewed banks have borrowers with reported PDs.
[52] The sum of all credit to safer firms of all reviewed banks amounts to a total of EUR 1,568 billion as at end of September 2013. Using the estimated coefficient on Safe*AQR*Reviewed from Table 2 column 4, results suggest an increase by EUR 42.02 billion, i.e., 2.68%*EUR 1,568 billion.

firm fixed effects) and 2.74% (with firm*bank fixed effects) after the AQR announcement (Figure 3 also shows similar results without any control).

As a robustness check, we also restrict the sample of both reviewed and non-reviewed banks to those whose total value of total assets lies within the range of plus/minus EUR 10 billion around the EUR 30 billion threshold. Our results remain qualitatively similar but somewhat larger in magnitude (see Table A5 of the Appendix). In addition, there is also a significant reduction in the overall supply of credit by reviewed banks to firms (coefficient on 'AQR*Reviewed' in Table 2), i.e. reviewed banks not only cut the supply of riskier credit, but also downsize credit supply in general.

In sum, the results (stemming from Figure 2 and 3 without controls, from Table 1 and 2 with controls and from the Appendix) suggest that, after the announcement of the AQR, reviewed banks increase their share of safe assets, both bonds and loans. Economically, we find for all reviewed banks there is an increase of safe securities by EUR 11.80 billion and an increase of credit supply to safer firms by EUR 42.02 billion, together amounting to an average increase in safe assets (both securities and credit) of EUR 53.82 billion, which is high given the very short period of time (basically two months between announcement and compliance) and accounts for 29% of reviewed banks' overall common equity capital. Finally, results are not due to a general end-of-year effect, but only related to the 2013 last quarter's ECB supervisory audit, as we do not find (statistical or economic) significant effects in the last quarter of 2012 or of 2014 (see Table A6 of the Appendix).

XIII.2 Dialing-down of Safe Assets after the AQR

The second testable hypothesis that we examine in this paper is that –after the AQR compliance exercise is concluded– banks will liquidate the previously acquired safer assets and invest in holdings with a relatively higher risk. To examine this mechanism, we extend our security and credit analysis from the previous section (Equations (1) and (2) respectively) by just adding all the different AQR time periods (following Figure 1), with identical dependent variables and identical asset risk (*safe*) and bank (*reviewed*) variables. We extend our sample but maintain a symmetric window around the AQR period, i.e. nine months before the AQR announcement and nine months after the AQR due date, yielding a total sample of 21 months covering the period from January 2013 to September 2014 (recall that our sample ends in October 2014, i.e. before the comprehensive stress test results are released and the ECB becomes the European banking supervisor). This allows us to estimate the differential effects across the different periods related to the overall AQR exercise as depicted in Figure 1.

Table 3 presents the results. ‘AQR’ is constructed as before and thus equals the value of one only for the months October, November, December 2013, and zero otherwise. ‘AQR-Compliance’ is a binary variable that equals the value of one for the months January to June 2014, and zero otherwise. ‘Post-AQR’ refers to a dummy variable that equals the value of one for the months from July 2014 onwards, and zero otherwise. This leaves the period before the AQR announcement as the benchmark period. That is, the three estimated coefficients in Table 3 (of the triple interactions of the three different time periods with asset risk and reviewed bank) measure the differential effect during each individual sub-period relative to the period before the AQR announcement. If reviewed banks indeed dial down on safe assets after the AQR compliance exercise is concluded, we expect the coefficient associated to ‘Post-AQR’ to be insignificant, i.e. suggesting that the differential holdings of safe securities (or safer credit) after the AQR compliance period do not statistically differ from the levels held before the AQR announcement.

In Table 3, column 1, we find that the increase of safe securities during the AQR period persists during the AQR-compliance period. In the period after the AQR compliance exercise though, the coefficient on Safe*Post-AQR*Reviewed is negative and significant, though it becomes insignificant by restricting the sample of non-reviewed banks to the largest ones (see column 2) and to within reviewed banks only (column 3). That is, the holdings of safe securities after the overall AQR exercise are back to the levels held before the AQR announcement. This suggests that reviewed banks indeed reduce safe securities after temporarily increasing them during the AQR period (see also Figure 2, which graphically illustrates this behavior).

In columns 4 to 6, we mimic the security analysis and examine the differential effect on credit supply by reviewed banks versus non-reviewed banks during the AQR cycle. Similar to our security regressions, we find that –during the AQR-compliance period– reviewed banks’ credit supply to safer firms remain at elevated levels as compared to the period before the AQR announcement. However, in contrast to the security analysis, in the period after the AQR compliance period we find that these levels continue to be elevated similar to the levels observed during the AQR period (columns 5 and 6) (see also Figure 3 without controls, which graphically illustrates this behavior).[53] This result is intuitive as the credit portfolio is more difficult to be adapted on short notice in the same way as for instance the (traded) security portfolio, as banks need to have opportunities to lend to riskier borrowers.

As discussed in Section XI, the AQR intended to focus especially on the most risky portfolios on the banks' balance sheets and thus gave special attention to banks with significant trading books. Banks with a larger trading book may therefore feel more pressured to adjust their asset portfolio for the AQR exercise than other banks. Moreover, Abbassi, Iyer, Peydró, and Tous (2016) show a positive relationship between banks' trading expertise and the change in their securities investments: banks that rely more on trading will have more expertise in security trading on short notice;[54] therefore, in a next step we use the same proxy as in that paper and examine whether the investment behavior after the AQR announcement differs even within the group of reviewed banks based on their trading expertise.

In Table 4, we interact our main variable 'Safe*AQR' with the binary variable 'Trading bank', which equals the value of one if the reviewed bank has membership to the largest fixed-income platform in Germany (Eurex Exchange), and zero otherwise. In column 1 of Table 4, we find that during the AQR period there is no additional differential effect for securities holdings within the group of reviewed banks depending on trading expertise (i.e., during the AQR period reviewed banks increase safe securities holdings irrespective of further bank-specific characteristics).[55] However, after the AQR overall exercise, we find that reviewed banks with trading expertise reduce their safe assets to levels below that observed before the AQR period (i.e., the estimated coefficient of 'Safe*Post-AQR*Trading bank' is negative and significant).

[53] It is statistically insignificant in column 4 but not in column 5 and 6.

[54] To proxy for active presence and expertise in securities markets, Abbassi, Iyer, Peydró, and Tous (2016) use the notion that banks that generally engage in trading activities and thus have expertise will have a trading desk in place and the necessary infrastructure, such as direct membership to the trading platforms to facilitate trading activities. Using this line of reasoning, they proxy for trading expertise by direct membership of banks to the largest, fixed-income trading platform in Germany (Eurex Exchange). Supporting this classification, Abbassi, Iyer, Peydró, and Tous (2016) find that the amount of securities traded (as a fraction of total assets) are consistently larger for banks with trading expertise, across all the periods. They also find this measure to be highly correlated with the fraction of trading income to net income (in the pre-crisis period), with a correlation coefficient of 60%. Thus, the trading expertise dummy is highly correlated with banks that have a higher fraction of income generated from trading activities.

[55] In unreported robustness regressions, we have also tried other bank-specific variables such as the bank's leverage ratio, its Tier-1 capital adequacy ratio, its size, or the share of non-performing loans. Yet, we do not find any further differential heterogeneity at the bank level.

In column 2, we find that reviewed banks with trading expertise increase credit to safer firms more than other reviewed banks after the AQR announcement. During the post-AQR period though, we find that both reviewed banks with and without trading specialization remain at roughly similar elevated levels of safe credit as observed during the AQR period. All in all, trading banks that are reviewed reduce risk as the others in securities but increase it more than other banks during the post-AQR period, whereas in lending, trading banks stay at the same level during the post-AQR period than before.

XIV. CONCLUSIONS

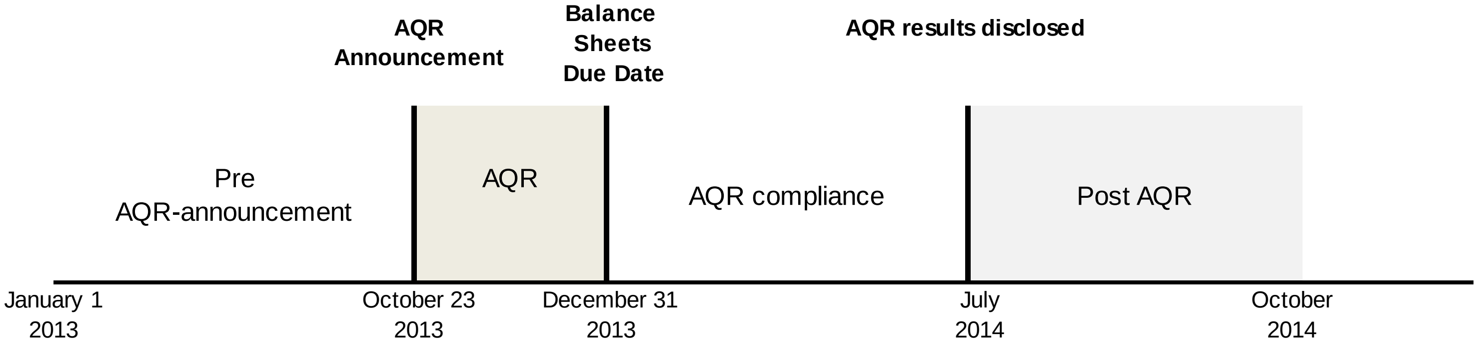
Government regulation requires effective supervision, but regulated entities may window-dress to supervisors. For empirical identification, we analyze the banking sector exploiting a quasi-natural experiment —ECB's 2014 asset quality review (AQR)— in conjunction with the security and credit registers. The banking sector is interesting, not only for empirical identification of window-dressing to supervisors, but also for the difficulties in supervision, as banks hold more liquid assets, which are easy to change relatively fast, and also hold assets that are more opaque than in other industries. Moreover, there has been a substantial increase in banking regulation after the financial crisis of 2008.

We examine how banks behave before and after the largest-ever supervisory exercise, i.e., the European Central Bank's 2014 AQR, by examining the change in the portfolio holdings of German banks that were reviewed as a part of the AQR. For identification, we exploit the fact that the AQR was based on the portfolio holdings of banks at a single point in time. Thus, we test whether, after the announcement of the AQR, reviewed (versus non-reviewed) banks rebalance their assets by buying more safe assets and then unload them after the culmination of the supervisory exercise (i.e., whether reviewed banks window-dress for supervisory audits).

We find that, after the ECB's announcement of the AQR, reviewed banks increase their share of securities that have top-tier rating and reduce their share of supply of credit to riskier firms. In the period after the AQR compliance though, we find that reviewed banks fully reload back on riskier securities (similar to the pre-ECB announcement level); however, this is not the case for riskier credit. Results are more pronounced for banks with higher trading expertise; in particular, trading banks that are reviewed reduce risk as the others in securities after the ECB announcement of AQR, but increase it more than other banks during the post-AQR period; whereas in lending, the trading banks stay at the same level during the post-AQR period than before. The results suggest that banks change the composition of their assets before a supervisory exercise in favor of safer assets and undo this after the exercise.

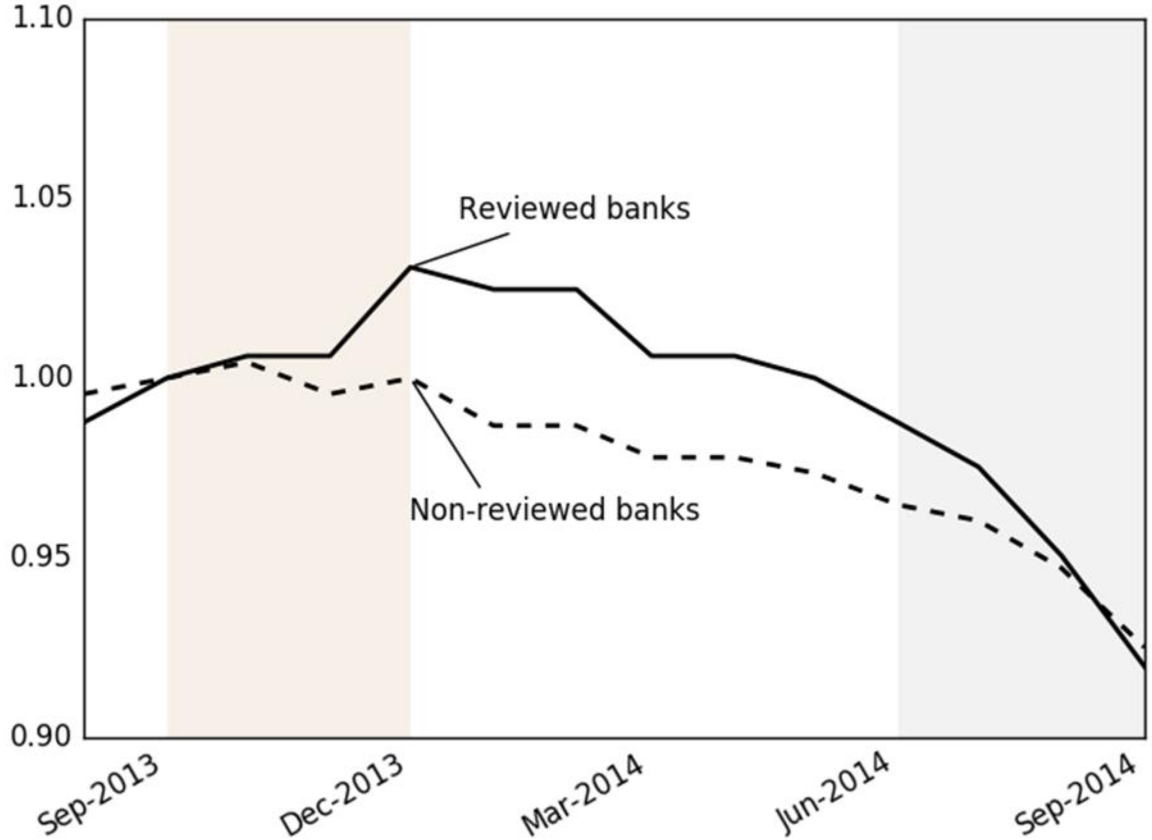
The results hold important policy implications for stress-testing in particular, and for the design of supervision in general. The results suggest that pre-defining the timing and structure of a supervisory exercise incentivizes window-dressing behavior of banks, as it is optimal from a bank's perspective (see e.g., Tarullo, 2014; Goldstein and Sapra, 2014; Coen, 2017). Thus, it might be necessary to have an element of surprise in the supervisory exercise, both in the timing of the audits (either more continuous or random in time) and also in the transparency of the specific process (i.e., methods and models used, and assets and type of risks assessed). The results also indicate that it is easier for banks to change the composition of liquid assets (securities trading) than illiquid assets (loans to firms). Thus, the results also point to the notion that regulation of banks with substantial volume of marketable assets may pose significant challenges for supervision.

FIGURE 1: TIMELINE OF THE ASSET QUALITY REVIEW



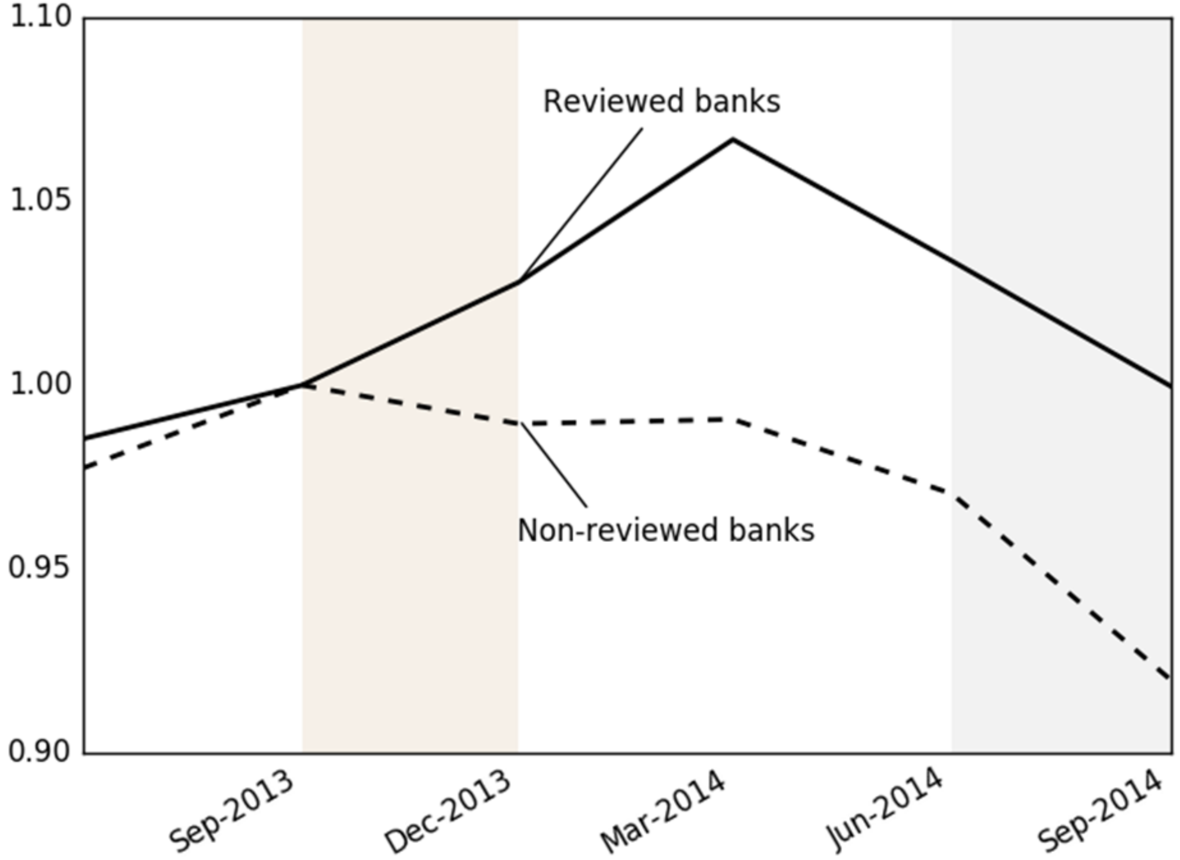
This figure displays the timeline of the comprehensive asset quality review (AQR) by the European Central Bank (ECB). For more information, please refer to Section 2 and https://www.bankingsupervision.europa.eu/banking/comprehensive/2014/html/index.en.html.

FIGURE 2: FRACTION OF SAFE SECURITIES BEFORE AND AFTER THE AQR



This figure shows the level of safe securities as a fraction of total assets by reviewed and non-reviewed banks during the period of the ECB's AQR cycle (normalized to September 2013). We define a security as safe when the security has a rating between AAA to AA-, which corresponds to the Eurosystem's harmonized rating scale for the definition of safe assets. 'Reviewed banks' refers to all banks that were reviewed under the AQR by the ECB. 'Non-reviewed banks' defines all banks that were not reviewed by the ECB under the AQR. The first shaded area refers to the period after the AQR announcement in October 2013 until the AQR due date, i.e., end of December 2013, and the second shaded area denotes the period after the AQR concluded in July 2014 until the end of our sample, end of September 2014.

FIGURE 3: FRACTION OF SAFE CREDITORS BEFORE AND AFTER THE AQR



This figure shows the level of safe creditors as a fraction of total assets by reviewed and non-reviewed banks during the period of the ECB's AQR cycle (normalized to September 2013). We define a creditor as safe when the borrower has a lower one-year probability of default (PD) than the cross-sectional mean of all borrowers' PDs. 'Reviewed banks' refers to all banks that were reviewed under the AQR by the ECB. 'Non-reviewed banks' defines all banks that were not reviewed by the ECB under the AQR. The first shaded area refers to the period after the AQR announcement in October 2013 until the AQR due date, i.e., end of December 2013, and the second shaded area denotes the period after the AQR concluded in July 2014 until the end of our sample, end of September 2014.

