Three Essays On The Behavioral Aspects Of Banking

BY

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THESIS
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LIST OF ABBREVIATIONS

BBD	Baker, Bloom and Davis
CDS	Credit Default Swaps
EBP	Earings before Provision
EPU	Economic Policy Uncertainty
FF	Fed Funds
FOC	First-order condition
GDP	Gross Domestic Product
GMM	Generalized Methods of Moments
HS	Ho and Saunders
LLP	Loan Loss Provision
MBS	Mortgage Backed Securities
MP	Monetary Policy
MPU	Monetary Policy Uncertainty
MTB	Markt-to-Book ratio
NBC	Naïve Bayes Classifier
NI	Net Income
NN	Neural Networks
NPL	Non-Performing Loans
QE	Quantitative Easing
ROA	Return of Assets
RSH	Rogers, Sun and Husted
VIX	The CBOE Volatility Index

SUMMARY

The three essays in my thesis study three selected behavioral factors and their impacts on banking activities. The first essay titled *The effect of monetary policy uncertainty on banks′ asset allocation : evidence from US bank level data* studies how banks allocate their assets between liquid assets and loans in response to changes in monetary policy uncertainty (MPU). Using US bank level data over the 1985-2015 period and two orthogonalized MPU proxies (Baker et al. (2016);Rogers et al. (2016)), I find that banks increase liquid assets holdings, and thus reduce their loan portfolios, when MPU increases, I also find that loan interest rates rise following rises in MPU. I develop a simple asset management model to study the role of several intermediate mechanisms that would be consistent with our empirical findings. I show that rising liquidity risks, higher security returns, and higher federal funds borrowing costs are all possible reasons of the observed banks' responses to MPU.

While the MPU is more of a “demand-side” behavioral factor, the rest two essays focus more on the supply-side, or the behavior of commercial banks themselves. The second essay titled *Annual report sentiment and accounting conservatism : evidence from US bank level data* examines the predictive power of annual report sentiment on future accounting conservatism. My paper has composed three measures of sentiment based on an establish dictionary

(Loughran and McDonald (2011b)) and a machine learning model (Naïve Bayes classifier, NBC) and one deep learning model (Neural networks, NN). I find that negative sentiment in annual reports is associated with more conservative accounting in the coming fiscal year. In particular, I find that higher fraction of negative words/sentences is predicting more timeliness in loss recognition and higher scores of conservatism (C_score). I conjecture that size and MTB are major passthroughs of the sentiment's predictive power. On one hand, negative words/sentences are more likely used by smaller sized banks. These banks have higher demand for accounting conservatism due to higher informational asymmetry. On the other hand, higher MTB banking firms use more negative words/sentences to avoid litigation risks caused by higher trading volatility due to more growth opportunities.

Behavior of CEOs also matter. The last essay titled *CEO optimism and Net interest margin : evidence from US bank level data* examines how CEO optimism affects commercial banks' profitability. I build a simple theoretical model that proposes two contrasting effects of optimism on profitability. On the one hand, CEO optimism reduces banks' required price of risk, leading to lower profitability. On the other hand, CEO optimism leads to higher propensity to take risks, thus increasing expected profitability. Using net interest margin as a proxy for bank profitability, I find empirically that there is no significant relationship between CEO optimism and bank profitability during the years prior to the 2007-09 financial crisis as well as the total period from 1994-2017. This suggests that, during this period, the two contrasting effects of optimism on profitability might offset each other as per our model prediction. Additional regression analysis reveals that it is lower credit risk price and higher interest risk taking that contribute to the insignificant difference in NIM in both periods.

1 The effect of monetary policy uncertainty on banks' asset allocation: evidence from US bank level data

1.1 Introduction

Commercial banks have played critical roles in the transmitting the effect of monetary policy (MP) to the real economy. In studying the transmission mechanism, Bernanke and Blinder (1992) highlighted the role of commercial banks' asset allocation in proposing the later known as bank lending channel. In their theory, tightening MP reduced the loanable funds and in the case where banks failed to substitute reduction in money supply, banks constrained their supply of credits. Their theory is later supported by the empirical findings by Kashyap and Stein (2000). In acknowledging the contribution of bank lending channel to understanding MP transmission mechanism, I also see both works (Bernanke and Gertler (1995); Kashyap and Stein (2000)) as attempts to uncover how first moment effect of MP on banks' asset allocation. Given that banks' lending influenced by the first moment, as evidenced by Kashyap and Stein (2000), is that possible that a higher moment effect of MP (e.g. second moment) also plays a role in their business decision?

The second moment of MP, or the monetary policy uncertainty (MPU, hereafter) also stands as important aspects of modern monetary policy practices. In one of his policy papers, Alan Greenspan noted that "uncertainty is not just an importance feature of the monetary policy landscape; it is the defining characteristic of that landscape" (Greenspan (2004); Kurov and Stan (2018)). However, crucial as it is, the difficulty underlying measuring MPU has resulted in a serious omission of literature. In fact, it wasn't until Baker et al. (2016) that credible measurements of MPU were proposed. Therefore, the major contribution of my paper is to fill in the gap and explore the effect of MPU in the supply of credits.

My regression analysis implies that banks allocate more of their assets towards liquid assets from loans in the face of unexpected MPU shocks. The later analysis on the interest rate on loans reveals that the change in loans is more likely driven by changes in the supply.

I have also associated the change in asset allocation with changing risk levels. As per my theoretical model, I pin down several possible risks that might lead to asset allocation. my empirical analysis has implied that heightened liquidity risks stemmed from amounting commitments, and rising return from securities are two possible drivers leading to banks' reduction in loan portfolios. Meanwhile, I also find that MPU increases the funding costs from the federal funds market, which might also add to banks' gains in accumulating liquid assets.

The bank level data has also allowed us to explore cross-section difference in response to MPU shocks. I find that smaller-sized banks are among the most responsive to the MPU shocks. This might be due to higher credit risks (as seen in higher loan loss reserves) given same MPU shocks. This finding is comparable to the results in Kashyap and Stein (2000), who have found that loan growth was lower among smaller banks under the same first moment change in MP. I also explore how the liability-side variable can explain the heterogeneous MPU effect and find that banks with higher transaction deposits are holding fewer liquid assets against the MPU shocks, a finding consistent with my prior.

The reminder of this paper is organized as follows: in section 1.2, the relevant literature is reviewed. In section 1.3, I introduced a liquidity management model that helps motivate a number of testable hypotheses. Details of data are included in section 1.4.In section 1.5, the major empirical findings are presented and I show how they can be reconciled with theoretical model's predictions. More empirical findings on heterogeneity are also seen in section 1.5. And all discussions are concluded in section 1.6.