TABLE 1: DIALING UP OF SAFE SECURITIES AFTER THE AQR ANNOUNCEMENT

+ / - 3 MONTHS AROUND AQR ANNOUNCEMENT

	Dependent variable: Log(securities holdings)					
	Reviewed vs. non-reviewed		Reviewed vs. largest non-reviewed		Within reviewed banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Safe*AQR*Reviewed	0.0236***	0.0264***	0.0314***	0.0337***	0.0190***	0.0225***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Safe*AQR	-0.0092***	-0.0039***	-0.0149***	-0.0113***		
	(0.00)	(0.00)	(0.01)	(0.00)		
Safe	0.1580***	0.0034	-0.0311	-0.0303		
	(0.03)	(0.01)	(0.05)	(0.04)		
AQR*Reviewed	-0.0394***	-0.0377***	-0.0333***	-0.0426***		
	(0.00)	(0.00)	(0.01)	(0.00)		
Safe*Reviewed	-0.3651***	0.0139	0.0792**	0.0484	0.0376	0.0193
	(0.03)	(0.05)	(0.03)	(0.06)	(0.05)	(0.04)
Security FE	Y	-	Y	-	Y	-
Bank FE	Y	-	Y	-	Y	-
Security*Bank FE	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	1,546,778	1,546,778	323,290	323,290	192,071	192,071
R-squared	0.687	0.996	0.615	0.987	0.553	0.978

The dependent variable is the logarithm of securities nominal holdings by each bank b of security s during month t in the period July 2013 to December 2013, i.e., +/- three months around the AQR announcement. 'Safe' is a dummy variable that equals the value of one whenever the security has a rating between AAA and AA-, and zero otherwise. 'AQR' is a dummy variable that equals the value of one during the months following the AQR announcement in October 2013 (post), i.e. end of October, November and December 2013, and zero before. We classify a bank as 'Reviewed' if it was reviewed under the AQR by the ECB. In columns 5 and 6, we restrict our sample to reviewed banks only, i.e., when 'Reviewed' equals the value of one for all banks. Fixed effects are either included ('Y'), not included ('N'), or spanned by another set of fixed effects ('-'). The definition of the main variables can be found in Appendix Table A1. A constant is included, but its coefficient is left unreported. Standard errors are clustered at bank and security level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 2: DIALING UP OF SAFE CREDITORS AFTER THE AQR ANNOUNCEMENT

+/- 3 MONTHS AROUND AQR ANNOUNCEMENT

	Dependent variable: Log(credit)					
	Reviewed vs. non-reviewed		Reviewed vs. largest non-reviewed		Within reviewed banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Safe*AQR*Reviewed	0.0284**	0.0189*	0.0426***	0.0268**	0.0281***	0.0274***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Safe*AQR	0.0013	0.0085	-0.0126	0.0006		
	(0.01)	(0.01)	(0.01)	(0.01)		
Safe	0.0419	0.0131	0.0018	0.0041		
	(0.04)	(0.01)	(0.05)	(0.02)		
AQR*Reviewed	-0.0350***	-0.0283***	-0.0489***	-0.0368***		
	(0.01)	(0.01)	(0.01)	(0.01)		
Safe*Reviewed	-0.0787	-0.0362**	-0.0304	-0.0272	-0.0283	-0.0231**
	(0.05)	(0.02)	(0.06)	(0.02)	(0.02)	(0.01)
Firm FE	Y	-	Y	-	Y	-
Bank FE	Y	-	Y	-	Y	-
Firm*Bank FE	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	166,208	166,208	161,328	161,328	142,436	142,436
R-squared	0.901	0.978	0.904	0.978	0.908	0.977

The dependent variable is the logarithm of loan amount by each bank b to borrower j during quarter t in the period September 2013 to December 2013, i.e., +/- three months around the AQR announcement. ‘Safe’ is a dummy variable that equals the value of one if loan j has a probability of default (PD) below the cross-sectional mean PD of all borrowers’ PDs in time t-1. ‘AQR’ is a dummy variable that equals the value of one during the months following the AQR announcement in October 2013 (post), i.e. end of December 2013, and zero before. We classify a bank as ‘Reviewed’ if it was reviewed under the AQR by the ECB. In columns 5 and 6, we restrict our sample to reviewed banks only, i.e., when ‘Reviewed’ equals the value of one for all banks. Fixed effects are either included (‘Y’), not included (‘N’), or spanned by another set of fixed effects (‘-’). The definition of the main variables can be found in Appendix Table A1. A constant is included, but its coefficient is left unreported. Standard errors are clustered at bank and firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 3: DIALING DOWN OF SAFE ASSETS AFTER THE AQR OVERALL EXERCISE

+ / - 9 MONTHS AROUND AQR ANNOUNCEMENT

	Dependent variable:					
	Log(securities holdings)			Log(credit)		
	Reviewed vs. non-reviewed	Reviewed vs. largest non-reviewed	Within reviewed banks	Reviewed vs. non-reviewed	Reviewed vs. largest non-reviewed	Within reviewed banks
	(1)	(2)	(3)	(4)	(5)	(6)
Safe*AQR*Reviewed	0.0212***	0.0132***	0.0160***	0.0185*	0.0305***	0.0346***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Safe*AQR-Compliance*Reviewed	0.0083**	0.0155***	0.0113***	0.0289***	0.0469***	0.0563***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Safe*Post-AQR*Reviewed	-0.0208***	-0.0058	-0.0061	0.0146	0.0375***	0.0572***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Safe*AQR	-0.0053***	0.0027		0.0159*	0.0040	
	(0.00)	(0.00)		(0.01)	(0.01)	
Safe*AQR-Compliance	0.0029***	-0.0043		0.0271***	0.0092	
	(0.00)	(0.00)		(0.01)	(0.01)	
Safe*Post-AQR	0.0144***	-0.0004		0.0422***	0.0192*	
	(0.00)	(0.00)		(0.01)	(0.01)	
Safe	-0.0060	-0.0233		0.0035	-0.0136	
	(0.01)	(0.02)		(0.01)	(0.01)	
AQR*Reviewed	-0.0417***	-0.0435***		-0.0339***	-0.0474***	
	(0.00)	(0.00)		(0.01)	(0.01)	
Safe*Reviewed	-0.0018	0.0143	-0.0124	-0.0313***	-0.0142	-0.0273***
	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.00)
AQR-Compliance*Reviewed	-0.0629***	-0.0734***		-0.0463***	-0.0746***	
	(0.00)	(0.00)		(0.01)	(0.01)	
Post-AQR*Reviewed	-0.0991***	-0.1021***		-0.0329***	-0.0662***	
	(0.00)	(0.00)		(0.01)	(0.01)	
Security*Bank FE	Y	Y	Y	-	-	-
Firm*Bank FE	-	-	-	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	5,306,169	1,118,632	663,380	614,236	592,800	524,731
R-squared	0.987	0.963	0.940	0.949	0.948	0.946

The dependent variable in column 1 to 3 is the logarithm of securities nominal holdings by each bank b of security s during month t in the period January 2013 to September 2014, i.e., +/- nine months around the AQR. The dependent variable in column 4 to 6 is the logarithm of loan amount by each bank b to borrower j during quarter t in the period January 2013 to September 2014, i.e., +/- nine months around the AQR. 'AQR' equals the value of one for the months October, November, December 2013, and zero otherwise; 'AQR-Compliance' equals the value of one for the months January to June 2014, and zero otherwise; 'Post-AQR' equals the value of one for the months from July 2014 onwards, and zero otherwise, which leaves the period before the AQR announcement as the benchmark period (i.e., each estimated coefficient measures the differential effect during each individual sub-period relative to the period before the AQR announcement). Note that our data on securities holdings is available at monthly frequency whereas our data on credit is available at quarterly frequency. We classify a bank as 'Reviewed' if it was reviewed under the AQR by the ECB. In columns 3 and 6, we restrict our sample to reviewed banks only, i.e., when 'Reviewed' equals the value of one for all banks. Fixed effects are either included ('Y') or spanned by another set of fixed effects ('-'). The definition of the main variables can be found in Appendix Table A1. A constant is included, but its coefficient is left unreported. Standard errors are clustered at bank and asset level (security or firm, respectively) and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 4: DIALING DOWN OF SAFE ASSETS AFTER THE AQR DEPENDING ON TRADING EXPERTISE

+ / - 9 MONTHS AROUND AQR

	Within reviewed banks	
	Dependent variable:	
	Log(securities holdings)	Log(credit)
	(1)	(2)
Safe*AQR	0.0280**	0.0171**
	(0.01)	(0.01)
Safe*AQR*Trading bank	-0.0176	0.0255**
	(0.02)	(0.01)
Safe*AQR-Compliance	0.0366*	0.0307***
	(0.02)	(0.01)
Safe*AQR-Compliance*Trading bank	-0.0344	0.0323***
	(0.02)	(0.01)
Safe*Post-AQR	0.0309	0.0273**
	(0.02)	(0.01)
Safe*Post-AQR*Trading bank	-0.0463*	0.0348**
	(0.03)	(0.01)
Safe	0.0349	0.0229***
	(0.07)	(0.01)
AQR*Trading bank	0.0175*	-0.0477***
	(0.01)	(0.01)
Safe*Trading bank	-0.0407	-0.0634***
	(0.08)	(0.01)
AQR-Compliance*Trading bank	0.0032	-0.0254***
	(0.01)	(0.01)
Post-AQR*Trading bank	-0.1100***	-0.0006
	(0.01)	(0.01)
Securities*Bank FE	Y	-
Firm*Bank FE	-	Y
Time FE	Y	Y
Observations	662,249	524,731
R-squared	0.941	0.947

The dependent variable in column 1 is the logarithm of securities nominal holdings by each bank b of security s during month t in the period January 2013 to September 2014, i.e., +/- nine months around the AQR. The dependent variable in column 2 is the logarithm of loan amount by each bank b to borrower j during quarter t in the period January 2013 to September 2014, i.e., +/- nine months around the AQR. 'AQR' equals the value of one for the months October, November, December 2013, and zero otherwise; 'AQR-Compliance' equals the value of one for the months January to June 2014, and zero otherwise; 'Post-AQR' equals the value of one for the months from July 2014 onwards, and zero otherwise, which leaves the period before the AQR announcement as the benchmark period (i.e., each estimated coefficient measures the differential effect during each individual sub-period relative to the period before the AQR announcement). Note that our data on securities holdings is available at monthly frequency whereas our data on credit is available at quarterly frequency. We restrict our sample to reviewed banks only, i.e., when 'Reviewed' equals the value of one. 'Trading bank' is a binary variable that equals one when the reviewed bank has membership to the largest-fixed income platform in Germany (Eurex Exchange), and zero otherwise, which proxies for banks with higher trading expertise. We classify a bank as 'Reviewed' if it was reviewed under the AQR by the ECB, i.e., when 'Reviewed' equals the value of one. Fixed effects are either included ('Y') or spanned by another set of fixed effects ('-'). The definition of the main variables can be found in Appendix Table A1. A constant is included, but its coefficient is left unreported. Standard errors are clustered at bank and asset level (security or firm, respectively) and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 5: SPILLOVERS

	Dependent variable:	
	Price	Credit
	(1)	(2)
Non-Safe*AQR*Reviewed	-1.1171***	-0.0204***
	(0.32)	(0.01)
Non-Safe*AQR	Yes	Yes
Non-Safe	Yes	Yes
AQR*Reviewed	Yes	Yes
Non-Safe*Reviewed	Yes	Yes
Securities FE	Yes	-
Firm FE	-	Yes
Time FE	Yes	Yes
Observations	9,618	133,336
R-squared	0.987	0.981

The dependent variable in column 1 is the price of security s during month t in the period September 2013 and December 2013, i.e., before and after the AQR announcement. 'Non-Safe' is a dummy variable that equals the value of one whenever the security has a below-investment-grade issuer rating, and zero otherwise. 'Reviewed' is a binary variable that equals one when the security is primarily held (i.e., more than 50th percentile) by reviewed banks as at September 2013, and zero otherwise.
The dependent variable in column 2 is the logarithm of loan amount borrowed by firm j during quarter t in the period September 2013 and December2013. 'Non-Safe' is a dummy variable that equals the value of one if loan j has a probability of default (PD) above the cross-sectional mean PD of all borrowers' PDs in time t-1, and zero otherwise. 'Reviewed' is a binary variable that equals one when the firm's total credit is exclusively (i.e., more than 50th percentile) provided by reviewed banks as at September 2013, and zero otherwise. 'AQR' equals the value of one for the month December 2013, and zero otherwise; this leaves the period before the AQR announcement as the benchmark period. Fixed effects are either included ('Y') or spanned by another set of fixed effects ('-'). Standard errors are clustered at bank and asset level (security or firm, respectively) and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

APPENDIX

TABLE A1: VARIABLE DEFINITION

Variable name	Definition
Log(securities holdings)	Logarithm of nominal holdings of security s by bank b at month t.
Log(credit)	Logarithm of the loan amount by bank b to firm j during quarter t.
Reviewed	Binary variable that equals the value of one if the bank is a financial institution reviewed as part of the Asset Quality Review (AQR), and zero otherwise.
AQR	Binary variable that equals the value of one for the months October, November, and December 2013, and zero otherwise.
AQR-Compliance	Binary variable that equals the value of one for the months January to June 2014, and zero otherwise.
Post-AQR	Binary variable that equals the value of one for the months July to September 2014, and zero otherwise.
Safe	For securities analysis: binary variable that equals the value of one if the security s has a rating of AAA to AA- in t-1, and zero otherwise. For credit analysis: binary variable that equals the value of one if loan j has a probability of default below the cross-sectional average probability of default of all loans in time t-1.
Trading bank	Binary variable that equals the value of one if bank *b* has membership to the largest fixed-income platform in Germany (Eurex Exchange), and zero otherwise.

TABLE A2: SUMMARY STATISTICS

Panel A: +/- 3 months around AQR announcement	Mean	Std.	Obs.
Securities holdings:			
Log(securities holdings) [in € th.]	11.61	2.87	1,546,778
Securities/TA	0.21	0.13	1,546,778
Safe	0.29	0.45	1,546,778
Reviewed	0.12	0.33	1,546,778
Trading bank	0.10	0.30	1,546,778
AQR	0.50	0.50	1,546,778
Credit:			
Log(credit) [in € th.]	7.73	2.06	166,208
Credit/TA	0.43	0.19	166,208
Safe	0.76	0.42	166,208
Reviewed	0.86	0.35	166,208
Trading bank	0.74	0.44	166,208
AQR	0.50	0.50	166,208

Panel B: +/- 9 months around AQR period	Mean	Std.	Obs.
Securities holdings:			
Log(securities holdings) [in € th.]	11.61	2.89	5,306,169
Securities/TA	0.21	0.13	5,306,169
Safe	0.29	0.45	5,306,169
Reviewed	0.13	0.33	5,306,169
Trading bank	0.10	0.30	5,306,169
AQR	0.15	0.36	5,306,169
AQR-Compliance	0.28	0.45	5,306,169
Post-AQR	0.16	0.37	5,306,169
Credit:			
Log(credit) [in € th.]	7.70	2.09	615,016
Credit/TA	0.44	0.19	615,016
Safe	0.75	0.43	615,016
Reviewed	0.85	0.35	615,016
Trading bank	0.73	0.45	615,016
AQR	0.14	0.35	615,016
AQR-Compliance	0.28	0.45	615,016
Post-AQR	0.13	0.34	615,016

This table reports the summary statistics of the main variables used in the paper. In Panel A, the variables refer to the regressions from Table 1 and 2, respectively, covering the period +/- 3 months before and after the AQR announcement in October 2013, i.e., end of July, August, September, October, November, and December. Panel B reflects the sample for our estimations presented in Table 3 (and 4) using the sample +/- 9 months before and after the AQR period, i.e. from January 2013 to September 2014. 'Log(securities holdings) is the logarithm of the notional security holdings (in EUR thousands) by a bank in a given month. 'Log(credit)' refers the logarithm of the loan amount (in EUR thousands) to a borrower by a bank in a given quarter. Note that our data on securities holdings is available at monthly frequency whereas our data on credit is available at quarterly frequency. 'Safe' for securities measures the percentage share of 'safe' securities to all securities. 'Securities/TA' measures the total investment in securities as a fraction of total assets. 'Safe' for credit measures the percentage share of 'safe' borrowers to all creditors. 'Credit/TA' measures the total loan amount as a fraction of total assets.

TABLE A3: DIALING UP OF SAFE SECURITIES AFTER THE AQR ANNOUNCEMENT

ROBUSTNESS: SEPTEMBER 2013 VS DECEMBER 2013 AND OTHER RISK MEASURES

	Dependent variable: Log(securities holdings)									
Variable:	Safe		High Yield		GIIPS		Long-Term		Long-Term Non-Safe	
	Reviewed vs. largest non-reviewed	Within reviewed banks	Reviewed vs. largest non-reviewed	Within reviewed banks	Reviewed vs. largest non-reviewed	Within reviewed banks	Reviewed vs. largest non-reviewed	Within reviewed banks	Reviewed vs. largest non-reviewed	Within reviewed banks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable *AQR*Reviewed	0.0204**	0.0132*	-0.0660***	-0.0552***	-0.0375***	-0.0194*	-0.0434***	-0.0419***	-0.2590***	-0.3259***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)	(0.06)
Variable *AQR	-0.0072		0.0108		0.0181**		0.0015		-0.0669***	
	(0.01)		(0.01)		(0.01)		(0.01)		(0.01)	
Variable	-0.0132		-0.0335***				-0.3178***		-0.1455	
	(0.05)		(0.01)				(0.08)		(0.11)	
AQR*Reviewed	-0.0388***		-0.0315***		-0.0253***		-0.0262***		-0.0277***	
	(0.01)		(0.01)		(0.00)		(0.00)		(0.00)	
Variable *Reviewed	-0.0005	-0.0138	0.0298	-0.0037			0.1452	-0.1726**	0.3717**	0.2263**
	(0.08)	(0.06)	(0.02)	(0.02)			(0.11)	(0.08)	(0.15)	(0.09)
Security*Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	106,952	63,414	78,526	45,044	106,952	63,414	106,952	63,414	106,952	63,414
R-squared	0.989	0.982	0.988	0.979	0.989	0.982	0.989	0.983	0.989	0.983

This table replicates Table 1, but restricts the sample to September 2013 and December 2013. The dependent variable is the logarithm of securities nominal holdings by each bank b of security s during month t. 'Safe' is a dummy variable that equals the value of one whenever the security has a rating between AAA and AA-, and zero otherwise. 'High Yield' is a dummy variable that equals the value of one whenever the security has a higher yield than the cross-sectional mean of all yields in t-1, and zero otherwise. 'GIIPS' is a dummy variable that equals the value of one whenever the issuer of the security is headquartered in Greece, Ireland, Italy, Portugal, or Spain, and zero otherwise. 'Long-Term' is a dummy variable that equals the value of one whenever the security has a residual maturity of higher than 10 years, and zero otherwise. 'Long-Term Non-Safe' is a dummy variable that equals the value of one whenever the security has a below-investment-grade issuer rating *and* a residual maturity of higher than 10 years, and zero otherwise. 'AQR' is a dummy variable that equals the value of one during the months following the AQR announcement in October 2013 (post), i.e. end of December 2013, and zero before. We classify a bank as 'Reviewed' if it was reviewed under the AQR by the ECB. In columns 2, 4, 6, 8, and 10 we restrict our sample to reviewed banks only, i.e., when 'Reviewed' equals the value of one for all banks. Fixed effects are included ('Y'). The definition of the main variables can be found in Appendix Table A1. A constant is included, but its coefficient is left unreported. Standard errors are clustered at bank and security level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE A4: DIALING UP OF SAFE CREDITORS AFTER THE AQR ANNOUNCEMENT

ROBUSTNESS: OTHER CUT-OFFS

	Dependent variable: Log(credit)							
Variable:	Median		75%		90%		Continuous	
	Reviewed vs. largest non-reviewed	Within reviewed banks	Reviewed vs. largest non-reviewed	Within reviewed banks	Reviewed vs. largest non-reviewed	Within reviewed banks	Reviewed vs. largest non-reviewed	Within reviewed banks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable *AQR*Reviewed	0.0172[a]	0.0248***	0.0231**	0.0262***	0.0279**	0.0287***	0.0393**	0.0447***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Variable *AQR	0.0076		0.0031		0.0008		0.0054	
	(0.01)		(0.01)		(0.01)		(0.01)	
Variable	0.0091		0.0259		0.0329		-0.0137	
	(0.03)		(0.02)		(0.02)		(0.03)	
AQR*Reviewed	-0.0248***		-0.0329***		-0.0401***		-0.0132**	
	(0.00)		(0.00)		(0.01)		(0.00)	
Variable *Reviewed	-0.0135	-0.0044	-0.0575**	-0.0315***	-0.0414	-0.0085	-0.0345	-0.0483*
	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.04)	(0.02)
Firm*Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	161,328	142,436	161,328	142,436	161,328	142,436	161,328	142,436
R-squared	0.978	0.977	0.978	0.977	0.978	0.977	0.978	0.977

This table replicates Table 2, but uses different cut-offs to compute 'safe' creditors. The dependent variable is the logarithm of loan amount by each bank b to borrower j during quarter t in the period September 2013 to December 2013, i.e., +/- three months around the AQR announcement. 'Median' ('75%' and '90%', respectively) is a dummy variable that equals the value of one if loan j has a probability of default (PD) below the cross-sectional median (75th percentile and 90th percentile, respectively) PD of all borrowers' PDs in time t-1. 'Continuous' equals the probability of default (PD) of borrower j in time t-1. For the sake of convenient presentation, we multiplied in columns 7 and 8 each coefficient that involves 'Continuous' with (-1). 'AQR' is a dummy variable that equals the value of one during the months following the AQR announcement in October 2013 (post), i.e. end of December 2013, and zero before. We classify a bank as 'Reviewed' if it was reviewed under the AQR by the ECB. In columns 2, 4, 6, and 8, we restrict our sample to reviewed banks only, i.e., when 'Reviewed' equals the value of one for all banks. Fixed effects are included ('Y'). The definition of the main variables can be found in Appendix Table A1. A constant is included, but its coefficient is left unreported. Standard errors are clustered at bank and firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level; [a]: Significant at 12% level.