1.2 Literature review

This paper is related to several strands of literature. The first strand is the literature explores the relations between macroeconomic uncertainty and banking. Baum et al. (2004) predict that rising macroeconomics uncertainty is likely to lead to uniform decrease in loans among commercial banks. The more homogeneity in loan reducing behavior could be seen in lower variance in the loan-to-assets ratio, which is confirmed by their empirical investigation. To the best of my knowledge, Baum et al. (2004) is the first to explore the link between bank asset allocation and economic uncertainty. Insightful as it is, the study of Baum et al. (2004) might have little room for the heterogeneous analysis. The bank lending link with macroeconomic uncertainty is later extended to many different settings with various specifications (Talavera et al. (2012); Ibrahim and Shah (2012)). Using a system GMM method, Talavera et al. (2012) finds significant increase in loan-to-capital ratio among Ukraine banks when the GARCH implied macroeconomic uncertainty is low. Likewise, a study of Malaysia finds that bank credit to private sector is adversely affected by the financial market uncertainty, as measured by the realized volatility of stock markets (Ibrahim and Shah (2012)). Calmes and Théoret (2014) found, in an EGARCH setting, that the macroeconomic uncertainty is also having a symmetric impact on banks' noninterest generated activities. And in a more recent study, Raunig et al. (2017) applies an event study method to identify the adverse effects of macroeconomic uncertainty on bank lending. This line of literature, which focuses on the interaction of macroeconomic uncertainty and bank lending, uniformly highlights the negative role of uncertainty on banks' lending decision. Unsurprising as the conclusion is, the quantitative aspects as well as the methodology adopted in these researches are inspiring to my study.

The second strand of papers studies the real effect of policy uncertainty. Ever since Friedman (1968) and Higgs (1997), it has been realized that indeterminacy in policy affects behavior of different agents of the economies. Then it comes to the problem on how to measure the policy uncertainty. Several recent studies have made attempts to develop indices using newspaper data (Baker et al. (2016); Rogers et al. (2016)). The indices developed by Baker, Bloom and Davis (2016, BBD hereafter) is later cited by many banking literature. Using the BBD index, Bordo, Duca and Koch (2016) studies the link of economic uncertainty with the loan growth over several decades. The analysis of Bordo et al. (2016) is conducted in both aggregate and bank level. The negative effects of EPU is robust with other business cycle controls across different sub-periods. Moreover, they have found that larger banks are more vulnerable to the shocks of EPU due to sensitivity of "national uncertainty" due to their geographical diversification. Berger et al. (2018) attributes drop in liquidity creation created by commercial banks caused by uncertainty to changes in the asset-side. Therefore, they conclude that the key function of providing liquidity to productive sector is hampered at times with high EPU. Bonaime et al. (2018) find a negative relation between firms' M&A activities and the BBD complied EPU. Meanwhile, their findings are robust when the uncertainty is instrumented using the partisan conflicts. These studies are all evidence that banks are not immune to the volatile economic environment.

As noted in Greenspan (2004), uncertainty in Monetary policy has played increasingly important roles in understanding nowadays monetary phenomenon. However, when it comes to studying the uncertainty in Monetary policy, measurement is always an issue. I then explore the line of literature that focuses on measuring MPU and find that before BBD (2016), uncertainty in monetary policy is measured by the market-based or derivative-based indices (Kaminska and Roberts-Sklar (2018)). For example, interest rate uncertainty, implied by volatility of the corresponding options (e.g. Eurodollar), is used by Bauer et al. (2012) to study how innovative MP practice like forward guidance affects market expectation. A more relevant study has been carried out byChang et al. (2014), who relate the implied and realized volatility to the timelines of Bank of Canada interest rate decision date. However, to the best of my knowledge, it wasn't until BBD (2016) that alternative measures are proposed. Following BBD, Rogers et al. (2016) also construct another index of MPU based on the newspaper methods. However, Rogers et al. (2016) include a smaller set of newspapers and used fewer keywords in constructing the index. The two indices have a correlation index of roughly 0.5.

Several recent studies, following the newly proposed MPU indices, have revealed that the MPU has an impact on the dynamics of the stock market. Kaminska and Roberts-Sklar (2018) find that MPU increased the equity return variance. Kurov and Stan (2018) found that high MPU reduces the sensitivity of stocks and crude oil price to macroeconomic news but strengthens that of the Treasuries. Banking is another industry heavily influenced by the policy rate uncertainty and as far as I am concerned, this is the first paper that builds a link between banking behavior and MPU.

With respects to the MPU, I have also reviewed a third line of literature centered on source of MPU and find that MPU can either be originated from the central bank or the households. In the central bank side, MPU sometimes is unintended. For example, when central bankers' decisions are based on models with parameter uncertainty, their policy levers would be a function of the parameter uncertainty (Wieland (2000)). In fact, Wieland (2000) had made the case about how monetary policy can be naturally uncertain from the policy side (central bank). In his example of German reunification in 1990, introduction of Deutsche Mark in east Germany required a huge one-time money supply. However, since little was known about the demand in the region, the growth in money reflected the best estimates of the demand given the central banks' projected demand.

On the other hand, some of the uncertainty is intentional. Researchers have long noticed that ambiguity in the monetary policy setting is not accidental (Rogers et al. (2016)). In fact, in the seminal theoretical model by Cukieman and Meltzer (1986), ambiguity is desirable under their assumption of a politically motivated monetary decisionmaker [1]. It has been held prior to the 90s that central banks should "say as little as possible" (Blinder et al. (2008)) and it wasn't until the late 90s and early 2000 that increased communication and more transparency in central bank decision process became mainstream. Even if so, some authors still point out the disadvantages behind such trends. The model by Jensen (2002) suggests that transparency of monetary policy increases the responsiveness of inflation to MP and thus draws too much attention of the central banker, reducing the significance of the output gap. Jensen (2002) then derives an optimal degree of uncertainty based on the balanced taste of inflation versus output gap. Other studies also defend the viewpoint of desirable central bank opacity, which results in greater MPU. A recent paper by Jitmaneeroj et al. (2019) have examined the trend of rising transparency and find that it does lead to lower uncertainty.

Households also contribute to the formation of MPU. Stulz (1986) has pointed out that households are generally more unsure about future policy changes in cases where monetary authority lacked credibility in his announcement. Meanwhile, the dynamics in the monetary regime are also another major source that affects the distribution of policy variables. For example, the

[1] The question on how monetary policy decision is influenced by political factors is also put to tests. In the context of the United States, studies have found that central bank decision face the pressure from the President and the Congress (Cukierman and Meltzer (1986)). Panel studies on OECD countries (Boix (2000); Belke and Potrafke (2012)) have found mixed results on how governmental ideology can lead to different monetary policy stances and uniform conclusions are yet to be made.

movements of interest rate under conventional monetary policies (e.g. open market operation) might differ from that under the unconventional ones (e.g. QE).