TABLE A5: DIALING UP OF SAFE SECURITIES AFTER THE AQR ANNOUNCEMENT

ROBUSTNESS: COMPARING BANKS OF SIMILAR ASSET SIZE

	20bn ≤ total assets≤ 40bn	
	Dependent variable:	
	Log(securities holdings)	Log(credit)
	(1)	(2)
Safe*AQR*Reviewed	0.1124***	0.0484**
	(0.03)	(0.02)
Safe*AQR	-0.0205**	-0.0083
	(0.01)	(0.01)
Safe	0.0032	0.0091
	(0.02)	(0.02)
AQR*Reviewed	-0.1200***	-0.0552***
	(0.02)	(0.02)
Safe*Reviewed	-0.0522	-0.0724
	(0.05)	(0.05)
Security*Bank FE	Y	-
Firm*Bank FE	-	Y
Time FE	Y	Y
Observations	45,647	25,216
R-squared	0.984	0.988

This table replicates column 2 of Table 1 and 2, respectively, but restricts the sample to all banks (both reviewed and non-reviewed) with a total asset size of +/- EUR 10 billion around the EUR 30 billion threshold that the ECB imposed to select the reviewed banks. In column 1 the dependent variable is the logarithm of securities nominal holdings by each bank b of security s during month t in the period July 2013 to December 2013. In column 2 the dependent variable is the logarithm of loan amount by each bank b to borrower j during quarter t in the period July 2013 to December 2013. In column 1 'Safe' is a dummy variable that equals the value of one whenever the security has a rating between AAA and AA-, and zero otherwise. In column 2 'Safe' is a dummy variable that equals the value of one if loan j has a probability of default (PD) below the cross-sectional mean PD of all borrowers' PDs in time t-1. 'AQR' is a dummy variable that equals the value of one during the months following the AQR announcement in October 2013 (post), i.e. end of October, November December 2013, and zero before. Note that our data on securities holdings is available at monthly frequency whereas our data on credit is available at quarterly frequency. We classify a bank as 'Reviewed' if it was reviewed under the AQR by the ECB. Fixed effects are either included ('Y') or spanned by another set of fixed effects ('-'). The definition of the main variables can be found in Appendix Table A1. A constant is included, but its coefficient is left unreported. Standard errors are clustered at bank and asset level (security or firm, respectively) and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE A6: PLACEBO TEST

PLACEBO TEST: 2012 AND 2014

	Reviewed vs. non-reviewed			
Placebo:	*Sept 2012 vs. Dec 2012*		*Sept 2014 vs. Dec 2014*	
	Dependent variable:			
	Log(securities holdings)	Log(credit)	Log(securities holdings)	Log(credit)
	(1)	(2)	(3)	(4)
Safe**Placebo**Reviewed	-0.0080	-0.0031	-0.0031	0.0042
	(0.02)	(0.01)	(0.01)	(0.01)
Safe**Placebo*	Y	Y	Y	Y
Safe	Y	Y	Y	Y
*Placebo**Reviewed	Y	Y	Y	Y
Safe*Reviewed	Y	Y	Y	Y
Security*Bank FE	Y	-	Y	-
Firm*Bank FE	-	Y	-	Y
Time FE	Y	Y	Y	Y
Observations	168,380	190,376	400,972	150,530
R-squared	0.982	0.978	0.997	0.977

This table replicates our estimation for 2012 and 2014, respectively. The dependent variable in columns 1 and 3 is the logarithm of securities nominal holdings by each bank b of security s during month t. The dependent variable in column 2 and 4 is the logarithm of loan amount by each bank b of borrower j during quarter t. Note that our data on securities holdings is available at monthly frequency whereas our data on credit is available at quarterly frequency. 'Placebo' is a dummy variable that equals the value of one for December 2012 (or 2014), and zero otherwise. We classify a bank as 'Reviewed' if it was reviewed under the AQR by the ECB. Fixed effects are either included ('Y') or spanned by another set of fixed effects ('-'). The definition of the main variables can be found in Appendix Table A1. A constant is included, but its coefficient is left unreported. Standard errors are clustered at bank and asset level (security or firm, respectively) and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

Chapter 3

CAPITAL CONTROLS, FOREIGN CAPITAL INFLOWS, AND THE LOCAL CREDIT CYCLE: EVIDENCE FROM THE COLOMBIAN CREDIT REGISTER AND CONTROLS

Joint with Andrea Fabiani, Martha López Piñeros and José-Luis Peydró

XV. INTRODUCTION

The decade following the last Great Financial Crisis of 2007-2008 and the related phenomena of stops and retrenchments of capital flows (Forbes and Warnock, 2012) has seen both academics and policy-makers reconsidering their traditionally pessimistic view on capital controls. An increasingly large body of literature has in fact highlighted the risks and policy trade-offs associated with the exposure to the global financial cycle (Miranda-Agrippino and Rey, 2015) through an open capital account, especially from the perspective of Emerging Economies.

Rapid and large deteriorations of the current account help predict financial crises (Jordà et al., 2011) and other forms of macroeconomic turbulence, such as hyperinflation episodes, foreign debt crises and sovereign default (Reinhart and Reinhart, 2008). Moreover, in the context of Emerging Economies, capital bonanzas are found to precede credit booms (Mendoza and Terrones, 2008), which are the best forecaster of episodes of financial distress (Schularick and Taylor, 2012; Reinhart and Rogoff, 2009; Gourinchas and Obstfeld, 2012). Capital inflows driven largely by short-term investments from abroad raise concerns over potential upcoming sudden stops, with related exacerbation of business cycle fluctuations (Mendoza, 2010).

The implications for macroeconomic policy are, by the same token, non-trivial. Rey (2015, 2016) argues that, by transmitting US monetary policy through movements in assets prices, the global financial cycle inhibits the ability of Emerging Economies to pursue an independent monetary policy. In a similar vein, Bruno and Shin (2014, 2015) provide evidence that US monetary policy propagates around the world by driving cross-border banking flows via variations of the relative value of the US dollar, the denomination currency in the global market for liquidity. Finally, other authors have pointed to the impossibility of achieving simultaneously independent financial policies, openness of the capital account and financial stability in a globalized world (Schoenmaker, 2011, 2013; Obstfeld 2015; Freixas, 2003).

Facing considerations of this nature with the inconclusive evidence on the gains from financial liberalization[56], the IMF has formally rehabilitated capital controls in its own "institutional approach" (International Monetary Fund, 2012; Ostry et al., 2010, 2011), after having supported this policy in selected countries. Measures aimed at slowing down capital inflows and outflows, they claim, can be beneficial when they bring financial distress that cannot be effectively managed through conventional macroeconomic policy. A class of macroeconomic models with financial frictions justifies this approach, whereby borrowing in foreign currency generates pecuniary externalities, since individuals do not internalize the larger losses associated with expanding leverage during a negative aggregate shock (Jeanne and Korinek, 2010; Bianchi, 2011; Korinek, 2017). Under the new paradigm capital controls would therefore act as a macroprudential tool to alleviate macroeconomic volatility and reduce the likelihood of credit crises. But, in practice, how effective are capital controls in curbing capital bonanzas? And, in case of an affirmative answer to the previous question, do economic agents easily replace the forgone foreign debt with domestic lending or are they rather forced to scale down the size of their operations under any dimension?

In this paper, we try to answer all these questions by looking at the case of Colombia between 2006 and the first half of 2008, which is paradigmatic of the problems connected to managing a credit boom while being opened to global financial markets. The annual growth rate of the Colombian economy has been constantly above 5% during this period, fueled by a dramatic

[56] For a comprehensive review on the costs and benefits of financial globalization, see Kose et al. (2006).

expansion of commercial credit. The central bank initially reacted by raising the policy rate, in an attempt to cool the economy down. However, this intervention not only fell on its stated goals, but likely contributed to the ongoing accumulation of external imbalances by further igniting capital inflows and currency appreciation. Finally, recognizing the exhausted room for standard monetary policy interventions, the Central Bank introduced a package of macroprudential measures in May of 2007. Among others, on the internal side, reserve requirements against savings deposits were raised for domestic banks and a counter-cyclical buffer was effectively put in place[57]. To slow down the large capital inflows, on the 6th of May capital controls were introduced in the form of a 6-month 40% Unremunerated Reserve Requirement (URR) on portfolio inflows. To avoid circumventions of the URR by financially complex companies, foreign currency derivatives exposure was limited to 500%. Importantly, all inflows appearing as a domestic bank's liability was exempted from this intervention. Eventually, all measures were eliminated in October of 2008, amid signs that the credit boom was indeed decelerating and concerns related to the unraveling of the Great Financial Crisis beyond the US border.

We exploit the fact that foreign currency loans in Colombia can be obtained in two ways. Typically, firms ask a local Colombian financial intermediary (called *Intermediarios del Mercado Cambiario* or IMCs) to intermediate the loan between the firm and the foreign bank providing the FX debt. Alternatively, a firm may finance the loan directly with the foreign bank (labeled *Entidades Financieras del Exterior* or EFEs) without the intermediation of the IMC. The former is referred throughout the paper as IMC debt while the latter is referred to as EFE debt. Both types of foreign debt were subject to the capital controls through a 40% URR.

We perform the analysis in three main steps. First, we check that the URR indeed reduced firms' reliance on foreign bank-debt[58]. We do so by focusing on the sample of companies active in the foreign bank-debt market before the implementation of the URR and by running regressions of foreign-bank debt flows (rescaled by asset size) against a policy dummy. The model is augmented with a vector of lagged firm-level and macroeconomic controls and seasonal and firm fixed effects. On average, the URR reduced FX bank-debt *flows* by 86%,

[57] For a detailed account of the macroprudential measures targeting domestic banks, and for an assessment of their effectiveness, see Gómez et al. (2017).
[58] We do not observe corporate bonds issuance. However, given the very low capitalization of Colombian companies, this is less than a concern. For the very large majority of the companies in our sample, bank debt - either foreign or domestic - is the main source of external finance [to be documented].

which represents roughly 0.7 percentage points of total assets. We then dig further into this result and find that the main source of firm heterogeneity which drives the reduction in foreign debt is the pre-policy exposure to this form of external finance. We exploit the heterogeneity in pre-policy foreign debt flows over total assets - and interact it with the policy dummy. We augment the model with industry*time fixed effects to account for industry-wide time varying shocks using the fine 4-digit disaggregation of companies into more than 200 industries provided by the National Administrative Department of Statistics (DANE). The regression results suggest that a 1 standard deviation increase in the pre-policy exposure to foreign bank-debt prompts an additional average reduction of 2 percentage point of foreign bank-debt flows. In other words, companies that used to rely heavily on foreign bank-debt were those which cut this source of financing the most.

Our analysis of the interaction between capital inflows and the local credit cycle starts by investigating whether companies hit by the URR resorted to domestic bank-debt relatively more than in the pre-policy period. We adapt the Becker and Ivashina (2014) identification strategy to the corporate choice between domestic and foreign bank-debt. The matching of credit registry data and firm-level information on foreign bank-debt inflows allows us to sort firm-quarter pairs according to whether a company issued only domestic or foreign bank debt, or both. The latter pairs are excluded from the analysis, so that we ultimately focus on quarters with positive demand for external finance and where only one of the two forms of debt was issued. We then run a linear probability model where a 0-1 dummy for external-domestic debt issuance, respectively, is regressed against the interaction between the URR time-dummy and the usual proxy for foreign bank-debt exposure. Again, the model is saturated with a vector of lagged firm-level controls, firm and industry*time fixed effects. The resulting coefficients indicate that firms highly exposed to the URR switched more drastically to domestic bank-debt. In fact, a one standard deviation increase in the pre-policy exposure to foreign bank-debt raises the likelihood of issuing domestic debt (relative to that of issuing foreign bank debt) by 6.3 percentage points.

The combination of results presented so far does not tell us anything about the performance of companies hit by the URR in the domestic bank-debt market. Here, the natural comparison is with firms that borrowed only domestically. As a matter of fact, their relation to Colombian banks was independent of the URR, as the capital controls did not limit Colombian banks' ability to borrow from abroad. We exploit the fact that some firms which were active borrowed from abroad solely via IMCs, others directly via EFEs, and the rest used both avenues for foreign currency debt. Formally, we regress the log of the firm-bank stock of debt against the interaction of the policy dummy with a categorical variable indicating whether a company obtained FX debt through IMCs or EFEs only, or both . The usual lagged firm controls are included, as well as a set of firm*bank, industry*time and bank*time fixed effects. The inclusion of bank*time fixed effects shut down any layer of observed and unobserved (constant and time-varying) bank-level heterogeneity, so that the macroprudential policies adopted internally - reserve requirements and counter-cyclical buffer - are completely controlled for. Moreover, we do not lose track of potential channels of transmission of the URR, as banks liabilities were excluded from the policy. We find that firms borrowing in FX from Colombian intermediaries only received better lending conditions through larger loan quantities and lower interest rates relative to firms which were inactive in the FX debt market pre-policy. Firms which used both IMC and EFE for foreign debt faired no different, while firms which relied on solely EFE debt were penalized through lower quantities and higher rates relative to inactive firms. When we condition on firms active in the FX debt market pre-policy, we find a similar ordering. Firms whose foreign debt came only through direct financing received 14% lower domestic loans and 0.75% higher interest rates relative to those firms which relied solely on their IMCs for FX debt. To shed light on the types of firms which were better able to substitute foreign credit for domestic credit we exploit two pre-policy firm characteristics. First, as Colombia is heavily dependent on exports for their economy, the policy provided leeway for exporters through a 11% URR in lieu of the 40% rate applied to the typical firm borrowing from abroad. Consistent with such policy design, we find that among EFE companies, exporters were less penalized. Second, we test whether banking relationships matter for the extent of the substitution of FX debt with peso debt. We do so by generating a firm-bank dummy which equals 1 if firm *f* borrowed in foreign currency from domestic intermediary *b* pre-policy. We find that the bank intermediating the FX loan to firm *f* pre-policy was more likely to substitute for peso loans at lower interest rates, and these results are strengthened by higher pre-policy FX lending through IMCs.

The combined reading of results from firm-level inflows regressions and loan-level regressions on domestic credit suggests that companies borrowing directly from abroad were those which had to reduce total debt issuance after controls were introduced. In line with this argument, our firm-level analysis on the real effects of the Colombian URR reveals that such companies had to scale down their imports activity, with reductions proportional to the pre-policy exposure in

EFE market. Also, they are the only non-financial corporations (NFCs) reducing imports relatively to NFCs borrowing only in pesos before the policy. The fact that companies borrowing in FX form Colombian IMCs did not have to scale down their operations is further corroboration that substitution between FX debt and peso debt for these types of firms allowed them to continue their operations as they did pre-policy.

In the final step of the paper, we test an important benefit of capital controls: insulation from the Global Financial Cycle. Several recent contributions to the understanding of capital controls suggest co-movements between the VIX and capital inflows (Forbes and Warnock, 2012; Bruno and Shin, 2014, 2015; Miranda-Agrippino and Rey, 2015, 2016). Prior to the introduction of capital controls, we find consistent evidence that IMC debt flows increased following declines in the level of the VIX. We use data at the firm-bank-currency-quarter level and regress loan amounts on a dummy for FX debt interacted with the lagged level of the VIX, and then interact this variable with a dummy for the introduction of capital controls to see how the response changed post policy. We include bank*time, firm*bank and firm*time fixed effects, along with interactions with the lagged interbank rate. Our results suggest prior to the capital controls, foreign currency denominated debt within Colombia increased in reaction to declines in the VIX. In other words, global financial conditions, as proxied by the VIX, seem to drive the extent of dollarization of domestic credit. Nonetheless, our results suggest that this link is broken after the introduction of capital controls, thereby offering empirical evidence of insulation from the Global Financial Cycle. We run similar regressions using flow data of IMC FX debt and find similar effects.

Our paper speaks to several strands of literature. First, our results contribute to the literature assessing the effectiveness of capital controls. Most of these articles rely on cross-country macroeconomic data and seem to suggest that capital controls do alter the composition of capital flows towards safer securities and enhance national monetary policy autonomy from the US (Magud and Reinhart, 2006; Magud et al., 2011). Similar effects are described by the few studies on the Colombian URR of 2007 (Baba and Kokenye, 2011; Clements and Kamil, 2009). In general, however, macro-data-based evidence is thought to be largely inconclusive (Blanchard et al., 2013), either because time-series studies are based on aggregates which do not consider the specifics of the capital controls provision or because, most importantly, in cross-country settings selection into capital controls is clearly non-random. A recent attempt to overcome this problem is represented by Forbes et al. (2015), who apply a propensity score matching algorithm to predict capital controls in a cross-country setting and find that capital controls perform better in slowing down credit growth rather than exchange rate pressures and credit inflows and outflows. Our focus on micro-data allows us to overcome the issue of relying on aggregate measures of liabilities targeted by capital controls. In fact, the URR under scrutiny exempted many securities within the class of portfolio inflows, including for instance foreign bank-debt of size smaller than US$ 10000 and/or with shorter maturity than 1 year. Thanks to the granularity of our dataset, we can exclude liabilities based on the specifics of the Colombian URR and avoid attributing improper effects to such policy. Also, micro-data allows us to dissect the channels of transmission of capital controls. The evidence that capital controls would slow down domestic aggregate credit growth, in fact, does not tell us whether this is due to the reduced cross-border banking flows, for instance, in the spirit of Bruno and Shin (2014), or to other mechanisms. In fact, we show that one possible channel of transmission is represented by complementarities between foreign and domestic lending, a key innovative result of this paper that we comment below.

Evidently, our article is not the first to analyze capital controls using micro-data. The traditional focus has rested on the negative impact of controls on financially constrained companies, either in terms of augmented sensitivity of investments to cash flows and cost of capital (Forbes 2007a,b; Harrison et al., 2004) or in terms of reduced stock returns (Alfaro et al., 2017). In all these papers the sample of analysis is restricted to listed companies, a restriction that we do not need to apply and would make our analysis highly non-representative of the Colombian market. Moreover, we are the first to use firm-specific measures of exposure to the URR, whereas the yet cited studies simply compare total debt issuance before and after capital controls, with a clear measurement problem of the heterogeneity of the intensity of the treatment. Indeed, our results show that this is very important in predicting the firm-level debt reduction linked to the URR irrespectively of other characteristics.

Our investigation on the relation between domestic and foreign credit supply naturally links our work to the literature on the bank lending channel. First, we extend the Kashyap et al. (1993) and Becker and Ivashina (2014) result that companies issue relatively more bonds than bank debt when credit supply tightens to the foreign/domestic domain, by showing that the issuance of domestic debt becomes relatively more frequent than that of foreign debt under capital controls. In this sense, our work provides a causal bridge between the literature on bank lending and Allayannis et al. (2003), who show a positive correlation between foreign currency debt issuance and home-abroad interest rate differentials.

A key further contribution of our paper is to provide evidence of potential complementarities between foreign and domestic lending. In fact, the evidence that companies borrowing in FX directly from abroad were penalized *vis-a-vis* other domestic companies can be interpreted in light of a recent class of models (Bebchuck and Goldstein, 2011; Vives, 2014) which highlight the possibility that lenders might coordinate on an equilibrium where they reduce credit in reaction to an initial cut in credit by a different group of intermediaries. Indeed, Chen et al. (2010) and Hertzberg et al. (2010) provide empirical support for this hypothesis in the context of mutual funds and domestic lending, respectively. Nonetheless, we are the first to provide evidence in favor of complementarities in lending between national and foreign financial institutions. From a policy standpoint, this highlights one additional channel through which capital controls can limit credit growth. Likewise, the result that the penalization for EFE companies is milder in the case that they already borrowed in FX from a Colombian bank tells us that the costs of the policy in terms of domestic market performance are going to be shaped by relationship lending (Sharpe, 1990; Rajan, 1992; Berger and Udell, 1995) and that the proposed mechanism is likely to be more relevant in financial systems where domestic institutions are relatively less involved in FX lending.

With regards to real effects, our result that the overall reduction in debt issuance following the URR triggered a reduction in imports for EFE firms connects the empirical literature on trade to that of lending in correspondence of financial shocks (Paravisini et al., 2014; Amiti and Weinstein, 2011; Chor and Manova, 2012) and to the finding in Alfaro and Hammel (2007) that stock market liberalizations cause firms to import more capital goods from abroad. Our contribution here is that we are the first to document the negative impact of capital controls on imports through a worsening of firms' ability to borrow from both domestic and global bank-lending markets.

Lastly, our paper provides evidence of an important benefit to shutting down capital inflows: insulation from the Global Financial Cycle. Empirical evidence has suggested co-movements between the VIX and capital inflows (Forbes and Warnock, 2012; Bruno and Shin, 2014, 2015; Miranda-Agrippino and Rey, 2015). Rey (2015) illustrates the tradeoffs of exposure to the global financial cycle. With a low VIX, risk appetite increases leading to credit and asset price growths in emerging economies. However, retraction of capital flows from emerging economies can lead to severe retrenchments. We find that only after capital controls were introduced in Colombia did the VIX cease to influence the stock of domestic credit and flows of foreign bank debt in foreign currency.

The rest of the paper is articulated as follows. In Section XVI, we discuss the specifics of the capital controls implementation in Colombia in 2007. In section XVII, we present data and summary statistics. In section XVIII, we present results. The paper is closed with some conclusive thoughts.

XVI. THE COLOMBIAN EXPERIENCE 2006-2008

Beginning in early 2006, Colombia experienced a surge in domestic and foreign credit. Figure 1 illustrates rising commercial credit alongside strong aggregate growth in GDP. As inflationary pressures spread throughout the economy, the central bank raised interest rates from 6-8% in the span of one year. The sluggish monetary policy sparked a further appreciation in the currency as capital flows from abroad poured into the country, as seen in Figure 2. High interest rates alongside open borders made investments from abroad into Colombia a highly lucrative option with inflows surpassing outflows beginning in the third quarter of 2006.

To curb the credit growth from abroad and with the ineffectiveness of monetary policy, the central bank introduced a series of macroprudential measures in May 2007. First, the central bank placed capital controls in the form of Unremunerated Reserve Requirements (URR) on portfolio inflows. Upon disbursement of the foreign credit to the Colombia firm, 40% of the loan amount was placed in the central bank and released after 6 months. Early withdrawal of the URR was possible with penalties[59]. Exemptions to the capital controls included any Foreign Direct Investments (FDI), initial public offerings, and loans of less than $10,000 or with a maturity of less than 6 months used to finance imports. Importantly, bank liabilities were exempted from the capital controls. Secondly, to avoid circumventions by firms of the capital controls, limits were placed on foreign currency derivative exposures to 500% of the firm's equity. Third, the central bank increased the reserve requirements against savings accounts from 6% to 8.3%[60]. In the appendix, we provide context for the rationale of capital controls along

[59] For example, withdrawing the reserves after only 1 month was associated with a 9.4% fee. A withdrawal after 5 months led to a 1.6% fee.
[60] Checking deposit reserve requirements were moved from 13 to 8.3%.

with several further details of the implementation.

The capital controls and reserve requirements domestically were enforced immediately in May 2007 and eliminated by October 2008.

XVII. DATA

We have access to the micro data provided by the *Superintendencia Financiera de Colombia* from 2005 to 2008[61]. The data comprises predominantly of the domestic credit register which contains the outstanding debt (stock) of peso loans provided by a bank to a firm on a quarterly basis. Secondly, we obtain the firm-level FX debt flows from foreign banks (EFE debt) as well as FX debt intermediated by domestic banks (IMC debt) aggregated as a single variable at the firm-quarter level.

We complement the credit register with these firm-level foreign debt exposures. Third, we obtain balance sheet variables for firms, including total assets and return on assets (ROA) on a yearly basis and exports and imports on a quarterly basis. For each firm, we also retrieve information on their four-digit Clasificación Industrial Internacional Uniforme (CIIU) industry code. For domestic banks, we use balance sheet variables, such as total checking, savings and assets. We merge the balance sheet data with the credit register and foreign debt flows.

We trim the data as follows. For one, we restrict our sample to include firms for which we have observations on their balance sheet characteristics and CIIU industry code. Next, our sample of firms active in the foreign credit market (EFE and IMC firms) includes only those firms which are also present in the domestic credit register. That is, active firms refer to those which obtain FX debt either directly from an EFE institution or intermediated via an IMC and domestically with Colombian banks. Next, we exclude foreign debt flows which were exempted from the capital controls, in particular loans for pre-financing with balances of less than $10,000. Lastly, we focus our attention to commercial credit, both abroad and domestically. To mitigate the effect of severe outliers found in the data, bank-level, firm-level and loan-level data are winsorized at the 1% and 99% level, while export and import data is winsorized at the 5% and 95% level. Our final sample consists of 6,666 firms, 2,941 of which are active in the market for

[61] While our data runs until 2008 Q4, we intentionally omit observations from Q3 and Q4 of 2008 to not confound the estimation with the global financial crisis initiated in September 2008.

FX credit prior to the capital controls, and 14 banks in Colombia providing loans domestically. The sample of loans in our dataset account for roughly 35% of the outstanding commercial debt in Colombia in 2007.

Table 1 provides summary statistics of the variables used in this paper. We show the mean, median and standard deviation for active firms and inactive firms prior to the enactment of capital controls in May 2007. The sample of all firms contain an average Log(Assets) of 8.25 million of Colombian pesos. The average ROA is nearly 4% and the median firm is a non-exporter and non-importer. Among observables, we see the group of active and inactive firms exhibit noticeable differences, as firms which obtain foreign debt are larger and tend to export and import more. Bank characteristics are relatively similar among the active and inactive groups. Active firms receive larger peso loans, with loans averaging 5.33 million pesos for active and 4.33 for inactive, while interest rates are larger for firms which only borrow from the domestic credit market.

We partition active firms depending on the way in which they obtain foreign debt to obtain more comparable comparison groups. In Table 2, we provide similar summary statistics depending if the firm obtained FX debt via Colombian intermediaries (IMC Only firms), through both Colombian intermediaries and directly via foreign banks abroad (Both IMC and EFE firms), or solely through foreign banks abroad (EFE Only firms). Firms in the first group are called IMC Only firms, while those in the second group we label Both IMC and EFE firms, and the last group are referred to as EFE Only firms. While differences among observables are apparent, the firms are slightly better balanced as all firms are relatively large and active in exports and imports. Nonetheless, considering noticeable differences along these dimensions, all regressions will control for these variables as well as an interaction term between each variable and a time dummy for the introduction of capital controls.

XVIII. EMPIRICAL STRATEGY AND RESULTS

Our empirical strategy begins with analyzing how capital controls affected foreign debt flows, then illustrating the interaction between capital controls and domestic credit, and lastly providing evidence of the policy's real effects on firms imports and insulation of the global financial cycle.

XVIII.1 FOREIGN DEBT FLOWS

We begin our analysis by documenting the reduction in foreign debt flows resulting from the URR introduced in May 2007. Figure 1 documents the average foreign debt flows summed across IMC and EFE debt, over total assets, after controlling for quarterly trends. Following the first quarter of 2006, firms active in the foreign debt market received larger inflows of credit. Beginning in the second quarter of 2007, when the capital controls were put in place, average foreign debt flows dropped.

We test the statistical significance of the relationship between the introduction of capital controls and lower foreign debt flows econometrically using the following specification:

$$\frac{FXDebt}{Assets}_{f,t} = \beta_1 CapitalControls_t + controls_{f,t-1} + \delta_s + \delta_f + \varepsilon_{f,t}$$

where $\frac{FXDebt}{Assets}_{f,t}$ is the amount of foreign debt flows of firm *f* at quarter *q* rescaled by total assets, $CapitalControls_t$ is a dummy equal to one after and including 2007 Q2, and $controls_{f,t-1}$ is a vector of controls including i) firm characteristics: lagged log assets, ROA, log exports, log imports, and the firms average bank's savings to checking ratio and ii) macroeconomic variables: interest rate, inflation rate, GDP growth and VIX at quarter *t-1*. Lastly, we complement the model with seasonal fixed effects (quarter of year dummies) and firm fixed effects to control for observed and unobserved time-invariant firm characteristics. We estimate the regression quarterly from 2006 Q1 to 2008 Q2.

Results are reported in Table 3. We observe that the timing of the capital controls led to a reduction in total foreign debt flows, as seen in column (1). In columns (2) and (3) we separate the dependent variable by the type of foreign debt, either EFE or IMC debt. We see the reduction in total debt flows is apparent in IMC flows but not in EFE flows, as seen by the negative and significant coefficient on the time trend in column (3). On average, the introduction of the URR reduced total foreign bank-debt flows, scaled by total assets, by nearly 0.7 percentage points. This translates to roughly an 86% reduction in foreign debt flows.[62]

To better understand which firms experienced a larger reduction in their foreign debt flows, we allow the coefficient β_1 to vary depending on the pre-policy foreign debt exposure of firms. We estimate the model:

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[62] 86% corresponds to the coefficient of $CapitalControls_t$ when replacing the left-hand variable of (1) with $Log(1 + FXDebt_{f,t})$ Results are reported in table A.1 in Appendix 2.

$$\frac{FXDebt}{Assets}_{f,t} = \beta_1 CapitalControls_t * \frac{FXDebt}{Assets}_{f,pre} + (\beta_2 + \beta_3 CapitalControls_t) * controls_{f,t-1} + \delta_{ind,t} + \delta_f + \varepsilon_{f,t}$$

where $\frac{FXDebt}{Assets}_{f,pre}$ is the average foreign debt of firm *f* prior to the introduction of capital controls. To control for relevant industry level characteristics each quarter, such as industry-wide demand, we introduce industry*time fixed effects, $\delta_{ind,t}$. Additionally, as firm characteristics changed following the introduction of the policies, which may be associated with pre-policy foreign debt exposure, we include time varying controls pre and post 2007 Q2. Column (1) of Table 4 shows that an increase in pre-policy foreign bank-debt flows is associated with a larger reduction in bank-debt flows over total assets following the URR introduction. Across both types of debt, IMC and EFE, larger reliance on foreign bank-debt pre-policy led to larger reductions post-policy. Importantly, controlling for time-varying industry variables through industry*time fixed effects do not remove economic nor statistical significance, suggesting the reduction of foreign debt inflows following the policy introduction are orthogonal to industry-wide factors.

XVIII.2 Substitution from Foreign to Domestic Bank Debt

In this section, we illustrate how capital inflows interact with the local credit cycle. We begin by assessing whether domestic debt became more prevalent in the post policy period. To help shed light on the choice of debt, we employ the Becker and Ivashina (2014) identification strategy to stratify the sample into three groups: i) firms with domestic but no foreign bank debt ii) firms with foreign but no domestic bank debt iii) firms with both domestic and foreign bank debt. Our analysis uses only firms pertaining to i) and ii), as we hope to comment on which firms chose domestic debt and which firms chose foreign debt. Econometrically, we test this in the following framework:

$$Type_{f,t} = \beta_1 CapitalControls_t * \frac{FXDebt}{Assets}_{f,pre} + (\beta_2 + \beta_3 CapitalControls_t) * controls_{f,t-1} + \delta_{ind,t} + \delta_f + \varepsilon_{f,t}$$

with $Type_{f,t}$ equal to 1 if a firm issued solely domestic debt in quarter *t* and 0 if solely foreign debt was issued by the firm. The results are shown in Table 5. Column (1) shows that firms which relied more on foreign debt were more likely to switch to domestic peso-denominated debt. In columns (1) and (2) we see that the results hold for both IMC and EFE debt. A one standard deviation increase in total FX debt pre-policy (0.04) led to an 8% higher likelihood of moving to domestic debt, conditional on obtaining debt. The effect is robust to various specifications, most importantly the inclusion of industry*time fixed effects.

XVIII.3 DOMESTIC CREDIT

To investigate the extent to which active firms could substitute their foreign capital inflows with domestic credit we now turn to the credit register data. As the domestic credit market experienced large credit growths, we compare firms active in the foreign debt market with those firms which obtained debt solely from domestic banks. The credit register data allows us to observe a firms borrowing behavior at the loan level, hence the ability to saturate regression models with appropriate fixed effects. Furthermore, as we know the avenue in which a firm obtained foreign debt, we separate active firms into three groups. We refer to IMC Only firms as firms which relied solely on domestic banks to intermediate any debt from abroad. We use the term EFE Only for those firms which directly contacted themselves the bank outside of Colombia to service their foreign debt. Lastly, we call firms using both IMC and EFE debt as Both firms.

Our analysis using the domestic credit register begins by comparing IMC Only, Both and EFE Only firms to their inactive counterparts, that is firms which never took out foreign debt. The following specification allows us to assess differences in credit outcomes among the different groups of firms:

$$Loan_{f,b,t} = \beta_1 CapitalControls_t * OnlyIMC_{f,pre} + \beta_1 CapitalControls_t * Both_{f,pre} + \beta_1 CapitalControls_t * OnlyEFE_{f,pre} + (\beta_2 + \beta_3 CapitalControls_t) * controls_{f,t-1} + \delta_{ind,t} + \delta_{f,b} + \delta_{b,t} + \varepsilon_{f,b,t}$$

where $Loan_{f,b,t}$ represents the loan amount of firm f from bank b at quarter t. $OnlyIMC_{f,pre}$ is a dummy equal to 1 if the firm only intermediated foreign debt via IMCs prior to the policy enactment in May 2007. $OnlyEFE_{f,pre}$ is a dummy equal to 1 if the firm relied on direct financing from foreign banks for their FX debt. $Both_{f,pre}$ is a dummy equal to 1 if the firm used both EFE and IMC debt pre-policy. As before, to control for industry-wide demand varying over time, we include industry*time fixed effects $\delta_{ind,t}$. Similarly, we include a vector of firm controls including lagged size, ROA, exports and imports, along with their interaction with the $CapitalControls_t$ dummy variable. As the national authorities enforced stricter domestic reserve requirements of savings accounts for domestic banks, it is important to control for bank characteristics which vary over time in our sample. Hence, we include bank*time fixed effects, $\delta_{b,t}$, to shut down the channel of policies affecting domestic banks and, more generally, control for time-varying characteristics of the banks. Lastly, we include bank*firm fixed effects to help control for unobserved bank-firm relationship variables.

Table 6 shows the credit outcomes comparing active with inactive firms. In the first row, we see upon the inclusion of both firm*bank fixed effects and firm controls in column (3), domestic credit fell on average after the macroprudential policies were introduced. In columns (4)-(5) we include bank*time and industry*time fixed effects and observe IMC Only firms faring better off than inactive firms with 7% larger loan amounts following the capital controls. EFE Only firms do not differ statistically at the 5% level, however the negative coefficient suggests these firms received roughly 7% less domestic credit than their inactive counterparts. Both firms do not exhibit any economic nor statistical differences. In column (6) we include further loan-level controls including the maturity and a dummy variable for whether the loan is collaterized and see our results still hold. Table 7 repeats the analysis replacing the dependent variable with the interest rate of the loan. While still identifying the policy time dummy variable in column (3), we observe that while loan quantities decreased, interest rates experienced a jump of 6.7% unconditionally following the capital controls. Furthermore, as is evident in the most saturated specification in column (6), IMC Only firms received lower interest rates relative to inactive firms. While insignificant, the coefficient on EFE Only firms suggests slight penalization of firms obtaining foreign credit via direct financing through larger interest rates. Taken together, Tables 6 and 7 suggest not all firms active in the foreign debt market pre-policy were penalized, with firms relying only on IMCs to service their FX debt faring better off with larger loan quantities and lower interest rates compared to inactive firms.

We produce a similar analysis within active firms, comparing IMC Only firms to Both and EFE Only firms to shed light on who was better able to substitute foreign currency debt for domestic credit. Table 2 suggests these three groups are more comparable as they appear larger and more active in exporting and importing relative to inactive firms. We first test for any noticeable differences in loan amounts within active firms in Table 8. In the strictest specification in column (6), we see that EFE Only firms received 14% less lending than IMC Only firms, while firms with both IMC and EFE bank debt saw nearly 8% less credit. Table 9 similarly shows results for interest rates, and we observe a similar ordering. Firms with both IMC and EFE debt received 31 basis point increases on interest rates, while EFE Only firms were penalized more with 76 basis point increases. Results survive the inclusion of the complete set of fixed effects and firm and loan controls. Tables 8 and 9 illustrate differences in credit outcomes among active firms, with banks penalizing firms which solely relied on foreign banks for FX debt and favoring those firms which had their loans intermediated by them.

As Colombia's economy is heavily dependent on exporting, the policy introduced lower URR rates for exporters. While all other firms paid 40% URR for 6 months on foreign debt, exporters only needed to deposit 11% of the loan amount as reserves. Previous results suggest EFE Only firms were heavily penalized in favor of other firms. We hypothesize that firms heavily reliant on exports were penalized less, as their activities were less impaired through capital controls. We replicate the previous domestic credit regressions with additional interactions for the intensity of exporting activity pre-policy of firm *f*, which we proxy with total exports the quarter prior to the capital controls in 2007Q1 normalized by total assets pre-policy. Table 10 reports the results for loans while Table 11 repeats the analysis for interest rates. In column (1), we compare active firms and inactive firms. We find that relative to inactive firms, EFE Only firms received 8% less credit and 0.34 higher spreads on interest rates. However, the triple interaction on $\text{CapitalControls}_t * \text{OnlyEFE}_{prepolicy,f} * \text{Variable}_{prepolicy,f}$ shows this penalization is attenuated with higher exporting reliance. In column (2) we see that compared to IMC Only firms, EFE Only firms received 17% less credit and 86 basis point increases in interest rates, with lower penalizations as well for EFE Only firms with larger exporting activity pre-policy. In columns (3) and (4) we measure the effect of importing activities on this penalization both relative to inactive firms (column (4)) and within active firms (column (3)). While effects are insignificant, we see coefficients with economic significance as higher import reliance pre-policy led to higher credit cutbacks and interest rates. Firms which relied more on imports need foreign currency to purchase imports from abroad, hence capital controls on foreign currency debt would impair these firm's activities more and corroborates the penalization we find in columns (3) and (4). Lastly, in columns (5) and (6) we measure the penalization depending on the net exporting activity pre-policy, which we measure as exports less imports in 2007Q1 rescaled by total assets. Firms which were larger net exports were penalized less relative to both inactive firms as well as IMC Only firms.

Next, we assess the extent to which banking relations helped mitigate the frictions arising from substituting foreign with domestic debt. A natural set of firms to study would be IMC firms. These types of firms had already established a banking relationship with a domestic Colombian bank, the intermediary which serviced their foreign debt. We first test whether firms with higher pre-policy IMC debt received better credit outcomes following the introduction of capital controls. We run the following specification:

$$Loan_{f,b,t} = \beta_1 CapitalControls_t * \frac{FXDebt}{Assets}_{f,pre} + (\beta_2 + \beta_3 CapitalControls_t) * controls_{f,t-1} + \delta_{ind,t} + \delta_{f,b} + \delta_{b,t} + \varepsilon_{f,b,t}$$

$\frac{FXDebt}{Assets}_{f,pre}$ is the average foreign debt of firm *f* prior to the capital controls. As before, we include policy-varying firm controls as well as industry*time, firm*bank, and bank*time fixed effects. The estimations are shown in Tables 12 for domestic loan amounts. In column (1), we find that higher reliance of foreign credit pre-policy led to negligible changes in loan amounts after the policy was introduced. Upon conditioning the sample of firms to only those which borrowed IMC debt prior to the capital controls in 2007Q2 in column (2) and replacing $\frac{FXDebt}{Assets}_{f,pre}$ with $\frac{IMCDebt}{Assets}_{f,pre}$, the amount of FX debt intermediated via IMCs, we find that banks on average lent more to firms which had higher amounts of IMC debt pre-policy. We find higher pre-policy EFE debt did not significantly reduce peso debt for EFE firms, however the negative coefficient suggests lending decreased on average. Table 13 displays similar results for interest rates. Firms which borrowed any form of IMC debt received less penalization through decreased interest rates.

Next, considering IMC firms were less penalized than their EFE counterparts, we test if IMC firms were able to use the IMC which serviced their foreign debt to provide them with peso loans. The hypothesis builds off the high costs of establishing new bank-firm relationships, with existing relationships performing better than firms who must find new banks to supply credit. We use the following specification to test this hypothesis:

$$Loan_{f,b,t} = \beta_1 CapitalControls_t * \frac{IMCDebt}{Assets}_{f,pre} * IMCBank_{f,b} + \delta_{f,t} + \delta_{f,b} + \delta_{b,t} + \varepsilon_{f,b,t}$$

where $IMCBank_{f,b}$ is a dummy variable equal to 1 if bank *b* was a provider of IMC debt to firm *f* at any point before the policy. Through this specification we can augment the model with firm*time fixed effects and fully capture time-varying demand for credit at the firm level. As before, we include firm*bank and bank*time fixed effects. Results are shown in Table 14. Column (1) reports estimations with firm*bank and policy varying firm controls. The positive and significant coefficient on the triple interaction suggests firms with higher amounts of pre-policy IMC debt received larger loan quantities from the bank which serviced their FX loan pre-policy. In column (2) we include bank*time fixed effects and in column (3) we include industry*time fixed effect to find similar statistical significance of the triple interaction. In column (4), we control for time-varying firm level demand through firm*time fixed effects and see estimates of the strictest regression. The coefficient on $CapitalControls_t * IMCBank_{f,b}$ suggests a firm received 10% more domestic debt from their IMC bank than other banks within Colombia. Furthermore, among the banks clients, a firm with one standard deviation higher

IMC debt pre-policy received roughly 12% more credit (0.02*5.9157). In Table 15 we see results replacing the dependent variable with the interest rate at the loan-level. IMC banks passed along 58 basis point increases in interest rates, however the effects from larger pre-policy IMC debt is statistically insignificant.

Our results using the credit register establish several insights into the interaction between foreign debt and domestic credit. First, we find EFE firms, that is those which borrowed directly from abroad without the use of domestic intermediaries, received similar credit conditions compared to inactive firms, while firms using IMCs obtained larger loan amounts and lower interest rates than inactive firms. Within those firms that obtained foreign currency debt pre-policy, we find that banks preferred IMC firms to EFE firms. EFE firms which were larger exporters and net exporters were able to mitigate the penalization after the capital controls. IMC firms were more likely to receive from the bank which serviced their foreign currency loan from abroad, suggesting benefits arising from existing banking relationships.