The final strand of literature is about liquidity (asset) management of commercial banks. As would be seen from my model section, the model of Poole (1968) on liquidity management is of great influence on this paper. Although Poole's model has a great emphasis on the management of reserves, his research is among the earliest to incorporate uncertainty in banks' asset allocation problem. Other similar researches/extensions to Poole (1968) also provides clues on my modeling section. For example, the model by Sprenkle (1987), using the basic framework of Poole (1968), analyze how other sources of financing uncertainty (e.g. loan and deposits) would impact banks' asset allocation decision. In some more recent publications, the framework laid out by Poole is used to analyze newly rising banking issues. Keister and Bech (2012) find that under the new Basel III regulation requirement, the traditional link between open market operation and overnight interest rate could change. Using the same framework, Afonso et al. (2019) find that the distribution of reserves among banks is one key factor affecting the fed funds rate when fed normalizes their supply of reserves in the post-crisis period. In terms of the empirical part, Berrospide (2012) had identified several key factors in driving the liquidity hoarding behavior during the financial crisis. The findings in Berrospide (2012) are also inspiring to us in terms of choosing what variables to use as proxies of loan and securities portfolio risk (e.g. loan loss reserves, unused commitments, etc).

1.3 The model

In this section a simple model of asset management is presented with one representative bank and firm. Banks allocate their asset holdings to hedge against two types of risks: the credit risk and liquidity risk.

1.3.1 The firm

The Firm need funding to finance their project. The project has a probability of success p. A successful project yields a return of R but pays back the loans at rate r^L. Meanwhile a project with size has production costs $\frac{\theta L^2}{2}$. Therefore, a successful project yields profit $\pi = RL - r^L L - \frac{\theta L^2}{2}$. On the other hand, if the projects fail, the project had a lower return $\underline{R}$ and the firm defaults on his loan contract. Still, he pays the production costs, and yields a profit $\pi = \underline{R}L - \frac{\theta L^2}{2}$. In the discussions below, I assume $\underline{R} = 0$ for simplicity. Also, I assume in a MM environment; the bank is indifferent between loan financing and equity financing. Thus, the expected profits of firms are:

$$E\pi = p\left(RL - r^L L\right) - \frac{\theta L^2}{2} \qquad (1.4.1)$$

Maximizing the expected profits in equation (1.4.1), I derive the loan(credit) demand function as:

$$L^D = \frac{p\left(R - r^L\right)}{\theta} \tag{1.4.2}$$

From equation (1.4.2), and I find that:

Proposition 1.1 *A lower p(higher credit risk) shifts the demand curve leftward.*

1.3.2 The bank

The bank's problem in my model is in many ways similar to the inventory model in Poole (1968). Alternative methods of modelling banks' decision can be found in Talavera et al. (2012) where banks are programmed to maximize discounted sums of dividend payments. However, in my case, a static setting as in Poole (1968) is sufficient to illustrate the channels of MPU on banks' asset allocation rather than a dynamic one as Talavera et al. (2012). The bank maximizes his (expected) profits by allocating his total assets A between loans L and securities S. Loans to the firm has a return r^L with probability p and zero otherwise. Securities S have a return r^S and I assume the expected loan return $pr^L < r^S + r^B$ and $pr^L > r^S$ to guarantee an interior solution. The bank faces liquidity risk xA and bank has to meet the random liquidity demand with his securities holding S. If his securities are below xA, he borrows the difference $xA - S$ from the external market at a price r^B. The ex-post profit is writtenas:

$$\pi^B = rL + r^S S - r^B (xA - S) \, 1 (xA \geq S) \tag{1.4.3}$$

where $A = L + S$. The probability of risk has the following distribution: with probability $r = r^L$ and zero otherwise. And the cumulative probability distribution function of is known to the bank, $F(x)$, where $f(x) = F'(x)$. The ex-ante profit function is:

$E\pi^B = pr^L L + r^S S - r^B \int_{\frac{S}{A}}^{\infty} (xA - S) \, dF$, assuming the two risks are mutually independent.

The first order condition with respect to S is

$$r^S + r^B \left(1 - AF\left(\frac{S}{A}\right)\right) = pr^L \tag{1.4.4}$$

The LHS of the FOC in (1.4.4) is the marginal benefits of security holding. One can see that the marginal benefit is twofold: an explicit return r^S and implicit return $r^B \left(1 - AF\left(\frac{S}{A}\right)\right)$. The implicit return is related with the probability of securities falling short of liquidity demands. And I see that as banks hold more securities, the implicit return is decreasing.

Maximizing the expected profits, the optimal loan(credit) supply is $L^S = A\left(1 - F^{-1}\left(\frac{r^S + r^B - pr^L}{r^B}\right)\right)$. Same as before, I derive an upward sloping supply curve. Several of the following factors govern the property of the supply curve.

Proposition 1.2 *A lower p(higher credit risk) shifts the supply curve leftward. Note that p(credit risk) also has a demand-side effect.*

Proposition 1.3 *Higher r^S shifts the supply curve leftward.*

Proposition 1.4 *r^Bhas ambiguous effect on the location of supply curve, depending on the relative return of loans versus securities. If loans have higher expected return than securities, then lower r^B shifts the supply curve to the right, and vice versa.*

1.3.3 The equilibrium

The market is clear at the loan rate r^L when the loan demand equals to the loan supply,$L^S = L^D$. In other words, the equilibrium loan rate r^{L*}satisfies the condition

$$\frac{p\left(R - r^{L*}\right)}{\theta} = A\left(1 - F^{-1}\left(\frac{r^S + r^B - pr^L}{r^B}\right)\right) \tag{1.4.5}$$

The equilibrium loan level can be derived given the loan rate . In other words, my model implies:

$$\begin{aligned} L^* &= f\left(p, r^S, r^B, F\right) \\ r^{L*} &= g\left(p, r^S, r^B, F\right) \end{aligned} \tag{1.4.6}$$

A comparative static analysis reveals that:

Remark 1.1 *(credit risk channel). A lower p(higher credit risk) leads to reduction in both supply and demand, with ambiguous effect on the loan rate.*

Remark 1.2 *(liquidity risk channel). A first order dominant function* F' *over* F*, where* $F^{'} \geq F, \forall x$ *only casts negative effect on supply with increase in loan rate.*

Remark 1.3 *(security return channel). Higher* r^S *increases the relative return of loans, resulting in higher loan supply and loan rate.*

Remark 1.4 *(borrowing cost channel).* r^B *has ambiguous effect on loan levels and loan rate due to its ambiguous effect on supply.*

1.3.4 MPU and the equilibrium

I assume that all the aforementioned parameters are affected by MPU, manifested by the uncertainty in interest rate. To illustrate how MPU is placed in my model, I make the following assumptions:

Assumption 1.1 *p is increasing in MPU.*

The assumption 1.1 is based on the idea of the balance sheet channel of MP as outlined in Bernanke and Gertler (1995). I argue that increase in MPU has equivalent effects to rise in money market rates where firms' net values are negatively impacted. Lower net values might lead to higher risks of bankruptcy, or failure of projects in my model. And I also found recent empirical studies by Wang et al. (2019) , who find that higher economic policy uncertainty (EPU) increased the spread of CDS.

Assumption 1.2 *higher MPU results in F', where $F^{'} \geq F, \forall x$.*

Assumption 1.2 is related to the option nature of loan commitments. Imagine a scenario where MPU is mainly manifested by the uncertainty in interest rate. Borrowers would have higher willingness to enter commitment contracts so as to lock in the borrowing rates.