XVIII.4 Real Effects

In this section, we provide evidence of real effects associated with the introduction of capital controls. In the previous section, we find EFE Only firms were penalized through credit cutbacks. Therefore, we expect these firms whose credit from abroad was cut-off after the capital controls, and who were unable to substitute for peso denominated debt, were more likely to cutback operations. We test this assertion by assessing the impact of imports and exports on the type of pre-policy foreign credit obtained by the firm:

$$\log(Y)_{f,t} = \beta_1 CapitalControls_t * OnlyIMC_{f,pre} + \beta_1 CapitalControls_t * Both_{f,pre} + \beta_1 CapitalControls_t * OnlyEFE_{f,pre} + (\beta_2 + \beta_3 CapitalControls_t) * controls_{f,t-1} + \delta_{ind,t} + \varepsilon_{f,t}$$

where $\log(Y)_{f,t}$ is the logarithm of imports or exports of firm *f* at quarter *q*. As in the credit register section, we interact the policy time dummy with dummy variables depending on if the firm obtained foreign currency loans directly from abroad (EFE Only), through only domestic intermediaries (IMC Only) or through both EFE and IMCs (Both). We include policy-varying lagged firm controls as well as industry*time fixed effects.

In Table 16, we estimate differences in imports among the three types of active firms before and after the policy introduction. Column (1) shows results with no controls or fixed effects included. Firms which relied solely on direct financing from abroad experienced 21% lower imports to inactive firms. This result survives the inclusion of firm controls (column (2)), bank controls (column (3)), firm fixed effects, (column (4)), and industry*time fixed effects (column

(5)). The strictest specification in column (5) suggests firms with both IMC and EFE debt experienced 13% fewer imports to inactive firms. In Table 17, we repeat the analysis with exports. None of the active firms appeared to be affected through their exporting activities relative to inactive firms. The policy provided leeway regarding exports through lower URR rates for exporters, hence for a heavily export dependent economy such as Colombia, the lack of differences among active and inactive firms is reassuring because it suggests exporting activity was not hampered from the policy. In Table 18 we condition the sample only on firms active within the foreign debt market pre-policy and refer to IMC Only as the benchmark comparison. EFE Only firms imported 16% less than IMC Only firms after the policy, while firms with both IMC and EFE debt exhibited no differences to IMC Only firms. We also test whether the reduction in imports increases with the intensity of foreign debt exposure pre-policy by replacing interacting the policy dummy variable with the amount of foreign debt pre-policy. Table 19 displays the results. In column (1), we condition on EFE firms and find a one standard deviation increase in pre-policy EFE debt is associated with a 13% reduction in imports. The magnitude remains relatively similar for EFE Only firms as seen in column (2) and including the set of firms which borrowed from both IMCs and EFEs in column (3). We do not see imports changing as a function of IMC debt pre-policy, as seen in the regressions conditioning on IMC firms in column (4) and IMC Only firms in column (5).

Reductions in foreign currency loans directly influences the balance of payments of Colombia, hence the transmission to imports is rather clear. As EFE firms could not substitute foreign debt with local, peso-denominated debt, buying foreign goods in other currencies proved to be burdensome for them. The credit register regressions illustrated the credit cutbacks associated with EFE Only firms, and the evidence of lower imports for these same types of firms suggests the cut from bank debt acted as a binding constraint for their activities. Firms which borrowed through IMCs directly were not impacted in their exporting or importing activities.

XVIII.5 INSULATION FROM THE GLOBAL FINANCIAL CYCLE

In the last section of this paper, we ask about an important benefit to shutting down capital inflows in an open economy: did capital controls in Colombia insulate the country from the Global Financial Cycle? Empirical evidence has suggested co-movements between the VIX and capital inflows (Forbes and Warnock, 2012; Bruno and Shin, 2014, 2015; Miranda-Agrippino and Rey, 2015). Rey (2015) illustrates the tradeoffs of exposure to the global financial cycle. With a low VIX, risk appetite increases leading to credit and asset price growths in emerging economies. However, retraction of capital flows from emerging economies can lead to severe retrenchments. Furthermore, Rey (2015) argues sovereign monetary policy can only be attained in a floating currency environment if and only if capital flows are controlled. We test the impact of capital controls on foreign debt first using stocks from the domestic credit registry:

$$Loan_{f,b,d,t} = \beta_1 VIX_{t-1} * FX_{f,b,t} * CapitalControls_t + \beta_2 VIX_{t-1} * FX_{f,b,t} + \beta_3 CapitalControls_t * FX_{f,b,t} + Control_{f,b,d,t-1} + \delta_{f,t} + \delta_{f,b,d} + \delta_{b,t} + \varepsilon_{f,t}$$

where $Loan_{f,b,d,t}$ represents the loan amount in currency *d* bank *b* to firm *f* at quarter *t*. In order to understand how firms switch between different currency debt due to variation in the VIX, this analysis is restricted to the use of IMC debt. That is, our analysis incorporates only firm-bank relationships where the bank provides the firm both peso denominated debt and FX debt at least once throughout the sample. $FX_{f,b,t}$ is a dummy equal to 1 if the loan from *b* to *f* is in a currency other than Colombian pesos at time *t*. VIX_{t-1} is the value of the VIX at quarter *t-1*. $Control_{f,b,d,t-1}$ are interactions of the overnight interest rate with $FX_{f,b,t}$ and $CapitalControls_t$ to control for time-varying movements in the demand for credit which might comove with the VIX. Lastly, we saturate the model with firm*time, firm*bank*FX and bank*time fixed effects. The coefficient β_2 identifies the effect of the lagged VIX on foreign currency denominated credit, while β_1 identifies the effect of the VIX following the introduction of capital controls.

Results are reported in Table 20. Following 2007 Q2 once capital controls were initiated, we observe a reduction in the foreign currency lending, as seen by the negative and significant coefficient on $CapitalControls_t * FX_{f,b,t}$. Furthermore, prior to capital controls, the negative and significant coefficient on $VIX_{t-1} * FX_{f,b,t}$ suggests lower levels of the lagged VIX led to an increase in foreign currency debt relative to peso denominated debt. Hence, Colombia displayed the appearance of a typical open emerging economy through exposure to the global financial cycle as proxied through the VIX. Following the policy introduction, we see the negative interaction of $VIX_{t-1} * FX_{f,b,t}$ is offset by the positive and significant triple interaction on $VIX_{t-1} * FX_{f,b,t} * CapitalControls_t$. The total effect of the lagged VIX on foreign currency denominated debt following capital controls is muted to nearly 0 (-0.0956+0.0886). Results are robust to the inclusion of granular fixed effects, as seen in even the strictest regression with firm*bank*FX, firm*time and bank*time fixed effects in column (5). To ensure results are driven by new loans, we rerun the analysis using flow data on disbursements. The specification we use is the following:

$$Loan_{f,t} = \beta_1 VIX_{t-1} * CapitalControls_t + \beta_2 VIX_{t-1} + Control_{f,t-1} + \delta_f + \varepsilon_{f,t}$$

where the sample is restricted to only IMC debt flows in foreign currency. $Control_{f,t-1}$ includes controls for the firms lagged size, ROA, exports and imports as well as a time-varying control for movements in the overnight interest rate. We report the estimations in Table 21. The negative and significant coefficient on the lagged VIX once again suggests prior to the capital controls Colombia was exposed to the global financial cycle as lower levels of the VIX led to larger inflows of foreign IMC debt. However, following the capital controls, this effect is muted as seen through the positive and significant coefficient on $VIX_{t-1} * CapitalControls_t$.

Evidence of larger credit inflows following depreciations in the global financial cycle, as proxied through the lagged VIX, has been shown in several papers. However, this paper offers new insight into the efficacy of capital controls in nullifying the effects of the VIX on credit inflows. While benefits can arise from exposure to the global financial cycle, insulation can also lead to control over sovereign monetary policy as well as leverage in credit markets. Our results point to benefits of Colombia's capital controls through insulation of movements in the global financial cycle.

XIX. Conclusion

Recent developments in the global financial cycle have allowed academics and policy-makers to reconsider their pessimistic view of the efficacy of capital controls. However, comprehensive data relating inflows to domestic economies have not been readily available or largely used across studies. In this paper, we link micro-level domestic credit registry data with detailed bank-debt inflows at the firm level to shed light on the impact of capital controls on an open economy. Our setting is the 2007 Q2 introduction of Unremunerated Reserve Requirements (URR) to Colombia as a response to the large surge in foreign bank-debt inflows of domestic firms.

We first find that capital inflows decreased following the introduction of capital controls, with the intensity of the reduction increasing with firms much more reliant on foreign bank-debt. We measure reliance of this type of external financing with the amount of bank-debt acquired by

Colombian firms prior to the policy. Furthermore, we find that domestic bank debt became much more prevalent following the capital controls.

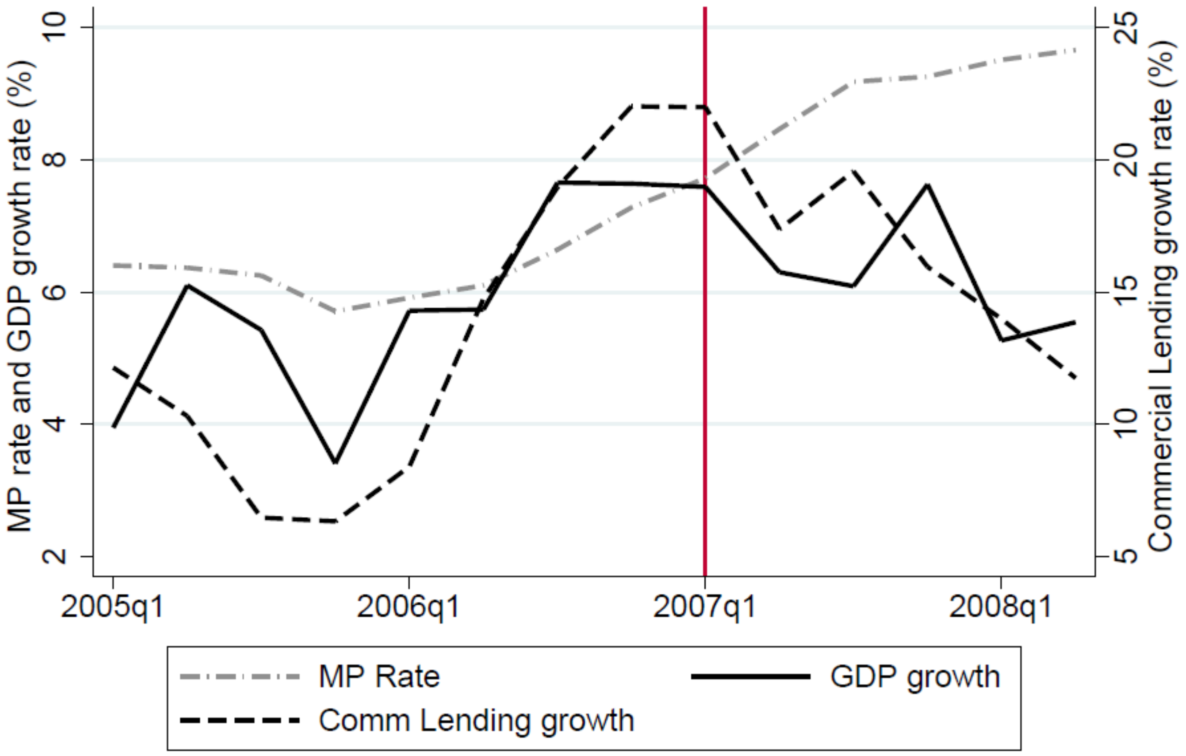
Using loan-level data from the Colombia credit register, we document that firms which were active in the foreign bank-debt market through direct financing, EFE firms, were penalized with lower amounts of domestic bank credit, while firms which obtained foreign debt via Colombian intermediaries, IMC firms, were more likely to substitute to domestic peso debt. Similarly, we find penalization to be a binding constraint for firms with direct financing from abroad as they received larger interest rates compared to IMC firms. EFE firms with larger net exports pre-policy were more likely to receive credit at lower rates, as the policy provided flexibility to exporters. Among IMC firms, the same bank which intermediated their foreign debt was more likely to provide credit upon the introduction of capital controls.

Furthermore, we document real effects for firms which were penalized from the capital controls. Results from the credit register suggested firms with direct financing from foreign banks were penalized in domestic credit. Larger exposure to this foreign bank-debt market was associated with fewer imports. The results speak to frictions arising from credit constraints and firms cutting back operations because of their inability to switch seamlessly between foreign and domestic credit.

Lastly, we document that the capital controls insulated Colombia from the global financial cycle. Prior to the capital controls, lower levels of the VIX led to larger capital inflows, consistent with literature that suggests risk appetite and cross-border capital flows comove with each other. Following the introduction of controls on foreign bank debt, the effect of the VIX on FX debt within Colombia was muted, suggesting insulation from the global financial cycle.

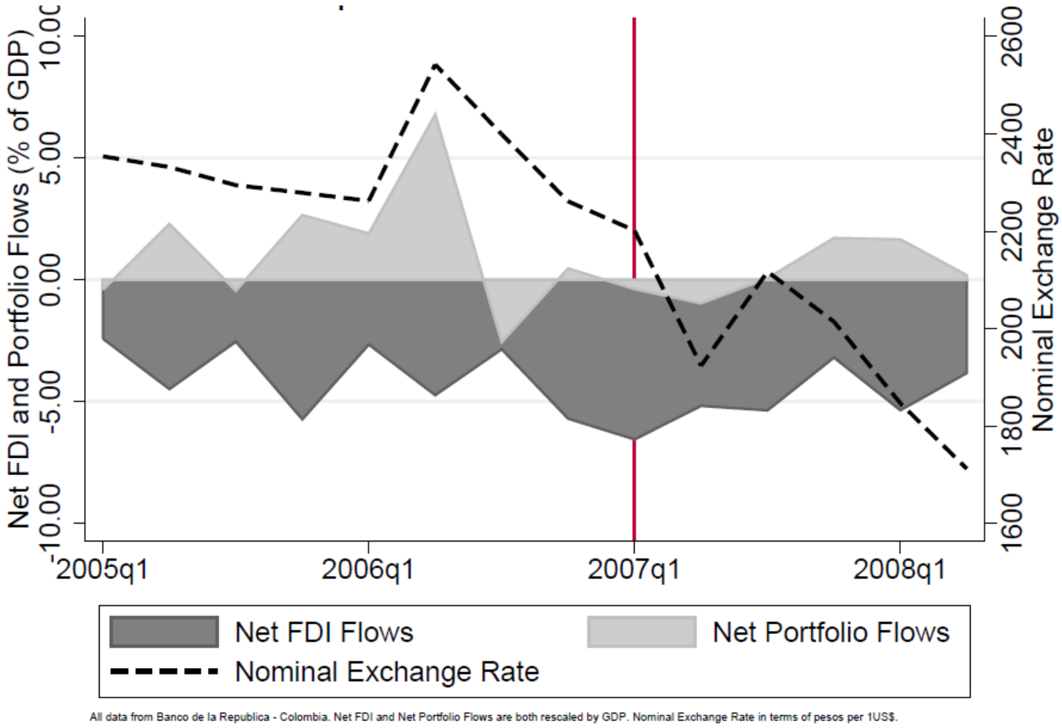
Our paper sheds light on the interaction of foreign capital inflows and the domestic economy, using micro-level data on bank-debt. Given recent considerations of capital controls, our paper highlights externalities which could arise following restrictions in foreign bank-debt. Firms which rely heavily on direct financing from abroad may not be able to substitute one-to-one with domestic bank credit, therefore affecting their means of production. Simultaneously, firms with strong connections to Colombian intermediaries are more likely to access the domestic credit markets when the FX market is shut down. Furthermore, insulation from the global financial cycle from capital controls offers benefits to Colombian regulators in being better able to control their sovereign monetary policy and domestic leverage. We hope this paper could open future avenues of research highlighting the interaction of capital controls with domestic real effects and contribute to our understanding of the trade-offs associated with exposure to the global financial cycle.

FIGURE 1: ECONOMIC BOOM OF COLOMBIA



This figure shows the monetary policy rate (MP Rate), commercial lending growth rate (Comm Lending growth) and GDP growth rate during 2005Q1 until the end of our sample 2008Q2. All data are from the Banco de la Republica, Colombia. Growth rates are computed on a yearly basis.

FIGURE 2: DEVELOPMENTS IN THE EXTERNAL SECTOR



This figure shows Net Foreign Direct Investment and Net Portfolio Flows rescaled by GDP during 2005Q1 until the end of our sample 2008Q2. The Nominal Exchange Rate is expressed in terms of pesos per 1 U.S. dollar. All data are from the Banco de la Republica, Colombia.

FIGURE 3: TOTAL FX DEBT FLOWS (DETRENDED)

This figure shows foreign debt flows for both EFE and IMC debt rescaled by total assets between 2006Q1 and 2008Q2 and filtered for seasonality (dummy variables for each quarter of the year). All data are from the Banco de la Republica, Colombia.

TABLE 1: SUMMARY STATISTICS ALL FIRMS

	All Firms N=6,666			Firms Active Before 2007Q1 N=,2941			Inactive Firms N=3,725		
Variable	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Firm Characteristics									
Log Assets	8.25	8.13	1.65	8.95	8.88	1.62	7.72	7.57	1.46
ROA	0.04	0.03	0.07	0.04	0.03	0.07	0.04	0.03	0.07
Log(Exports)	1.17	0.00	2.54	2.24	0.00	3.22	0.36	0.00	1.39
Log(Imports)	2.12	0.00	3.10	3.97	4.78	3.37	0.71	0.00	1.90
Total FX Debt Flows (over assets)	0.00	0.00	0.03	0.01	0.00	0.04	0.00	0.00	0.00
Log Total FX Debt Flows	1.98	0.00	3.70	4.50	4.85	4.45	0.00	0.00	0.00
Bank Characteristics									
Log Assets	16.50	16.77	0.59	16.48	16.51	0.57	16.50	16.77	0.61
Tier1 Ratio	0.04	0.03	0.01	0.04	0.03	0.01	0.04	0.03	0.01
Domestic Loan Characteristics									
Log(Loan)	4.88	4.97	2.14	5.33	5.52	2.18	4.33	4.38	1.96
Interest Rate (%)	15.58	15.55	4.92	14.90	14.62	4.94	16.41	16.57	4.76

This table reports the summary statistics of the main variables used in the paper. The data uses observations from 2006Q1 to 2008Q2. Firms Active Before 2007Q1 refers to firms which borrowed foreign currency debt prior to the introduction of capital controls in May 2007Q1. Note that our data on firm Log Assets, firm ROA, bank Log Assets and bank Tier1 Ratio are at a firm/bank-quarter frequency. Log(Exports), Log(Imports) and foreign debt flows are at a firm-quarter level frequency, while Log(Loan) and Interest Rates are at a firm-bank quarter frequency.

TABLE 2: SUMMARY STATISTICS FIRMS ACTIVE IN FOREIGN DEBT MARKET PRE-POLICY

	IMC Only N=1,732			Both IMC and EFE N=791			EFE Only N=418		
Variable	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Firm Characteristics									
Log Assets	8.44	8.40	1.47	9.95	9.93	1.49	9.17	9.23	1.50
ROA	0.04	0.03	0.07	0.03	0.03	0.06	0.02	0.03	0.08
Log(Exports)	1.38	0.00	2.58	4.06	4.60	3.73	2.35	0.00	3.16
Log(Imports)	2.83	0.00	3.15	6.10	6.81	2.73	4.62	5.43	3.20
Total FX Debt Flows (over assets)	0.00	0.00	0.02	0.02	0.00	0.06	0.02	0.00	0.05
EFE Flows (over assets)	0.00	0.00	0.00	0.01	0.00	0.03	0.01	0.00	0.05
IMC Flows (over assets)	0.01	0.00	0.02	0.01	0.00	0.03	0.00	0.00	0.00
Log Total FX Debt Flows	1.92	0.00	3.56	8.91	8.92	2.60	6.92	6.73	2.27
Log EFE Debt Flows	0.00	0.00	0.00	7.97	7.97	2.38	6.88	6.71	2.26
Log IMC Debt Flows	4.55	3.89	3.16	7.47	8.09	3.26	0.00	0.00	0.00
Bank Characteristics									
Log Assets	16.49	16.77	0.59	16.47	16.51	0.57	16.51	16.77	0.6
Tier1 Ratio	0.04	0.03	0.01	0.04	0.03	0.01	0.04	0.03	0.01
Domestic Loan Characteristics									
Log(Loan)	4.97	5.14	2.04	6	6.32	2.27	5.17	5.33	2.16
Interest Rate (%)	15.3	15.16	4.81	13.91	13.34	5.11	15.71	15.39	4.66

This table reports the summary statistics of the main variables used in the paper. The data uses observations from 2006Q1 to 2008Q2. Firms in this sample are those which borrowed foreign currency debt prior to the introduction of capital controls in May 2007Q1. IMC Only refers to firms that only borrowed foreign currency debt via domestic Colombian financial intermediaries (Intermediarios del Mercado Cambiario). EFE Only firms are firm that strictly borrowed through direct financing. Both IMC and EFE firms are those which used both avenues, IMC and EFE financing, for their foreign currency debt. Note that our data on firm Log Assets, firm ROA, bank Log Assets and bank Tier1 Ratio are at a firm/bank-quarter frequency. Log(Exports), Log(Imports) and foreign debt flows are at a firm-quarter level frequency, while Log(Loan) and Interest Rates are at a firm-bank quarter frequency.

TABLE 3: TIME TREND REDUCTION OF FOREIGN DEBT FLOWS

	(1) Total	(2) EFE	(3) IMC
$CapitalControls_t$	-0.0068***	-0.0018	-0.0065***
	(0.001)	(0.002)	(0.001)
N	28495	11276	24399
R^2	0.3903	0.3835	0.3930
Season FE	YES	YES	YES
Firm FE	YES	YES	YES
Macro Controls	YES	YES	YES
Firm Controls	YES	YES	YES
Bank Controls	YES	YES	YES

The dependent variable is the foreign debt flows over total assets of firm *f* at quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify 'Total' debt flows as all foreign currency debt flows. 'EFE' debt flows are foreign currency debt flows from direct financing from abroad, while 'IMC' refers to debt flows which were intermediated by domestic Colombian financial intermediaries. Season FE refer to seasonality fixed effects. Macro Controls refer to lagged interbank interest rates, GDP, inflation and VIX. Firm Controls are lagged log of exports, imports, size and profitability. Bank Controls refer to the firm's domestic banks average and lagged tier1 ratio and size. Standard errors are clustered at the firm and industry*time level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *:

TAB LE 4: REDUCTION OF FOREIGN DEBT FLOWS BY DEPENDENCY

	(1) Total	(2) EFE	(3) IMC
$CapitalControls_t * ForeignDebt_{prepolicy,f}$	-0.4902***	-0.5267***	-0.3982***
	(0.042)	(0.082)	(0.041)
N	28495	11276	24399
R^2	0.4599	0.4906	0.4571
Firm Controls	YES	YES	YES
Bank Controls	YES	YES	YES
Quarter FE	YES	YES	YES
Firm FE	YES	YES	YES

The dependent variable is the foreign debt flows over total assets of firm *f* at quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify 'Total' debt flows as all foreign currency debt flows. 'EFE' debt flows are foreign currency debt flows from direct financing from abroad, while 'IMC' refers to debt flows which were intermediated by domestic Colombian financial intermediaries. Quarter FE refer to quarter fixed effects. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Bank Controls refer to the firm's domestic banks average and lagged tier1 ratio and size, interacted with the 'Capital Controls' dummy variable. Standard errors are clustered at the firm and industry*time level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 5: PROBABILITY OF DOMESTIC CREDIT

	(1) Total	(2) EFE	(3) IMC
$CapitalControls_t * ForeignDebt_{prepolicy,f}$	2.2908***	2.7177***	1.2925**
	(0.404)	(0.496)	(0.648)
N	13471	6301	11941
R^2	0.5037	0.5783	0.4751
Firm FE	YES	YES	YES
Industry*Time FE	YES	YES	YES
Firm Controls	YES	YES	YES
Bank Controls	YES	YES	YES

The dependent variable is a dummy variable equal to 1 if the firm took out domestic debt but no foreign currency debt flows at quarter *t* in the period 2006Q1 to 2008Q2, and zero otherwise. We restrict the sample to firms which borrowed either only domestic credit and no foreign currency debt flows, or foreign currency debt flows but no domestic credit at quarter *q*. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. '$ForeignDebt_{prepolicy,f}$ ' refers to one of three types of debt: 'Total' debt flows are all foreign currency debt flows, 'EFE' debt flows are foreign currency debt flows from direct financing from abroad, while 'IMC' refers to debt flows which were intermediated by domestic Colombian financial intermediaries. Quarter FE refer to quarter fixed effects. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Bank Controls refer to the firm's domestic banks average and lagged tier1 ratio and size, interacted with the 'Capital Controls' dummy variable. Standard errors are clustered at the firm and industry*time level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 6: ACTIVE VS INACTIVE- DOMESTIC CREDIT SUPPLY BY PRE-POLICY FOREIGN DEBT TYPE

	(1)	(2)	(3) Loans	(4)	(5)	(6)
$CapitalControls_t$	-0.3675***	-0.2360***	-0.2236***			
	(0.03)	(0.06)	(0.06)			
$CapitalControls_t * OnlyIMC_{prepolicy,f}$	0.6718***	0.2077***	0.0853***	0.0686***	0.0737***	0.0751***
	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
$CapitalControls_t * Both_{prepolicy,f}$	1.6172***	0.2921***	0.0151	-0.0007	-0.0054	0.0020
	(0.06)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)
$CapitalControls_t * OnlyEFE_{prepolicy,f}$	0.7911***	-0.0529	-0.0608	-0.0669*	-0.0569	-0.0634*
	(0.09)	(0.07)	(0.04)	(0.04)	(0.04)	(0.04)
N	190979	190979	190979	190979	190979	190979
R^2	0.0381	0.2758	0.8191	0.8204	0.8248	0.8302
Firm Controls	N	Y	Y	Y	Y	Y
Firm*Bank FE	N	N	Y	Y	Y	Y
Bank*Time FE	N	N	N	Y	Y	Y
Industry*time FE	N	N	N	N	Y	Y
Loan Controls	N	N	N	N	N	Y

The dependent variable is the is the logarithm of loan amount by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. ‘CapitalControls’ is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify firms which only borrowed via domestic Colombian financial intermediaries prior to the capital controls as $OnlyIMC_{prepolicy,f}$. $OnlyEFE_{prepolicy,f}$ refers to firms which only received foreign debt from direct financing from abroad, while $Both_{prepolicy,f}$ refers to firms which borrowed externally via IMC and EFE. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the ‘Capital Controls’ dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 7: ACTIVE VS INACTIVE- DOMESTIC INTEREST RATES BY PRE-POLICY FOREIGN DEBT TYPE

	(1)	(2)	(3)	(4)	(5)	(6)
			Interest Rates			
$CapitalControls_t$	4.4247***	6.9279***	6.7237***			
	(0.07)	(0.26)	(0.27)			
$CapitalControls_t$ * $OnlyIMC_{prepolicy,f}$	-1.7579***	-0.7932***	-0.1423	-0.5439***	-0.5021***	-0.4809***
	(0.11)	(0.11)	(0.11)	(0.09)	(0.10)	(0.10)
$CapitalControls_t$ * $Both_{prepolicy,f}$	-3.5819***	-0.8415***	0.1775	-0.2392*	-0.2499*	-0.2093
	(0.14)	(0.17)	(0.16)	(0.14)	(0.14)	(0.14)
$CapitalControls_t$ * $OnlyEFE_{prepolicy,f}$	-0.8309***	0.8886***	0.3354*	0.1697	0.2025	0.2399
	(0.22)	(0.22)	(0.20)	(0.17)	(0.17)	(0.17)
N	190979	190979	190979	190979	190979	190979
R^2	0.0649	0.1027	0.5573	0.6396	0.6472	0.6515
Firm Controls	N	Y	Y	Y	Y	Y
Firm*Bank FE	N	N	Y	Y	Y	Y
Bank*Time FE	N	N	N	Y	Y	Y
Industry*time FE	N	N	N	N	Y	Y
Loan Controls	N	N	N	N	N	Y

The dependent variable is the is the interest rate of the loan by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify firms which only borrowed via domestic Colombian financial intermediaries prior to the capital controls as $OnlyIMC_{prepolicy,f}$. $OnlyEFE_{prepolicy,f}$ refers to firms which only received foreign debt from direct financing from abroad, while $Both_{prepolicy,f}$ refers to firms which borrowed externally via IMC and EFE. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 8: WITHIN ACTIVE- DOMESTIC CREDIT SUPPLY BY PRE-POLICY FOREIGN DEBT TYPE

	(1)	(2)	(3)	(4)	(5)	(6)
			Loans			
$CapitalControls_t$	0.2042***	-0.1309	6.7237***			
	(0.02)	(0.09)	(0.27)			
$CapitalControls_t$ * $Both_{prepolicy,f}$	-0.0373	-0.1385***	-0.0637*	-0.0648*	-0.0813**	-0.0751**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$CapitalControls_t$ * $OnlyEFE_{prepolicy,f}$	0.1193	-0.2828***	-0.1423***	-0.1306***	-0.1284***	-0.1409***
	(0.10)	(0.07)	(0.04)	(0.04)	(0.04)	(0.04)
N	104587	104587	104587	104587	104523	104523
R^2	0.0417	0.2321	0.7882	0.7902	0.7980	0.8025
Firm Controls	N	Y	Y	Y	Y	Y
Firm*Bank FE	N	N	Y	Y	Y	Y
Bank*Time FE	N	N	N	Y	Y	Y
Industry*time FE	N	N	N	N	Y	Y
Loan Controls	N	N	N	N	N	Y

This table restricts the sample to firms active in the foreign debt market prior to the introduction of capital controls in 2007Q2. The dependent variable is the is the logarithm of the loan amount by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify firms which only borrowed via domestic Colombian financial intermediaries prior to the capital controls as $OnlyIMC_{prepolicy,f}$. $OnlyEFE_{prepolicy,f}$ refers to firms which only received foreign debt from direct financing from abroad, while $Both_{prepolicy,f}$ refers to firms which borrowed externally via IMC and EFE. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 9: WITHIN ACTIVE- DOMESTIC INTEREST RATES BY PRE-POLICY FOREIGN DEBT TYPE

	(1)	(2)	(3)	(4)	(5)	(6)
			Interest Rates			
$CapitalControls_t$	2.8244***	6.5150***	6.3641***			
	(0.07)	(0.37)	(0.36)			
$CapitalControls_t$ * $Both_{prepolicy,f}$	-0.4431***	0.6715***	0.3451***	0.3211***	0.3147**	0.3101**
	(0.12)	(0.14)	(0.13)	(0.12)	(0.13)	(0.13)
$CapitalControls_t$ * $OnlyEFE_{prepolicy,f}$	0.9270***	1.7432***	0.4788***	0.6408***	0.7165***	0.7588***
	(0.23)	(0.22)	(0.18)	(0.16)	(0.17)	(0.17)
N	104587	104587	104587	104587	104523	104523
R^2	0.0513	0.0867	0.5365	0.6086	0.6213	0.6265
Firm Controls	N	Y	Y	Y	Y	Y
Firm*Bank FE	N	N	Y	Y	Y	Y
Bank*Time FE	N	N	N	Y	Y	Y
Industry*time FE	N	N	N	N	Y	Y
Loan Controls	N	N	N	N	N	Y

This table restricts the sample to firms active in the foreign debt market prior to the introduction of capital controls in 2007Q2. The dependent variable is the is the interest rate of the loan by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify firms which only borrowed via domestic Colombian financial intermediaries prior to the capital controls as $OnlyIMC_{prepolicy,f}$. $OnlyEFE_{prepolicy,f}$ refers to firms which only received foreign debt from direct financing from abroad, while $Both_{prepolicy,f}$ refers to firms which borrowed externally via IMC and EFE. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 10: WITHIN ACTIVE- DOMESTIC CREDIT SUPPLY BY EXPORTING ACTIVITY

	(1)	(2)	(3)	(4)	(5)	(6)
	Loans					
	All	Active Only	All	Active Only	All	Active Only
	Exports		Imports		Net Exports	
CapitalControls_t * $\text{OnlyIMC}_{prepolicy,f}$	0.0771***		0.0690***		0.0723***	
	(0.02)		(0.02)		(0.02)	
CapitalControls_t * $\text{Variable}_{prepolicy,f}$	0.0732	0.0155	0.6503**	0.6372***	-0.0742	-0.2517*
	(0.08)	(0.17)	(0.26)	(0.22)	(0.10)	(0.14)
CapitalControls_t * $\text{OnlyIMC}_{prepolicy,f}$ * $\text{Variable}_{prepolicy,f}$	-0.0826		0.0565		-0.1906	
	(0.16)		(0.29)		(0.15)	
CapitalControls_t * $\text{Both}_{prepolicy,f}$	-0.0052	-0.0868**	-0.0002	-0.0721*	0.0009	-0.0702*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
CapitalControls_t * $\text{Both}_{prepolicy,f}$ * $\text{Variable}_{prepolicy,f}$	0.2511	0.3945	0.0321	-0.0697	-0.1002	0.1451
	(0.28)	(0.32)	(0.34)	(0.32)	(0.20)	(0.22)
CapitalControls_t * $\text{OnlyEFE}_{prepolicy,f}$	-0.0843**	-0.1689***	-0.0207	-0.0885*	-0.0391	-0.1074**
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)
CapitalControls_t * $\text{OnlyEFE}_{prepolicy,f}$ * $\text{Variable}_{prepolicy,f}$	0.8114**	1.0618**	-0.7073	-0.8118*	0.4955*	0.7922***
	(0.41)	(0.45)	(0.43)	(0.43)	(0.27)	(0.29)
N	190979	104523	190979	104523	190979	104523
R^2	0.8302	0.8026	0.8303	0.8026	0.8303	0.8026
Firm Controls	Y	Y	Y	Y	Y	Y
Loan Controls	Y	Y	Y	Y	Y	Y
Firm*Bank FE	Y	Y	Y	Y	Y	Y
Bank*Time FE	Y	Y	Y	Y	Y	Y
Industry*time FE	Y	Y	Y	Y	Y	Y

The dependent variable is the is the logarithm of the loan amount by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify firms which only borrowed via domestic Colombian financial intermediaries prior to the capital controls as $\text{OnlyIMC}_{prepolicy,f}$. $\text{OnlyEFE}_{prepolicy,f}$ refers to firms which only received foreign debt from direct financing from abroad, while $\text{Both}_{prepolicy,f}$ refers to firms which borrowed externally via IMC and EFE. $\text{Variable}_{prepolicy,f}$ equal to Total Exports in 2007Q1 over 2006Q4 total assets (Columns (1) and (2)), Total Imports in 2007Q1 over 2006Q4 total assets (Columns (3) and (4)), or Net Exports in 2007Q1 over 2006Q4 total assets (Columns (5) and (6)). Columns (1), (3) and (5) include both active and inactive firms, while Columns (2), (4) and (6) restricts the sample to only firms active in the foreign debt market prior to 2007Q2. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 11: WITHIN ACTIVE- DOMESTIC INTEREST RATES BY EXPORTING ACTIVITY

	(1)	(2)	(3)	(4)	(5)	(6)
	Interest Rates					
	All	Active Only	All	Active Only	All	Active Only
	Exports		Imports		Net Exports	
CapitalControls$_t$ * OnlyIMC$_{prepolicy,f}$	-0.4680***		-0.4232***		-0.4772***	
	(0.10)		(0.10)		(0.10)	
CapitalControls$_t$ *Variable$_{prepolicy,f}$	0.2985	-0.5793	1.0842	-0.6694	0.0770	-0.0324
	(0.40)	(0.70)	(1.03)	(1.00)	(0.33)	(0.62)
CapitalControls$_t$ * OnlyIMC$_{prepolicy,f}$ * Variable$_{prepolicy,f}$	-1.0371		-2.0061		-0.0620	
	(0.67)		(1.25)		(0.61)	
CapitalControls$_t$ * Both$_{prepolicy,f}$	-0.1104	0.3948***	-0.0193	0.4212***	-0.2186	0.2913**
	(0.14)	(0.13)	(0.16)	(0.16)	(0.14)	(0.13)
CapitalControls$_t$ * Both$_{prepolicy,f}$ * Variable$_{prepolicy,f}$	-3.5621***	-2.6504**	-3.5047***	-1.3862	-0.4148	-0.4691
	(1.10)	(1.15)	(1.29)	(1.23)	(0.75)	(0.81)
CapitalControls$_t$ * OnlyEFE$_{prepolicy,f}$	0.3388*	0.8637***	0.1407	0.5965***	0.1280	0.6248***
	(0.17)	(0.17)	(0.20)	(0.20)	(0.18)	(0.18)
CapitalControls$_t$ * OnlyEFE$_{prepolicy,f}$ * Variable$_{prepolicy,f}$	-4.4697**	-4.1004**	0.4504	2.3482	-2.5836**	-2.8503**
	(1.83)	(1.79)	(1.59)	(1.55)	(1.09)	(1.15)
N	190979	104523	190979	104523	190979	104523
R^2	0.6516	0.6266	0.6516	0.6265	0.6515	0.6265
Firm Controls	Y	Y	Y	Y	Y	Y
Loan Controls	Y	Y	Y	Y	Y	Y
Firm*Bank FE	Y	Y	Y	Y	Y	Y
Bank*Time FE	Y	Y	Y	Y	Y	Y
Industry*time FE	Y	Y	Y	Y	Y	Y

The dependent variable is the is the interest rate of the loan by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify firms which only borrowed via domestic Colombian financial intermediaries prior to the capital controls as OnlyIMC$_{prepolicy,f}$. OnlyEFE$_{prepolicy,f}$ refers to firms which only received foreign debt from direct financing from abroad, while Both$_{prepolicy,f}$ refers to firms which borrowed externally via IMC and EFE. Variable$_{prepolicy,f}$ equal to Total Exports in 2007Q1 over 2006Q4 total assets (Columns (1) and (2)), Total Imports in 2007Q1 over 2006Q4 total assets (Columns (3) and (4)), or Net Exports in 2007Q1 over 2006Q4 total assets (Columns (5) and (6)). Columns (1), (3) and (5) include both active and inactive firms, while Columns (2), (4) and (6) restricts the sample to only firms active in the foreign debt market prior to 2007Q2. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 12: WITHIN ACTIVE- INTENSITIES

	(1)	(2)	(3)
		Loans	
	Total	IMC	EFE
$CapitalControls_t * ForeignDebt_{prepolicy,f}$	1.1266	3.2657***	-1.2761
	(0.84)	(1.26)	(1.03)
N	104523	92687	45449
R^2	0.8025	0.7986	0.7876
Firm Controls	Y	Y	Y
Loan Controls	Y	Y	Y
Firm*Bank FE	Y	Y	Y
Bank*Time FE	Y	Y	Y
Industry*time FE	Y	Y	Y

This table restricts the sample to firms active in the foreign currency debt market prior to 2007Q2. The dependent variable is the logarithm of the loan amount by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. $ForeignDebt_{prepolicy,f}$ refers to the firms average total foreign (1), IMC (2), or EFE (3) debt flows over total assets prior to 2007Q2. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 13: WITHIN ACTIVE- INTENSITIES

	(1)	(2)	(3)
		Interest Rates	
	Total	IMC	EFE
$CapitalControls_t * ForeignDebt_{prepolicy,f}$	-10.7736***	-27.9710***	4.6600
	(2.90)	(4.24)	(3.92)
N	104523	92687	45449
R^2	0.6264	0.6185	0.6456
Firm Controls	Y	Y	Y
Loan Controls	Y	Y	Y
Firm*Bank FE	Y	Y	Y
Bank*Time FE	Y	Y	Y
Industry*time FE	Y	Y	Y

This table restricts the sample to firms active in the foreign currency debt market prior to 2007Q2. The dependent variable is the interest rate of the loan by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. $ForeignDebt_{prepolicy,f}$ refers to the firms average total foreign (1), IMC (2), or EFE (3) debt flows over total assets prior to 2007Q2. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 14: WITHIN IMC FIRMS- DOMESTIC CREDIT SUPPLY

	(1)	(2)	(3)	(4)
	Loans			
$CapitalControls_t$ * $IMCDebt_{prepolicy,f}$	-1.1917	-1.1385	-1.3674	
	(2.14)	(2.08)	(2.02)	
$CapitalControls_t$ * $IMCBank_{prepolicy,f,b}$	0.1704***	0.0782**	0.0804**	0.1017***
	(0.03)	(0.04)	(0.04)	(0.04)
$CapitalControls_t$ * $IMCDebt_{prepolicy,f}$* $IMCBank_{prepolicy,f,b}$	4.2029*	5.3667**	4.8214**	5.9157**
	(2.43)	(2.40)	(2.26)	(2.48)
N	92755	92755	92687	89775
R^2	0.7837	0.7857	0.7942	0.8499
Firm Controls	Y	Y	Y	-
Loan Controls	Y	Y	Y	Y
Firm*Bank FE	Y	Y	Y	Y
Bank*Time FE	N	Y	Y	Y
Industry*time FE	N	N	Y	-
Firm*time FE	N	N	N	Y

This table restricts the sample to firms which obtained foreign currency financing via IMCs prior to the introduction of capital controls in 2007Q2. The dependent variable is the logarithm of the loan amount by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. ‘CapitalControls’ is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. $IMC_{prepolicy,f}$ refers to the firms average IMC debt flows over total assets prior to 2007Q2. $IMCBank_{prepolicy,f,b}$ is a dummy equal to 1 if bank b provided firm f IMC financing prior to 2007Q2. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the ‘Capital Controls’ dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 15: WITHIN IMC FIRMS- INTEREST RATES