Assumption 1.3 *higher MPU results in lower security returns.*

Assumption 1.3 shares similar logics with assumption 1.2. I assume that demand for risk-free securities is higher when the future monetary policy stance is more unpredictable.

Assumption 1.4 *higher MPU results in higher borrowing cost.*

Combining my previous findings and assumptions, following predictions are made :

TABLE I: MPU AND DOMINANT CHANNELS

Dominant channel	parameter	results
credit risk	$p \downarrow$	$L \downarrow, r^L?$
liquidity risk	$F \uparrow$	$L \downarrow, r^L \uparrow$
security return	$r^S \uparrow$	$L \downarrow, r^L \uparrow$
borrowing cost	$r^B \downarrow$	$L?, r^L?$

1.4 The data

My data is collected from both the bank-level and the macroeconomic level sources. The bank level data is mainly from the quarterly filed consolidated reports of incomes and conditions (also known as the Call report), which are publicly available through the Wharton research data services. I list all the constructed bank-level variables in the tables below:

As the two major explanatory variables in table II, I find that the sum of liquid assets and loans make up the majority (over 90 percent) of total assets. At the same time, I construct a list of interest rate variables given the bank level data. The methodology in constructing these interest variables is similar: I divide the interest income by the corresponding income-generating assets (e.g. I divide the loan interest yields by total loans). Such methods are commonly used in the Uniform Bank Performance Report (UBPR) and some previous literature, for example, Craig and Dinger (2013). All interest rates are annualized. The loan interest rate has a higher return to other liquid assets (federal funds, Treasury securities or MBS), consistent with my intuition of positive risk premium among loan portfolios.

Other bank-level measures in the table are also constructed in ways consistent with existing works. For example, the loan loss reserves, normalized by total loans, are used in Berrospide (2012) and efficiency is computed by the ratio of total income over expense as Delis and Kouretas (2011). All the commercial bank level variables are aggregated to the top regulatory holder (RSSD9348) and winsorized at 5 percent level.

TABLE II: SUMMARY STATISTCS

Variable name	Obs	Mean	Std.dev	Min	Max	definition
liquid	766,946	35.03	13.80	4.20	73.08	liquidity assets over total assets
loan	766,946	60.14	13.65	21.26	88.41	total loans over total assets
intloan	770,819	7.85	2.35	0.00	13.65	sum of interest on loans and receivables on leases over total loans
loanloss	766,946	60.14	13.65	21.26	4.17	loan loss reserves over total assets
unuse	775,971	1.42	0.63	0.00	31.21	unused commitments over total assets
intfedexp	271,580	2.58	2.55	0.00	20.00	interest expense on fed funds over Federal funds purchased and securities sold under agreements to repurchase
intfedinc	552,830	4.42	4.28	0.00	43.33	interest income on fed funds over Federal funds sold and securities purchased under agreements to resell
inttreas	351,172	3.27	1.55	0.09	8.21	interest on treasuries over treasuries holdings
intmbs	328,366	3.46	1.66	0.00	10.19	interest on MBS over MBS holding
size	766,949	11.58	1.09	9.12	15.38	logarithm of total assets
cap	783,226	9.81	3.01	0.00	22.56	equity capital over total assets
roa	763,315	0.22	0.17	-1.67	0.63	net income over total assets
eff	727,299	1.28	0.16	0.69	1.96	total income over total expense
BBD	1,083,756	4.46	0.48	3.21	5.66	logarithm of the BBD index (1985Q1-2017Q4)
RSH	1,037,855	4.54	0.32	3.77	5.51	logarithm of the RSH index(1985Q1-2015Q4)
VIX	854,342	2.91	0.32	2.33	4.07	logarithm of the CBOE VIX (1990Q1-2017Q4)
GDP	1,549,748	2.97	2.18	-3.90	8.60	YoY real GDP growth
chg_fed	1,512,500	-0.01	1.01	-3.99	6.02	Quarterly change of fed funds rate
residual BBD	854,342	0.03	0.30	-0.64	0.69	residual logarithm of the BBD index (1990Q1-2017Q4)
residual RSH	808,441	-0.01	0.33	-0.82	0.86	residual logarithm of the RSH index(1990Q1-2015Q4)

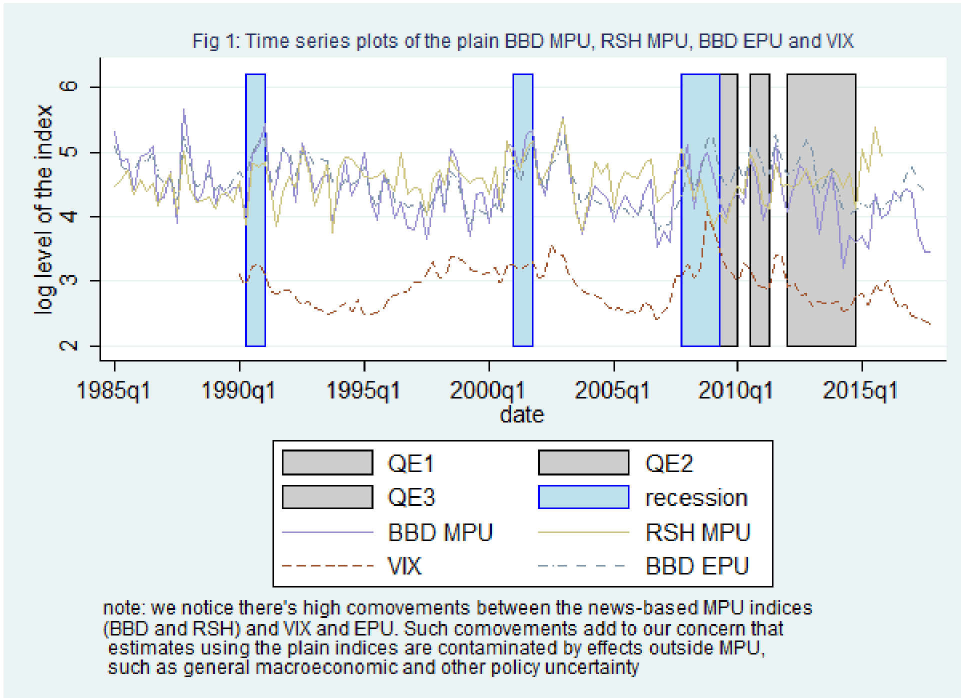
The bank level variables have the earliest data available in the late 70s. However, in the regression analysis below, I limit the time window of my analysis from 1990Q1 to 2017Q4 due to the availability of the MPU proxies.

The above table also contains all the macroeconomic variables included in the regression analysis section. Two news-based indices, the BBD (2016) and RSH (2017) are used. These two time-series have relatively short duration, with BBD starting at 1985Q1, RSH ending at 2015Q4. All these indices are taken logarithm to account for the difference in levels.