	(1)	(2)	(3)	(4)
	Interest Rates			
$CapitalControls_t$ * $IMCDebt_{prepolicy,f}$	-18.7654***	-19.1593***	-20.5456***	
	(6.20)	(6.00)	(6.28)	
$CapitalControls_t$ * $IMCBank_{prepolicy,f,b}$	2.7222***	0.4573***	0.4656***	0.5365***
	(0.15)	(0.15)	(0.15)	(0.17)
$CapitalControls_t$ * $IMCDebt_{prepolicy,f}$* $IMCBank_{prepolicy,f,b}$	-48.2795***	-15.2313*	-14.0629*	-15.2807
	(8.49)	(8.29)	(8.37)	(10.39)
N	92755	92755	92687	89775
R^2	0.5338	0.5994	0.6132	0.7135
Firm Controls	Y	Y	Y	-
Loan Controls	Y	Y	Y	Y
Firm*Bank FE	Y	Y	Y	Y
Bank*Time FE	N	Y	Y	Y
Industry*time FE	N	N	Y	-
Firm*time FE	N	N	N	Y

This table restricts the sample to firms which obtained foreign currency financing via IMCs prior to the introduction of capital controls in 2007Q2. The dependent variable is the interest rate of the loan by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. $IMC_{prepolicy,f}$ refers to the firms average IMC debt flows over total assets prior to 2007Q2. $IMCBank_{prepolicy,f,b}$ is a dummy equal to 1 if bank b provided firm f IMC financing prior to 2007Q2. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Loan Controls refer to the loans maturity and a dummy variable for whether the loan is collaterized. Standard errors are clustered at the firm level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 16: IMPORTS

	(1)	(2)	(3)	(4)	(5)
			Imports		
$CapitalControls_t$	0.0521	-0.2080	1.5157	0.3169	
	(0.05)	(0.25)	(1.12)	(0.45)	
$CapitalControls_t$ * $OnlyIMC_{prepolicy,f}$	-0.0047	-0.0545	-0.0475	-0.0216	-0.0326
	(0.07)	(0.08)	(0.08)	(0.03)	(0.03)
$CapitalControls_t$ * $Both_{prepolicy,f}$	-0.0478	-0.1759**	-0.1695*	-0.1177***	-0.1296***
	(0.10)	(0.09)	(0.09)	(0.04)	(0.04)
$CapitalControls_t$ * $OnlyEFE_{prepolicy,f}$	-0.2112***	-0.2630**	-0.2584**	-0.2388***	-0.2383***
	(0.08)	(0.10)	(0.10)	(0.06)	(0.06)
N	65417	65417	65417	65417	65417
R^2	0.3540	0.4543	0.4558	0.9181	0.9224
Firm FE	N	N	N	Y	Y
Industry Time FE	N	N	N	N	Y
Firm Controls	N	Y	Y	Y	Y
Bank Controls	N	N	Y	Y	Y

The dependent variable is the is the logarithm of imports by firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify firms which only borrowed via domestic Colombian financial intermediaries prior to the capital controls as $OnlyIMC_{prepolicy,f}$. $OnlyEFE_{prepolicy,f}$ refers to firms which only received foreign debt from direct financing from abroad, while $Both_{prepolicy,f}$ refers to firms which borrowed externally via IMC and EFE. Firm Controls are lagged log of exports, size and profitability, interacted with the 'Capital Controls' dummy variable. Bank Controls refer to the firm's domestic banks average and lagged tier1 ratio and size, interacted with the 'Capital Controls' dummy variable. Standard errors are clustered at the firm and industry*time level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 17: EXPORTS

	(1)	(2)	(3)	(4)	(5)
			Exports		
$CapitalControls_t$	-0.0071	0.0850	-1.5242	-0.6328*	
	(0.03)	(0.22)	(1.11)	(0.35)	
$CapitalControls_t$ * $OnlyIMC_{prepolicy,f}$	0.0332	-0.0089	-0.0136	-0.0089	0.0039
	(0.09)	(0.09)	(0.09)	(0.02)	(0.02)
$CapitalControls_t$ * $Both_{prepolicy,f}$	0.0795	0.0210	0.0158	0.0024	0.0078
	(0.17)	(0.13)	(0.13)	(0.04)	(0.04)
$CapitalControls_t$ * $OnlyEFE_{prepolicy,f}$	-0.0312	-0.0370	-0.0349	-0.0665	-0.0477
	(0.11)	(0.11)	(0.11)	(0.05)	(0.05)
N	65417	65417	65417	65417	65417
R^2	0.2268	0.3077	0.3082	0.9287	0.9333
Firm FE	N	N	N	Y	Y
Industry Time FE	N	N	N	N	Y
Firm Controls	N	Y	Y	Y	Y
Bank Controls	N	N	Y	Y	Y

The dependent variable is the is the logarithm of exports by firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify firms which only borrowed via domestic Colombian financial intermediaries prior to the capital controls as $OnlyIMC_{prepolicy,f}$. $OnlyEFE_{prepolicy,f}$ refers to firms which only received foreign debt from direct financing from abroad, while $Both_{prepolicy,f}$ refers to firms which borrowed externally via IMC and EFE. Firm Controls are lagged log of imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Bank Controls refer to the firm's domestic banks average and lagged tier1 ratio and size, interacted with the 'Capital Controls' dummy variable. Standard errors are clustered at the firm and industry*time level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 18: WITHIN ACTIVE- IMPORTS

	(1)	(2)	(3)	(4)	(5)
			Imports		
$CapitalControls_t$	0.0474	-0.2645	3.7083	0.0103	
	(0.11)	(0.34)	(2.29)	(0.98)	
$CapitalControls_t$ * $Both_{prepolicy,f}$	-0.0431	-0.0994	-0.0967	-0.0791^{*}	-0.0539
	(0.11)	(0.08)	(0.08)	(0.04)	(0.04)
$CapitalControls_t$ * $OnlyEFE_{prepolicy,f}$	-0.2065^{**}	-0.2025^{**}	-0.2142^{**}	-0.2052^{***}	-0.1602^{***}
	(0.08)	(0.09)	(0.09)	(0.06)	(0.06)
N	29126	29126	29126	29126	28668
R^2	0.1638	0.3399	0.3427	0.9005	0.9095
Firm FE	N	N	N	Y	Y
Industry Time FE	N	N	N	N	Y
Firm Controls	N	Y	Y	Y	Y
Bank Controls	N	N	Y	Y	Y

This table restricts the sample to firms which obtained foreign currency financing prior to the introduction of capital controls in 2007Q2. The dependent variable is the is the logarithm of imports by firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. $OnlyEFE_{prepolicy,f}$ refers to firms which only received foreign debt from direct financing from abroad, while $Both_{prepolicy,f}$ refers to firms which borrowed externally via IMC and EFE. Firm Controls are lagged log of exports, size and profitability, interacted with the 'Capital Controls' dummy variable. Bank Controls refer to the firm's domestic banks average and lagged tier1 ratio and size, interacted with the 'Capital Controls' dummy variable. Standard errors are clustered at the firm and industry*time level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 19: WITHIN ACTIVE- IMPORTS BY PRE-POLICY INTENSITY

	(1) EFE	(2) EFE Only	(3) Both	(4) IMC	(5) IMC Only
$CapitalControls_t$ * $EFEDebt_{prepolicy,f}$	-2.5994***	-2.1480	-3.2365**		
	(0.92)	(1.52)	(1.53)		
$CapitalControls_t$ * $IMCDebt_{prepolicy,f}$			0.4372	0.1403	0.2651
			(2.19)	(1.22)	(1.59)
N	11446	3398	7347	24529	16464
R^2	0.8961	0.8955	0.9003	0.9144	0.9003
Firm FE	Y	Y	Y	Y	Y
Industry Time FE	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y

This table restricts the sample to firms depending on if the firm took out EFE debt (1), only EFE debt (2), both IMC and EFE debt (3), IMC debt (4), or only IMC Debt (5) prior to the introduction of capital controls in 2007Q2. The dependent variable is the is the logarithm of imports by firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. $EFEDebt_{prepolicy,f}$ ($IMCDebt_{prepolicy,f}$) refers to the firms average EFE (IMC) debt flows over total assets prior to 2007Q2. Firm Controls are lagged log of exports, size and profitability, interacted with the 'Capital Controls' dummy variable. Bank Controls refer to the firm's domestic banks average and lagged tier1 ratio and size, interacted with the 'Capital Controls' dummy variable. Standard errors are clustered at the firm and industry*time level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 20: INSULATION OF IMC DEBT CREDIT FROM GLOBAL FINANCIAL CYCLE

	(1)	(2)	(3)	(4)	(5)
			Loan		
VIX_{t-1}	0.0066	0.0066	0.0066		
	(0.01)	(0.01)	(0.01)		
$FX_{b,t}$	-0.0595	1.0166**			
	(0.30)	(0.44)			
$CapitalControls_t$	0.0838	0.0838	0.0549		
	(0.11)	(0.11)	(0.08)		
VIX_{t-1}* $CapitalControls_t$	0.0013	0.0013	-0.0000		
	(0.01)	(0.01)	(0.01)		
$FX_{,b,t}$ * $CapitalControls_t$	-0.9346***	-1.6840***	-1.5262***	-3.0883***	-3.8131***
	(0.31)	(0.56)	(0.35)	(0.38)	(0.48)
VIX_{t-1}* $FX_{,b,t}$	-0.0769***	-0.1065***	-0.0519***	-0.0877***	-0.0956***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
VIX_{t-1}* $FX_{,b,t}$ *$CapitalControls_t$	0.0733***	0.1103***	0.0574***	0.0858***	0.0886***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
N	173774	173774	173774	173774	173774
R^2	0.0228	0.0228	0.7954	0.7967	0.8484
Firm*Bank*FX FE	N	N	Y	Y	Y
Bank*Time FE	N	N	N	Y	Y
Firm*time FE	N	N	N	N	Y
Int Rate Control	N	Y	Y	Y	Y

This table restricts the credit register to firms active in the IMC debt market prior to the introduction of capital controls in 2007Q2. The dependent variable is the is the logarithm of the loan amount by each bank *b* to firm *f* during quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. VIX_{t-1} is the level of the VIX at *t-1*. $FX_{,b,t}$ is a dummy variable equal to 1 if the loan from bank *b* to firm *f* is denominated in foreign currency. Standard errors are clustered at the firm and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

TABLE 21: INSULATION OF IMC DEBT FLOWS FROM GLOBAL FINANCIAL CYCLE

	(1)	(2)	(3)	(4)	(5)	(6)
			IMC Flows			
$CapitalControls_t$	-0.0227***	-0.0230***	-0.0247***	-0.0227*	-0.0289***	-0.0412***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
VIX_{t-1}	-0.0018***	-0.0018***	-0.0019***	-0.0023***	-0.0025***	-0.0030***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VIX_{t-1} * $CapitalControls_t$	0.0018***	0.0018***	0.0020***	0.0028***	0.0029***	0.0033***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	24399	24399	24399	24399	24399	24399
R^2	0.0012	0.0448	0.0463	0.0477	0.3915	0.3924
Firm Controls	NO	YES	YES	YES	YES	YES
Bank Controls	NO	NO	YES	YES	YES	YES
Interest Rate Control	NO	NO	NO	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES	YES
Quarter FE	NO	NO	NO	NO	NO	YES

The dependent variable is the foreign debt flows intermediated via IMCs over total assets of firm *f* at quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. VIX_{t-1} is the level of the VIX at *t-1*. Quarter FE refer to quarter fixed effects. Firm Controls are lagged log of exports, imports, size and profitability, interacted with the 'Capital Controls' dummy variable. Bank Controls refer to the firm's domestic banks average and lagged tier1 ratio and size. Interest Rate Control refer to lagged interbank interest rates interacted with 'CapitalControls'. Standard errors are clustered at the firm and industry*time level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

APPENDIX: REGULATION OF FOREIGN CURRENCY DEBT IN COLOMBIA AND THE URR OF MAY OF 2007

1 The URR and other measures on external transactions of May 2007

In this section, we first describe the general institutional framework which regulated foreign currency operations in Colombia at the time of the URR. We will focus on the regulation of foreign currency inflows because they were affected by the URR introduced in May of 2007. The specifics of such URR provision are described in the second subsection. Finally, we analyze the rules concerning other external transactions.

1.1 Foreign currency credit flows: general rules

Regulation on credit in foreign currency stems from Resolución Externa 8/2000 emanated by the Banco de la República. Here, it is stated that residents (both individuals and legal entities) can borrow in any foreign currency from foreign legal entities, also through bond issuance in international capital markets. In general, any resident can lend to non-residents in foreign currency. Resident-to-resident foreign currency credit is however allowed only to the extent that the lender is a so-called Intermediario del Mercado Cambiario (IMC), and these operations are considered as external transactions as well from a Balance of Payment (BoP) perspective[63].

With the denomination of IMC, Banco de la República refers to commercial and mortgage banks and, more generally, financial companies and cooperatives with authorization from the Supervisory Authority. Importantly, IMCs also exert the function of certifying the legal validity (under Colombian rules) of foreign currency transactions that do not directly involve them. In practice, an IMC will appear in any Colombian *external transaction*, either in the role of lender/borrower and/or in that of foreign exchange commissioner[64]. Foreign currency borrowing by IMCs is strictly regulated and is in fact allowed *only* to the extent that is directed to one of the three following purposes[65]:

[63] Resident-to-resident foreign currency lending will constitute a zero-balance transaction in the BoP.
[64] Any *external transaction* is recorded at the Banco de la República through the *Formulario No 6,* concerning "*Información de Endeudamiento Externo otorgado a Residentes*"
[65]See *Resolución Externa 4/2005,* which modified art.59 of *Resolución Externa 8/2000.*

1. Loans in same foreign currency and with non-longer maturity than that of the borrowing

2. Active operations in Colombian pesos with non-longer maturity than that of the borrowing aimed at (synthetically) hedging FX positions due to derivative contracts

3. Operations of leasing exports.

Through *Resolución 8/2000,* Banco de la República explicitly left space opened for a subsequent introduction of a tax on external debt. In fact, art. 26 prescribes that *external transactions* involving debt intake in foreign currency by residents are effective upon disbursement of a deposit to be paid at the Banco de la República. The cost of the deposit is always borne by the debtor[66]. Initially, art. 83 set the deposit to 0% of the nominal amount of the debt transaction, so that in practice foreign currency borrowing did not imply further administrative costs. However, a tax on external debt could be introduced subsequently by simply modifying the provision of art. 83. Importantly, credit outflows are always deposit-free. Exemptions within the class of credit inflows in foreign currency are discussed below.

We conclude this section highlighting how the ability of IMCs to take large FX positions through derivative contracts has been limited well before the introduction of the external measures of May of 2007. With reference to the measures explained in Table R.1, IMCs global FX net position - *posición propia* (PP) - cannot be larger than 20% of IMC capital (defined as the sum of Tier-1 and Tier-2 capital and required to be not smaller than 9% of risk-weighted assets) and is bounded below by a -5% floor[67]. Apart from in-balance-sheet assets and liabilities, right and obligations deriving from off-balance-sheet derivative contract (realized and contingent) and indexed assets and liabilities concur to the determination of the PP. On the other hand, the net FX position associated to in-balance-sheet assets and liabilities - *posición propia de contado* (PPC) - must be non-negative and smaller than 50% of bank capital[68]. Both PPC and PP are computed at the three-day horizon as the average mean of the relevant items.

[66] It is always an IMC to transfer funds to the Banco de la República in its role of Foreign Exchange Market commissioner.
[67] Res*olución Externa* 26/1991 and *Resolución Externa* 4/2001.
[68] The described rules come from *Resolución Externa* 12/1999 and *Resolución Externa* 1/2004. Starting in 2015, IMCs can have negative PPC, with lower bounds fixed at -20%.

TABLE R1. *External FX Position of IMCs*

	FX Balance of IMCs	
IMCs Balance Sheet	1. Assets	2. Liabilities
Off-Balance Derivatives	3. Rights	4. Obligations
Position Measures	PP = (1+3)-(2+4)	
	PPC = 1-2	
	PBA = 3+4	

1.2 The URR of May 2007.

Through the *Resolución Externa 2/2007,* Banco de la República modified the provision of art. 83 of the *Resolución 8/2000,* thereby introducing a URR on foreign currency debt transactions. In fact, the deposit discussed above was raised to 40% of the nominal amount of the debt. The deposit had to be paid in pesos - evaluated at current exchange rate - and held at the Banco de la República for 6 months without any remuneration. The measure was introduced on the 6th of May and was declared immediately effective. Early withdrawal of the deposit was allowed but subject to the penalty rates provisioned by the *Circular Reglamentaria Externa DFV-113* of 7th of May of 2007; these would range from 9.4% to 1.3% in case of withdrawal in the first and in the sixth month, respectively[69]. By May 23rd, the measure was extended to portfolio investments through *Decreto 1801* of the *Ministerio de Hacienda y Crédito Público.*

The most notable exemption from the URR concerns *IMCs,* who did not have to pay any deposit on foreign currency financing[70]. Hence, importantly for our paper, companies bear the cost of the URR on foreign currency debt lent by IMCs. Other important exceptions to the general rule include foreign currency debt obtained by a Colombian resident:

1. to pursue an FDI transaction abroad;

[69] Foreign currency debt for exports pre-financing was subject to a less stringent regime. The size and time-length of the deposit were fixed to 11% of nominal value of debt and to 12 month, respectively. Starting from December of 2007, the deposits for exports prefinancing could be paid in US dollars, in which case the deposit would correspond to 20% of the nominal value of debt. Penalty rates were also lower than those applied to other foreign currency debt transactions.

[70] See art 59.c of *Resolución Externa 4/2005.*

2. for imports prefinancing with maturity below 1 year and/or total amount below US$ 10,000;

3. for exports prefinancing granted by Banco de Comercio Exterior – BANCOLDEX - with
maturity equal or below 1 year and with total amount below US$ 550,000,000;

4. for importing or exporting capital goods;

5. for covering margins and guarantees associated to operations with foreign exchange futures and options.

Exceptions 1 and 2 were removed and introduced, respectively, in April of 2008 via *Resolución Externa 1/2008.* Finally, the URR was eliminated on the 9th of October of 2008, when the deposit was put back at 0% level through *Resolución Externa 7/2008.*

1.3 Other measures

As a complement to the URR regulation presented above, stricter rules on the *gross* foreign currency position of IMC were introduced on May 6th of 2007 through *Resolución Externa* 4/2007. A new FX position measure was introduced in addition to the already existing PP and PPC: the so-called *posición bruta de apalancamiento* (PBA). Looking at Table R.1, one can easily see that the PBA is given by the sum of all rights and obligations in foreign currency associated to derivatives holding. *Resolución Externa 4/2007* initially limited PBA to 500% of the IMC *patrimonio tecnico*, with this threshold subsequently raised to 550% in September of 2008 by *Resolución Externa 3/2008.* Finally, PBA restrictions are still effective.

2 "Domestic" prudential measures

Contemporaneously to the introduction of the URR and other measures on *external transactions*, Banco de la República adopted other prudential measures to slow down the growth of domestic credit. These involved changes in the reserve requirements applied to banks deposits funding and the application of a counter-cyclical buffer. The two policies are described in the next two subsections, respectively.

2.1 Reserve Requirements

On the 6th of May of 2007, Banco de la República emanated *Resolución Externa 3/2007,* which introduced marginal reserve requirements (*encaje marginal*) on banks deposits, to be applied on top of the ordinary reserve requirements (set up by *Resolución*

Externa 19/2000) to new deposits above the level of 7th of May of 2007. Both measures apply to deposits in Colombian pesos only, and the *encaje marginal* was not remunerated[71] and fixed at: 27% for checking and simple deposits; 12% for savings deposits and at 5% for certificate of deposits with shorter maturity than 18 months. The ordinary reserve requirements for the three categories of liabilities were unchanged at 12%, 6% and 2.5%, respectively.

Only one month later, by effect of *Resolución Externa ?/2007*, the encaje marginal was moved to 27% for savings and checking deposits. At the same time, ordinary reserve requirements for the latter two categories were put at an equal level of 8.3%[72]. The cost of savings deposits financing went up relative to that of all the other forms of bank financing. Starting from August of 2008, the *encaje marginal* was eliminated because of the application of *Resolución Externa 5/2008,* which also raised ordinary reserve requirements to 11.5% for savings and checking deposits. Minor changes to ordinary reserve requirements were finally introduced in October of 2008, to be enforced by December of 2008, with a half-percentage point reduction in ordinary reserve requirements.

2.2 Counter-cyclical buffer

In July 2005, Banco de la República announced the introduction of a counter-cyclical dynamic provisioning scheme for banks, which effectively entered in force in July of 2007 (Gomez et al., 2017). The specifics of the measure and rules for computation of the provisions are thoroughly described in appendix A of López et al. (2014).

[71] Only ordinary reserve requirements on savings deposits and on certificate of deposits with shorter maturity than 18 months were remunerated, at an annualized rate corresponding to 75% and 100% of the yearly inflation rate.

[72] The remuneration of ordinary reserve requirements on savings and checking deposits was leveled at annualized rate corresponding 37.5% of the yearly inflation rate.