As compared with the RSH, BBD is more widely cited. I attribute the credibility of the BBD to the intensive human audit work. In the context of constructing indices from newspapers, it's always challenging to establish criteria of identifying policy uncertainty relevant articles. BBD classifies an article as policy uncertainty relevant when certain words occur. This set of words used as classifying criteria is called term set. To derive proper term set, the authors conduct several rounds of audits: attempted audit, pilot audit and full-scale audit. The first two mainly aims to formalize the guidelines of classifications. These guidelines are then used to train student research assistants, who are hired to conduct the full-scale audit. During the full-scale audit, the readers also record key terms when they classify an article relevant with policy uncertainty. Those terms are then evaluated via a computer automated experiment. The experiment generates another set of policy uncertain article, which is then compared with the human audit labels. Only those terms with fewer discrepancy from human audit outcomes are then included in the finalized term set.

The intention of the BBD research is to construct measurements of the “overall” economic policy uncertainty, whereas RSH has specific focus on monetary policy. Therefore, RSH has focused on a smaller set of “elite” financial newspapers and their scaling scheme is different from BBD. The RSH uses articles that’s monetary policy relevant (e.g. contain such words as “Fed”) to scale the counts of policy uncertainty relevant, while BBD normalizes using the total volumes of articles. The scaling scheme by RSH is said to account for the seasonal coverage of Fed funds news. For example, the press increases coverage of Fed at certain point of time (e.g. before the FOMC) even when little uncertainty is present. Under the BBD setting, the MPU would increase due to more articles mentioning “Fed”, whereas under the RSH, since number of “Fed” article enter both the numerator and denominator, there would be little change in the RSH indices. Both of the indices survive several sensitivity tests, e.g. removal/addition of other plausible terms and exhibit desirable results of robustness. I also propose alternative measurements of monetary policy uncertainty based on the “plain” BBD and RSH. The key challenge of the two indices by BBD and RSH is that they might involve other uncertainty (e.g. macroeconomic or other economic policies). The following figures plot the time series of BBD and RSH as well as the CBOE VIX, which is one proxy of the macroeconomic uncertainty. The

Figure 1: Time series plots of the plain BBD MPU, RSH MPU, BBD EPU and VIX



two news-based indices have exhibited very similar trends, though there're some divergent patterns after the crisis. Meanwhile, I see that these two indices are highly correlated with the CBOE VIX. I have also highlighted the recessions periods as timed by the NBER timetables and the QE periods defined in Rodnyansky and Darmouni (2017). And from this figure only, I can see little pattern of divergence between VIX and the two news-based indices.

To address the above concern of plain indices, I regress the MPU indices of BBD and RSH on the EPU index by BBD and the CBOE VIX as control for the macroeconomic uncertainty. The residuals from this regression are by construction orthogonal with the EPU and VIX, and thus can be thought of as measures of "pure monetary" uncertainty. I then perform a linear regression of both BBD and RSH against VIX and the BBD complied EPU [2], keeping the residuals as a proxy of "purer" MPU measure. Similar treatment to the economic uncertainty index can also be seen in Wang et al. (2019) . It should be noted that once the variation of VIX is removed, the residual MPU, either BBD or RSH, is decreasing in the 2008 financial crisis. However, over my sample periods, it's still difficult to conclude any norms of the residual indices during the recession or QE. Meanwhile, the correlation between the news-based residual indices remains.

I have another finding regarding the widening difference between the plain MPU index and the residual during the crisis periods and QE. Although the BBD have very high correlation with the VIX, the RSH correlation with VIX is weaker, which can be seen by flat difference over my sample period. I also find that the linear components of the BBD MPU reach peaks during the

[2] It should be noted that the EPU construction method is not entirely the same as MPU. Apart from the newspaper source data, the EPU also include changes in tax code and dispersion in economic forecasts (Bonaime et al. (2018); Wang et al. (2019)). However, since the weight in the newspaper data is much heavier than the rest components. The conceptual difference is having limited effects on my results.

Figure 2: Time series residual plots of BBD, RSH

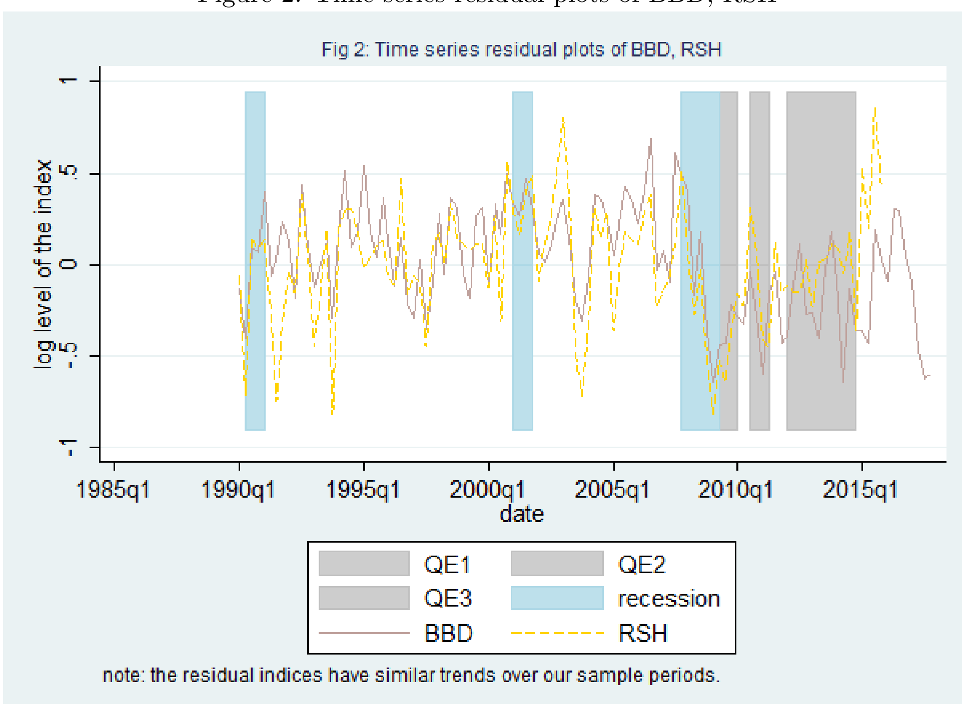
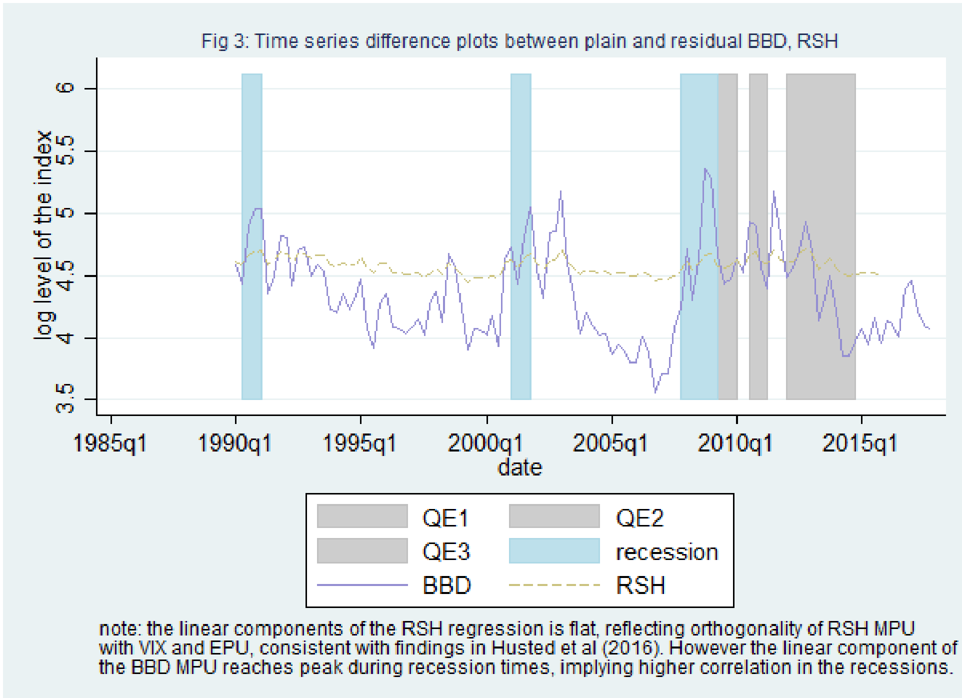


Figure 3: Time series difference plots between plain and residual BBD, RSH



recession time, implying the BBD MPU during recession time are more likely correlated with the macroeconomic and economic policy uncertainty.

1.5 The empirics

1.5.1 Regression specifications

I estimate two models based on different sets of controls:

$$y_{itq} = \sum_{j=1}^{4} \rho_i^y y_{itq-j} + \sum_{j=1}^{4} \pi_j^y mpu_{tq-j} + \gamma_i + \upsilon_q + \eta_t + \epsilon_{itq} \tag{1.6.1}$$

$$y_{itq} = \sum_{j=1}^{4} \rho_i^y y_{itq-j} + \sum_{j=1}^{4} \pi_j^y mpu_{tq-j} + \sum_{j=1}^{4} M_{tq-j}\theta_j^y + X_{itq-1}\tau^y + \gamma_i + \upsilon_q + \eta_t + \epsilon_{itq} \tag{1.6.2}$$

Where y_{itq} is variables of interests of bank i at year t and quarter q. In the sections to follow, I have assets allocation variables (liquid assets and loans to assets), measurements of loan rates, and other proxies that match the channels in the model (loan loss reserves, unused commitments, securities returns, and fed funds borrowing costs).mpu_{tq} are either the original or the residuals of BBD and RSH. in equation 1.6.2 are macro controls, which includes quarterly changes of Fed funds rate and YoY real GDP growth.X_{itq} are bank-specific controls, which includes ROA, size, capitalization and efficiency. As shown by Laeven and Levine (2009), these factors are highly correlated with the banks' risk taking. Differences in (1.6.1) and (1.6.2) results can provide hints on how the business cycle factors and bank specific risk taking could affect or bias the estimates of the MPU. All regression specifications control for bank, quarter-of-the-year and year fixed effects and cluster the standard error into the top holder level. my parameter of interest is the sum of all π^y coefficients. And I are interested in testing the following hypothesis for variables of interest :

$$H_0 : \sum_{j=1}^{4} \pi_j^y = 0$$

my specifications and statistical inference are similar to Kashyap and Stein (2000) and Bordo et al. (2016). I present my regression results using two different sets of MPU proxies: one is the original level of the (logarithm) indices (the plain in the table), and the other is the aforementioned residuals.

1.5.2 MPU and Market equilibrium of loan rate and banks' asset allocation

In this section, I explore the correlation between MPU and banks' asset allocation variables (liquid assets and loans), as well as the loan rates. Below are my regression results on liquidity and loans in table III:

Banks hoard more liquidity against more uncertain monetary policy. I find that all the estimated coefficients reject the zero-null hypothesis at the 0.01 significance level regardless of proxies and specifications. Meanwhile, my estimates are positive and roughly stable within the same proxies. For exam-

TABLE III: LIQUID ASSETS AND LOANS

	Panel A: liquidity-to-assets				Panel B: loans-to-assets			
	BBD (residual)		RSH (residual)		BBD (residual)		RSH (residual)	
	liquid	liquid	liquid	liquid	loan	loan	loan	loan
logmpu	1.094***	0.957***	0.22***	0.361***	-0.924***	-0.884***	0.126**	0.318***
	(0.0488)	(0.055)	(0.0429)	(0.0523)	(0.0482)	(0.0529)	(0.0417)	(0.0507)
chg_fed		0.243***		0.232***		-0.32***		-0.307***
		(0.0335)		(0.034)		(0.0324)		(0.0329)
gdp		-0.125***		-0.133***		0.138***		0.147***
		(0.00903)		(0.01)		(0.00871)		(0.00973)
N	672960	524456	638964	497909	669449	519583	635574	493231
Rsquare	0.826	0.845	0.82	0.84	0.827	0.849	0.821	0.844
hasbank	No	Yes	No	Yes	No	Yes	No	Yes
othermac	No	Yes	No	Yes	No	Yes	No	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
QoYFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All entries are the sum of all lagged 4 quarter estimates.The variables logmpu, chg_fed and gdp represent sum of all lagged 4 quarter estimates for logarithm of MPU, quarterly changes of fed funds rate and real GDP growth. The column hasbank indicates whether the regression specification has bank-specific variables (size, ROA, capitalization and efficiency) and BankFE, QoYFE and YearFE indicate whether the regression specification has bank-, quarter-of-year and year fixed effects. All standard errors are in parentheses.+, *, ** and *** denote 10, 5, 1 and 0.1 percent significance level

ple, the liquidity coefficients remain between 0.9-1 (see column 1 and 2) and 0.2-0.3 (see column 3 and 4) when MPU is proxy by BBD and RSH respectively. These residual proxy results imply that banks liquidate roughly 0.08

(1.094x0.3/4=0.08 and 0.957x0.3/4=0.07) percent and 0.03 (0.22x0.3/4=0.02 and 0.361x0.3/4=0.03) percent of total assets, given one standard increase in logarithm of BBD and RSH index respectively over the course of the year. To give more intuitive sense of the rise in one standard deviation, the drop in both residual BBD and RSH proxy during the great recession is roughly 1. Combining with the estimates on quarterly change in federal funds rate, which is roughly 0.23, I find that the effect on liquid assets is equivalent to annual drop of 0.35 (0.09/0.23 = 0.35) under BBD proxy, or the size of one FOMC interest drop over the year, and 0.13 (0.03/0.23=0.13) under the RSH proxy, or half the size of FOMC interest drop.

The estimates in the loans (see panel B in table III) are very close to that of liquid assets, with opposite signs. This is not surprising since the sum of liquid assets and loans hold stable fraction of total assets. Take the BBD estimates for example, my results indicate that one standard deviation increase of the MPU per quarter over the course of the year is associated with roughly 0.08 percent drop in loans over total assets. Again the effect on the first moment of MP is quite similar to the second moment. Therefore, the regression result suggests that the second moment weights as much as the first moment when it comes to the asset allocation of commercial banks.