TABLE A1: TIME TREND REDUCTION OF LOG FOREIGN DEBT FLOWS

	(1) Total	(2) EFE	(3) IMC
$CapitalControls_t$	-0.8572***	-0.1938	-1.0109***
	(0.100)	(0.152)	(0.111)
N	28495	11276	24399
R^2	0.5564	0.4368	0.5378
Season FE	YES	YES	YES
Firm FE	YES	YES	YES
Macro Controls	YES	YES	YES
Firm Controls	YES	YES	YES
Bank Controls	YES	YES	YES

The dependent variable is the logarithm of foreign debt flows of firm *f* at quarter *t* in the period 2006Q1 to 2008Q2. 'CapitalControls' is a dummy variable that equals the value of one during the quarters following the introduction of capital controls in 2007Q2, and zero before. We classify 'Total' debt flows as all foreign currency debt flows. 'EFE' debt flows are foreign currency debt flows from direct financing from abroad, while 'IMC' refers to debt flows which were intermediated by domestic Colombian financial intermediaries. Season FE refer to seasonality fixed effects. Macro Controls refer to lagged interbank interest rates, GDP, inflation and VIX. Firm Controls are lagged log of exports, imports, size and profitability. Bank Controls refer to the firm's domestic banks average and lagged tier1 ratio and size. Standard errors are clustered at the firm and industry*time level and reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

BIBLIOGRAPHY

Abbassi, P., Iyer, R., Peydró, J.L., and Soto, P., 2017. Dressing up for the regulators: Evidence from the largest-ever supervisory review. Mimeo.

Abbassi, P., Iyer, R., Peydró, J.L. and Tous, F.R., 2016. Securities trading by banks and credit supply: Micro-evidence from the crisis, Journal of Financial Economics, 121(3), 569-594.

Acharya, V., Engle, R. and Pierret, D., 2014. Testing macroprudential stress tests: The risk of regulatory risk weights, Journal of Monetary Economics, 65, 36-53.

Ahnert, T. and Nelson, B. F., 2016. Opaque assets and rollover risk. Technical report, Bank of Canada Staff Working Paper.

Alfaro, L. and Hammel, E., 2007. Capital flows and capital goods. Journal of international Economics, 72(1):128–150.

Alfaro, L., Chari, A., and Kanczuk, F., 2017. The real effects of capital controls: Firm-level evidence from a policy experiment. Journal of International Economics, 108:191–210.

Allayannis, G., Brown, G. W., and Klapper, L. F., 2003. Capital structure and financial risk: Evidence from foreign debt use in east asia. The Journal of Finance, 58(6):2667–2710.

Allen, L. and Saunders, A., 1992. Bank window dressing: theory and evidence, Journal of Banking and Finance, 16(3), 585-632.

Altonji, J. G., Elder, T. E., and Taber, C. R., 2005. Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. Journal of political economy, 113(1): 151–184.

Altonji, J., E. Todd, and Taber, C., 2005. Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools," Journal of Political Economy, 113(1), 151-184.

Amann, M., Baltzer, M. and Schrape, M., 2012. Microdatabase: Securities Holdings Statistics, a flexible multi-dimensional approach for providing user-targeted securities investments data, Bundesbank Technical Documentation.

Amiti, M. and Weinstein, D. E., 2011. Exports and financial shocks. The Quarterly Journal of Economics, 126(4):1841–1877.

Baba, C. and Kokenyne, A., 2011. Effectiveness of capital controls in selected emerging markets in the 2000's. IMF Working Paper: Effectiveness of Capital Controls in Selected Emerging Markets in the 2000s, 11(281).

Baker, S. R., Bloom, N., and Davis, S. J., 2016. Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4):1593–1636.

Baley, I. and Blanco, J. A., 2015. Menu costs, uncertainty cycles, and the propagation of nominal shocks.

Baskaya, Y. S., Di Giovanni, J., Kalemli-Özcan, Ş., Peydro, J.-L., and Ulu, M. F., 2017a. Capital flows and the international credit channel. Journal of International Economics, 108:S15–S22.

Baskaya, Y. S., Giovanni, J. d., Kalemli-Özcan, S., and Ulu, M. F., 2017b. International spillovers and local credit cycles. Technical report, National Bureau of Economic Research.

Bebchuk, L. A. and Goldstein, I., 2011. Self-fulfilling credit market freezes. The Review of Financial Studies, 24(11):3519–3555.

Becker, B. and Ivashina, V., 2014. Cyclicality of credit supply: Firm level evidence. Journal of Monetary Economics, 62:76–93.

Becker, B. and Opp, M., 2013. Regulatory reform and risk-taking: replacing ratings, NBER WP 19257.

Berger, A. N., & Udell, G. F., 1995. Relationship lending and lines of credit in small firm finance. Journal of business, 351-381.

Berger, D., Dew-Becker, I., and Giglio, S., 2017. Uncertainty shocks as second-moment news shocks.

Bernanke, B. S., Gertler, M., and Gilchrist, S. , 1999. The financial accelerator in a quantitative business cycle framework. Handbook of macroeconomics, 1:1341–1393.

Bernanke, B., 2013. Stress testing banks: What have we learned? Speech at the "Maintaining Financial Stability: Holding a Tiger by the Tail" financial markets conference sponsored by the Federal Reserve Bank of Atlanta, Georgia.

Bianchi, J., 2011. Overborrowing and systemic externalities in the business cycle. American Economic Review, 101(7):3400–3426.

Blanchard, O. J., Dell'Ariccia, M. G., and Mauro, M. P., 2013. Rethinking macro policy II: getting granular. International Monetary Fund.

Blei, D. M., Ng, A. Y., and Jordan, M. I. , 2003. Latent dirichlet allocation. Journal of machine learning research, 3(Jan):993–1022.

Bruno, V. and Shin, H. S. 2014. Cross-border banking and global liquidity. The Review of Economic Studies, 82(2):535–564.

Bruno, V. and Shin, H. S. 2015. Capital flows and the risk-taking channel of monetary policy. Journal of Monetary Economics, 71:119–132.

Buch, C. M., Bucholz, M., and Tonzer, L., 2014 Uncertainty and international banking. In Conference paper for the conference on International Banking: Microfoundations and

Macroeconomic Implications organized by the International Monetary Fund (IMF) and the Dutch National Bank (DNB).

Chen, Q., Goldstein, I., & Jiang, W., 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. Journal of Financial Economics, 97(2), 239-262.

Chor, D. and Manova, K., 2012. Off the cliff and back? credit conditions and international trade during the global financial crisis. Journal of international economics, 87(1):117–133.

Clements, B. and Kamil, H., 2009. Are capital controls effective in the 21st century? The recent experience of colombia. In IMF Working Papers 09/30, International Monetary Fund. Citeseer.

Coen, W., 2017. Regulatory equivalence and the global regulatory system. Keynote address at the International Financial Services Forum London, Thursday 25 May, Available online: http://www.bis.org/speeches/sp170525.htm.

Collin-Dufresne, P., Goldstein, R. S., and Martin, J. S. , 2001. The determinants of credit spread changes. The Journal of Finance, 56(6):2177–2207.

David, G., Markowitz, S., and Richards-Shubik, S. , 2010. The effects of pharmaceutical marketing and promotion on adverse drug events and regulation. American Economic Journal: Economic Policy, 2(4):1–25.

Degryse, H. and Ongena, S., 2005. Distance, lending relationships, and competition, The Journal of Finance, 60(1), 231-266.

Demers, E. A. and Vega, C., 2014. The impact of credibility on the pricing of managerial textual content.

Demirguc-Kunt, A., Detragiache, E. and Merrouche, O., 2013. Bank capital: Lessons from the financial crisis, Journal of Money, Credit and Banking, 45(6), 1147-1164.

Dewatripont, M. and Tirole, J., 1994. The prudential regulation of banks. Cambridge, MA: MIT Press.

European Central Bank, 2005. The new Basel capital framework and its implementation in the European Union, ECB Occasional Paper Series No. 42.

European Central Bank, 2013. Note comprehensive assessment October 2013, Available online: https://www.ecb.europa.eu/pub/pdf/other/notecomprehensiveassessment201310en.pdf.

European Central Bank, 2014. Aggregate report on the comprehensive assessment, Available online: https://www.ecb.europa.eu/pub/pdf/other/aggregatereportonthecomprehensiveassessment201410.en.pdf.

Fahlenbrach, R. and Stulz, R. M. , 2011. Bank ceo incentives and the credit crisis. Journal of financial economics, 99(1):11–26.

Flannery, M. J., Kwan, S. H., Nimalendran, M., 2004. Market evidence on the opaqueness of banking firms assets. Journal of Financial Economics, 71(3):419–460.

Fleming, S. and Steen, M., 2013. Draghi says bank tests need failures for credibility; ECB probe. Financial Times, London Ed1 (2013, October 24). Retrieved from Factiva database.

Fleming, S., 2017. Fed banking watchdog nominee plans more ‘transparency’ in stress tests, Financial Times, Available online: https://www.ft.com/content/130d3c40-383a-3567-96cb-4fbe5539d535.

Forbes, K. J., 2007a. The microeconomic evidence on capital controls: No free lunch. In Capital Controls and Capital Flows in Emerging Economies: Policies, Practices and Consequences, pages 171–202. University of Chicago Press.

Forbes, K. J., 2007b. One cost of the chilean capital controls: increased financial constraints for smaller traded firms. Journal of International Economics, 71(2):294–323.

Forbes, K. J. and Warnock, F. E., 2012. Capital flow waves: Surges, stops, flight, and retrenchment. Journal of International Economics, 88(2):235–251.

Forbes, K., Fratzscher, M., and Straub, R., 2015. Capital-flow management measures: What are they good for? Journal of International Economics, 96:S76–S97.

Freixas, X., 2003. Crisis management in europe. Financial Supervision in Europe, Cheltenham: Edward Elgar, pages 102–119.

Froot, K. A. and Stein, J. C. , 1998. Risk management, capital budgeting, and capital structure policy for financial institutions: an integrated approach. Journal of financial economics, 47(1):55–82.

Gissler, S., Oldfather, J., and Ruffino, D., 2016. Lending on hold: Regulatory uncertainty and bank lending standards. Journal of Monetary Economics, 81:89–101.

Glaeser, E.L. and Shleifer, A., 2001. A reason for quantity regulation, American Economic Review, 91(2), 431-435.

Goldstein, I. and Sapra, H., 2014. Should banks' stress test results be disclosed? An analysis of the costs and benefits, Foundations and Trends in Finance, 8(1), 1-54.

Gourinchas, P.-O. and Obstfeld, M., 2012. Stories of the twentieth century for the twenty-first. American Economic Journal: Macroeconomics, 4(1):226–65.

Gómez, E., Lizarazo, A., Mendoza, J., Murcia, A., et al., 2017. Evaluating the impact of macroprudential policies in colombia’s credit growth. Banco de la República Colombia Working Paper, (980).

Hansen, S., McMahon, M., and Prat, A., 2014. Transparency and deliberation within the fomc: a computational linguistics approach.

Harrison, A. E., Love, I., and McMillan, M. S., 2004. Global capital flows and financing constraints. Journal of development Economics, 75(1):269–301.

Hassan, T. A., Hollander, S., Lent, L., and Tahoun, A., 2016. Aggregate and idiosyncratic political risk: Measurement and effects.

He, J., Ng, L., and Wang, Q., 2004. Quarterly trading patterns of financial institutions, Journal of Business, 77(3), 493-509.

Healy, P. M., Myers, S. C., and Howe C. D., 2002. R&d accounting and the tradeoff between relevance and objectivity. Journal of accounting research, 40(3):677–710.

Hellwig, M.F., 2010. Capital regulation after the crisis: business as usual? Mimeo.

Hertzberg, A., Liberti, J., & Paravisini, D., 2010. Information and incentives inside the firm: Evidence from loan officer rotation. The Journal of Finance, 65(3), 795-828.

International Monetary Fund, 2012. The Liberalization and Management of Capital Flows- An Institutional View.

Ivashina, V. and Scharfstein, D., 2010. Bank lending during the financial crisis of 2008. Journal of Financial economics, 97(3):319–338.

Jeanne, O. and Korinek, A., 2010. Excessive volatility in capital flows: A pigouvian taxation approach. American Economic Review, 100(2):403–07.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J., 2014. Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? Econometrica, 82(2):463–505.

Joint Committee of the European Supervisory Authorities, 2014. Mapping of Standard & Poor’s ratings services’ credit assessments under the standardized approach, Available online: https://eiopa.europa.eu/Publications/Consultations/Draft%20Mapping%20Report%20-%20S_and_P.pdf

Jordà, Ò., Schularick, M., and Taylor, A. M., 2011. Financial crises, credit booms, and external imbalances: 140 years of lessons. IMF Economic Review, 59(2):340–378.

Jurado, K., Ludvingson, S. C., and Ng, S., 2015. Measuring uncertainty. The American Economic Review, 105(3):1177–1216.

Kashyap, A. K., Rajan, R., and Stein, J. C., 2002. Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. The Journal of Finance, 57(1):33–73.

Kashyap, A. K., Stein, J. C., and Wilcox, D. W., 1993. Monetary policy and credit conditions: Evidence from the composition of external finance. The American Economic Review, 83(1):78–98.

Khwaja, A.I. and Mian, A., 2008. Tracing the impact of bank liquidity shocks: Evidence from an emerging market, American Economic Review, 98(4), 1413-1442.

Korinek, A., 2017. Regulating capital flows to emerging markets: An externality view. Journal of International Economics.

Kose, M. A., Prasad, E., Rogoff, K. S., and Wei, S.-J., 2006. Financial globalization: a reappraisal. Technical report, National Bureau of Economic Research.

Kotomin, V. and Winters, D., 2006. Quarter-end effects in banks: preferred habitat or window dressing? Journal of Financial Services Research, 29(1), 61-82.

Laffont, J-J. and Tirole, J., 1993. A theory of incentives in procurement and regulation, Cambridge, MA: MIT Press.

Lakonishok, J., Shleifer, A., Thaler, R. and Vishney, R., 1991. Window dressing by pension fund managers, American Economic Review, 81(2), 227-231.

Loughran, T. and McDonald, B., 2011. When is a liability not a liability? textual analysis, dictionaries, and 10-ks. The Journal of Finance, 66(1):35–65.

Ludvingson, S. C., Ma, S., and Ng. S., 2015. Uncertainty and business cycles: exogenous impulse or endogenous response? Technical report, National Bureau of Economic Research.

López, M., Tenjo, F., & Zárate, H., 2014. Credit cycles, credit risk and countercyclical loan provisions. Ensayos sobre Política Económica, 32(74), 9-17.

Maaten, L. v. d. and Hinton, G., 2008. Visualizing data using t-sne. Journal of Machine Learning Research, 9(Nov):2579–2605.

Magud, N. and Reinhart, C. M., 2006. Capital controls: an evaluation. Technical report, National Bureau of Economic Research.

Magud, N. E., Reinhart, C. M., and Rogoff, K. S., 2011. Capital controls: myth and reality- a portfolio balance approach. Technical report, National Bureau of Economic Research.

Mayew, W. J. and Venkatachalam, M., 2012. The power of voice: Managerial affective states and future firm performance. The Journal of Finance, 67(1):1–43.

Mayew, W. J., 2008 Evidence of management discrimination among analysts during earnings conference calls. Journal of Accounting Research, 46(3):627–659.

Mehran, H., Morrison, A. D., and Shapiro, J. D., 2011. Corporate governance and banks: What have we learned from the financial crisis?

Mendoza, E. G., 2010. Sudden stops, financial crises, and leverage. American Economic Review, 100(5):1941–66.

Mendoza, E. G. and Terrones, M. E., 2008. An anatomy of credit booms: evidence from macro aggregates and micro data. Technical report, National Bureau of Economic Research.

Mikolov, T., Chen, K., Corrado, G., and Dean, J., 2013a. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.

Mikolov, T., Sutskeyer, I., Chen, K., Corrado, G. S., and Dean, J., 2013b. Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems, pages 3111–3119.

Miranda-Agrippino, S. and Rey, H., 2015. World asset markets and the global financial cycle. Technical report, National Bureau of Economic Research.

Morais, B., Peydro, J.-L., and Ruiz Ortega, C., 2015. The international bank lending channel of monetary policy rates and quantitative easing: credit supply, reach-for-yield, and real effects. Technical report, The World Bank.

Morgan, D., 2002. Rating banks: Risk and uncertainty in an opaque industry, American Economic Review, 92(4), 874-888.

Musto, D., 1999. Investment decisions depend on portfolio disclosures, Journal of Finance, 54(3), 935-952.

Myers, S.C. and Rajan, R.G., 1998. The paradox of liquidity, Quarterly Journal of Economics, 113(3), 733-771.

Ng, L. and Wang, Q., 2004. Institutional trading and the turn-of-the-year effect, Journal of Financial Economics, 74(2), 343-366.

Obstfeld, M., 2015. Trilemmas and trade-offs: living with financial globalisation.

Oster, E., 2017. Unobservable selection and coefficient stability: Theory and evidence. Journal of Business & Economic Statistics, pages 1–18.

Ostry, J., Ghosh, A., Habermeier, K., Chamon, M., Qureshi, M., and Reinhardt, D. B., 2010. Capital inflows: The role of controls. IMF Staff Position Note: Capital Inflows-The Role of Controls, 10(04).

Ostry, J., Ghosh, A., Habermeier, K., Laeven, L., Chamon, M., Qureshi, M., and Kokenyne, A., 2011. Managing capital inflows: What tools to use? IMF Staff Discussion Note: Managing Capital Inflows-What Tools to Use?, 11(6).

Owens, E. and Wu, J., 2015. Quarter-end repo borrowing dynamics and bank risk opacity, Review of Accounting Studies, 20(3), 1164-1209.

Paravisini, D., Rappoport, V., Schnabl, P., and Wolfenzon, D., 2014. Dissecting the effect of credit supply on trade: Evidence from matched credit-export data. The Review of Economic Studies, 82(1):333–359.

Petersen, M.A. and Rajan, R.G., 1995. The effect of credit market competition on lending relationships, Quarterly Journal of Economics, 110(2), 407-443.

Pignal, S. and Jenkins P., 2011. Dexia poses setback for EBA stress tests, Financial Times, Available online: https://www.ft.com/content/0f638a80-ef6a-11e0-bc88-00144feab49a.

Posner, R.A., 1975. The social costs of monopoly and regulation, Journal of Political Economy, 83(4), 807-827.

Rajan, R. G., 1992. Insiders and outsiders: The choice between informed and arm's-length debt. The Journal of finance, 47(4), 1367-1400.

Reinhart, C. M. and Reinhart, V. R., 2008. Capital flow bonanzas: an encompassing view of the past and present. Technical report, National Bureau of Economic Research.

Reinhart, C. M. and Rogoff, K. S., 2009. This time is different: Eight centuries of financial folly. princeton university press.

Reuters Staff, 2013a. AQR and stress tests could threaten European banks. Reuters, Available online: http://www.reuters.com/article/ecb-stress-tests-banks/aqr-and-stress-tests-could-threaten-european-banks-idUSL6N0I02OS20131015.

Reuters Staff, 2013b. European shares snap winning run as banks hit by ECB review. Reuters (October 23, 2013). Retrieved from Factiva database.

Reuters Staff, 2015. BoE sticks with anti "window dressing" rule for bank's leverage ratio. Reuters, Available online: http://www.reuters.com/article/boe-banks-regulations/boe-sticks-with-anti-window-dressing-rule-for-banks-leverage-ratio-idUSL8N13W1R220151207.

Rey, H., 2015. Dilemma not trilemma: the global financial cycle and monetary policy independence. Technical report, National Bureau of Economic Research.

Rey, H., 2016. International channels of transmission of monetary policy and the mundellian trilemma. IMF Economic Review, 64(1):6–35.

Roychowdhury, S. and Sletten, E., 2012. Voluntary disclosure incentives and earnings informativeness. The Accounting Review, 87(5):1679–1708.

Schoenmaker, D., 2011. The financial trilemma. Economics Letters, 111(1):57–59.

Schoenmaker, D., 2013. Governance of international banking: The financial trilemma. Oxford University Press.

Schularick, M. and Taylor, A. M., 2012. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. American Economic Review, 102(2):1029–61.

Sharpe, S. A., 1990. Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. The journal of finance, 45(4), 1069-1087

Standard & Poor's Ratings Services, 2012. Default, transition, and recovery: 2012 annual global corporate default study and rating transitions. Available online: https://www.nact.org/resources/NACT_2012_Global_Corporate_Default.pdf.

Steen, M. and Jenkins, P. and Fleming, S., 2013. Eurozone bank shares sink after ECB outlines health check plan. Financial Times (October 23, 2013), Retrieved from Factiva database.

Steen, M., 2013. ECB unveils checks in step to banking union; Eurozone crisis. Financial Times, USA Ed1 (October 23, 2013). Retrieved from Factiva database.

Stigler, G.J., 1971. The theory of economic regulation, The Bell Journal of Economics and Management Science, 3-21.

Stiglitz, J. E. and Weiss, A., 1992. Asymmetric information in credit markets and its implications for macro-economics. Oxford Economic Papers, 44(4):694–724

Tarullo, D.K., 2014. Stress testing after five years. Speech given at the Federal Reserve Third Annual Stress Test Modelling Symposium, Boston, Massachusetts. Available online: https://www.federalreserve.gov/newsevents/speech/tarullo20140625a.htm.

The White House, 2015. Occupational licensing: A framework for policymakers. The Council of Economic Advisers, July.

Tirole, J., 2014. Market failures and public policy. Nobel Prize Lecture, December 8, 2014.

Vives, X., 2014. Strategic complementarity, fragility, and regulation. The Review of Financial Studies, 27(12), 3547-3592.