Previous results in table II reveal that MPU posts negative shocks in banks' allocation of assets to loans. However, it remains unclear whether the drops in loans are dominated by effects in the demand side (e.g. reduced in willingness to borrow among borrowers) or supply side (e.g. reluctance among banks to extend credits). One possible way to address this issue is to see how the loan rates respond to the MPU shocks. The demand-dominated claim would predict decreases in loan rates as response to MPU shocks whereas the supply-dominated claim has an opposite prediction.

The full-blown regressions have returned positive cumulative effects of MPU on loan rate. To be more specific, one percent standard deviation of BBD is associated with roughly 0.05 percent increase in loan rate, as compared with 9.24 percent in the mean according to my summary statistics. The other MPU proxy, the RSH, has yielded results of similar magnitude. The regressions with no macroeconomic control yield estimates negative to close-to-zero estimates (see column 1 and column 3), which implies the business cycle factors have also played important roles when it comes to measuring the impacts of MPU on loan rate.

It should be noted that the effect on loan rate is smaller than the quantity in the table III. Results in table III suggests an equal second moment effect on assets allocation as first moment. However, the first moment effect is stronger on loan rate than the second order effect. As per table IV, the annual one-standard-deviation rise in fed funds rate (1 percent) is associated with 0.38 percent rise in loan rate whereas the one-standard-deviation rise links to a change of 0.03 percent change.

TABLE IV: LOAN RATE

	BBD (residual)		RSH (residual)	
	intloan	intloan	intloan	intloan
logmpu	-0.099***	0.118***	0.003	0.124***
	(0.0049)	(0.00579)	(0.00474)	(0.00598)
chg_fed		0.378***		0.383***
		(0.00449)		(0.00457)
gdp		0.005***		-0.007***
		(0.00101)		(0.00113)
N	663341	520016	629972	493339
Rsquare	0.946	0.953	0.941	0.949
hasbank	No	Yes	No	Yes
BankFE	Yes	Yes	Yes	Yes
QoYFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes

Notes: All entries are the sum of all lagged 4 quarter estimates.The variables logmpu, chg_fed and gdp represent sum of all lagged 4 quarter estimates for logarithm of MPU, quarterly changes of fed funds rate and real GDP growth. The column hasbank indicates whether the regression specification has bank-specific variables (size, ROA, capitalization and efficiency) and BankFE, QoYFE and YearFE indicate whether the regression specification has bank-, quarter-of-year and year fixed effects. All standard errors are in parentheses.+, *, ** and *** denote 10, 5, 1 and 0.1 percent significance level

My claim that MPU effect on banks' asset allocation is supply-dominated is consistent with my ex ante expectation. If one considers the federal funds rate as the major policy lever (at least before the crisis), and given that banks are among the most active trading parties in the federal funds market, then it isn't surprising that MPU is casting a direct effect, manifested itself as the supply-sided results I observed, when banks are indirectly impacted via the MPU effect on the borrowers.

1.5.3 The intermediate mechanism of MPU effect on asset allocation

The following sections proceed to study the driver of banks' shrinkage in loan supply. Table 4 includes all the intermediate variables I expect to be related with banks' asset allocation decision as per my model and other related papers. I will illustrate my choice of variables as well as my interpretations in the coming sections.

Under the setting of the theoretical model, loan supply shrinkage is the opposite to liquidity hoarding. And the hoarding of liquidity has always been linked with changes in various types of risks (Berrospide, 2012). To start, I relate the credit risk to MPU by regressing loan loss reserves against MPU (Table V, column 1). Accruals, such as loan loss provision, loan loss reserves or net charge-offs, are generally considered to be ex-ante credit risks, as compared with such ex-post measurements as non-performing loans (NPL) (Berrospide, 2012). I encounter a scenario where the estimates from the two proxies disagree in table V. Overall, it's very difficult to draw any meaningful conclusion between credit risk and MPU.

TABLE V: INTERMEDIATE MECHANISMS

MPU proxy: BBD (residual)

Dependent variables:	loanloss	unuse	intfedinc	inttreas	intmbs	intfedexp
logmpu	-0.005	0.068*	0.141+	0.043***	-0.006	0.557***
	(0.00305)	(0.0315)	(0.0825)	(0.00978)	(0.0128)	(0.0499)
chg_fed	-0.006**	0.074***	1.449***	-0.061***	-0.411***	1.17***
	(0.00183)	(0.0197)	(0.0465)	(0.00896)	(0.013)	(0.0345)
gdp	-0.004***	0.01*	-0.11***	-0.013***	0.017***	0.053***
	(0.000604)	(0.00489)	(0.0103)	(0.00201)	(0.00276)	(0.00712)
N	535223	536494	247683	217433	210425	123704
Rsquare	0.817	0.704	0.396	0.908	0.802	0.604

MPU proxy: RSH (residual)

Dependent variables:	loanloss	unuse	intfedinc	inttreas	intmbs	intfedexp
logmpu	0.003	0.083**	0.373***	0.018	0.124***	0.182***
	(0.00283)	(0.031)	(0.0668)	(0.0114)	(0.0196)	(0.0478)
chg_fed	-0.006**	0.082***	1.442***	-0.052***	-0.366***	1.093***
	(0.0019)	(0.0202)	(0.0452)	(0.00871)	(0.0126)	(0.0331)
gdp	-0.004***	0.008	-0.182***	-0.026***	-0.002	0.052***
	(0.000662)	(0.00548)	(0.0117)	(0.00223)	(0.00321)	(0.00784)
N	508187	509335	240109	198173	189228	117227
Rsquare	0.812	0.698	0.392	0.904	0.784	0.59
hasbank	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
QoYFE	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All entries are the sum of all lagged 4 quarter estimates.The variables logmpu, chg_fed and gdp represent sum of all lagged 4 quarter estimates for logarithm of MPU, quarterly changes of fed funds rate and real GDP growth. The column has bank indicates whether the regression specification has bank-specific variables (size, ROA, capitalization and efficiency) and BankFE, QoYFE and YearFE indicate whether the regression specification has bank-, quarter-of-year and year fixed effects. All standard errors are in parentheses.+, *, ** and *** denote 10, 5, 1 and 0.1 percent significance level

Liquidity risk might provide another perspective to approach the loan shrinkage/liquidity accumulating in response to mounting MPU. I find that the unused commitments are increasing in the news-based MPU indices. One standard deviation in the MPU residuals is associated with 1 basis points rise in loan commitments for both proxies. One possibility of the increase in unused commitments is the rise in demand to hedge against interest risk. If one sees the uncertainty in Monetary policy as uncertainty in future interest rate, then borrower may have the motive to enter a contractual arrangement to lock in their borrowing rates. The "lock-in" interest rate motive hypothesis can partially be confirmed with my estimates on the federal funds rate. I find that more loan commitments are initiated when interest rate is rising. The estimates on the fed funds rate change find positive correlation, which could serve as evidence for my previous claim.

The results in the unused commitments is also helpful in validating my model. As per my model, a supply-drive MPU is most likely related with liquidity risk channel being dominant, which is confirmed by my residual estimates on unused commitments. I also study other opportunity costs of lending, as measured by gains from the security market (see column 3-5, table V). The results are quite consistent across the security type (with the exception on BBD MPU proxy on MBS yield, results with little statistical significance). The rise in returns of securities is consistent with my findings in the liquidity risk above. The mounting liquidity risk stemmed from MPU increases the demand for liquid assets, which results in higher price(gain)for the corresponding class of securities.

It's also interesting to note that the first moment has larger impacts on these returns than the second moment, an observation quite consistent with my intuition. Another observation from the security return is that the first moment effect is only positive on lending gains of fed funds but negative on treasuries and MBS. The underlying reason is due to the composition of market participants. Over the majority of my sample periods, banks are the most active traders in the fed funds market. Higher fed funds rate is likely to increase the gains of lending out fed funds. But as for the other market where firms and entrepreneurs, higher fed funds rate is likely to increase their borrowing costs and cast negative shocks on their securities.

As the last piece of findings, the borrowing cost form federal funds market is more expensive when MP is uncertain. Although the borrowing cost from the FF market has ambiguous effect on the asset allocation as per my model, my regression results provide hints on how MPU is related with banks' funding cost. FF rate taken as the major policy lever, it's natural to expect FF is costlier when risk premium stemmed from policy uncertainty is added to the borrowing rate. my results using the residuals confirm this intuitive hypothesis, lending more support to the validity of measurements of MPU.

The results in this section points several possible pass-through of MPU on the liquid assets hoarding. First they imply a liquidity risk channel of MPU. Higher MPU, manifested by more uncertain interest rates, might lead to higher supply for loan commitments. The rising loan commitments could add to the liquidity risks which results in banks' hedge by holding more liquid assets and fewer loans. The reduction in supply of loans then levels up the loan rate. Results in the security return indicate another channel. Returns of several major types of securities (federal funds, treasuries and MBS) increase due to higher risk premium originated from MPU. Commercial banks thus allocate more of their assets toward these type of securities, which result in drop of loan portfolios accordingly. Similar to the liquidity risk story as mentioned above, the rising security returns has a positive impact on loan rate, which is consistent with my findings in table III.

Ambiguous as it is per the theoretical model, the costly FF could also lead to my observation in asset allocation and loan rate. Supposed decreasing liquid assets holding is associated with higher marginal cost, then the income effect of costly FF would imply a reduction in the loan portfolio and higher loan rate. To sum up, the regression in this section have validated several channels associated with my observation in asset allocation and loan rate. With the current single-equation regression scheme, it is challenging which is the major driver of the asset allocation. In other words, a structural-based method (e.g. panel VAR) might help more in disentangling the pass-through.

1.5.4 Regression by size heterogeneity and deposit financing heterogeneity

I next explore how banks' characteristics can affect their response to the MPU. In other words, my major variables of interest are the bank size and the transaction deposits. Namely, I interact both variables as follows:

$$y_{itq} = \sum_{j=1}^{4} \rho_i y_{itq-j} + \sum_{j=1}^{4} \beta_j size_{itq-j} mpu_{tq-j} + \sum_{j=1}^{4} \pi_j mpu_{tq-j} + \sum_{j=1}^{4} M_{tq-j}\theta_j + X_{itq-1}\tau + \gamma_i + \upsilon_q + \eta_t + \epsilon_{itq} \tag{6.1}$$

$$y_{itq} = \sum_{j=1}^{4} \rho_i y_{itq-j} + \sum_{j=1}^{4} \alpha_j transdep_{itq-j} mpu_{tq-j} + \sum_{j=1}^{4} \beta_j size_{itq-j} mpu_{tq-j} + \sum_{j=1}^{4} \pi_j mpu_{tq-j} + \sum_{j=1}^{4} M_{tq-j}\theta_j + X_{itq-1}\tau + \gamma_i + \upsilon_q + \eta_t + \epsilon_{itq} \tag{6.2}$$

I further conduct inferences on the sum of α, β coefficients.

I find that large banks hoard less liquidity and reduce fewer loans. To be more specific, under the BBD residuals, one unit increase over the course of the year is associated with 0.155 drop and 0.145 rise in the estimated coefficients of the MPU. my finding in interest rates imply that the demand side effect among larger banks might be stronger, as lower rise in loan rates are seen. I argue that the findings in table VI is comparable to Kashyap and Stein (2000), who find that smaller banks are among being most impacted by Monetary policy rate (the first moment effect), whereas my findings extend their conclusion to the case of the second moment.

TABLE VI: SIZE INTERACTION WITH MPU: LIQUID ASSETS, LOANS AND LOAN RATE

dependent variable:	liquid	liquid	loan	loan	intloan	intloan
proxy	BBD residual	RSH residual	BBD residual	RSH residual	BBD residual	RSH residual
size*MPU	-0.155***	-0.304***	0.145***	0.303***	-0.021***	-0.022***
	(0.026)	(0.0251)	(0.0252)	(0.0243)	(0.00212)	(0.00228)
N	522111	522111	517251	517251	517872	517872
Rsquare	0.845	0.845	0.85	0.85	0.953	0.953
hasbank	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
QoYFE	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes

dependent variable:	liquid	liquid	loan	loan	intloan	intloan
proxy	BBD residual	RSH residual	BBD residual	RSH residual	BBD residual	RSH residual
size*MPU	-0.162***	-0.333***	0.151***	0.333***	-0.019***	-0.02***
	(0.0281)	(0.0272)	(0.0272)	(0.0264)	(0.00239)	(0.00255)
trandep*MPU	-0.005+	-0.005+	0.006*	0.006*	0.001**	0.001**
	0.00318	0.00318	0.0031	0.0031	0.000276	0.000276
N	488632	488632	482718	482718	485130	485130
Rsquare	0.849	0.849	0.853	0.853	0.953	0.953
hasbank	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
QoYFE	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All entries are the sum of all lagged 4 quarter estimates.The variables size*MPU represent sum of all lagged 4 quarter estimates for interaction between logarithm of MPU and size. The column hasbank indicates whether the regression specification has bank-specific variables (size, ROA, capitalization and efficiency) and BankFE, QoYFE and YearFE indicate whether the regression specification has bank-, quarter-of-year and year fixed effects. All standard errors are in parentheses.+, *, ** and *** denote 10, 5, 1 and 0.1 percent significance level

TABLE VII: SIZE INTERACTION WITH MPU: LOAN LOSS RESERVES AND UNUSED COMMITMENTS

dependent variable:	loanloss	loanloss	unuse	unuse
proxy	BBD	RSH	BBD	RSH
size*MPU	-0.016***	-0.027***	0.068***	0.179***
	(0.0015)	(0.00157)	(0.0139)	(0.014)
N	532813	532813	534175	534175
Rsquare	0.816	0.816	0.704	0.704
hasbank	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes
QoYFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes

dependent variable:	loanloss	loanloss	unuse	unuse
proxy	BBD	RSH	BBD	RSH
size*MPU	-0.013***	-0.023***	0.061***	0.155***
	(0.00162)	(0.00166)	(0.0152)	(0.0152)
trandep*MPU	0.001***	0.001***	0.001	0.001
	0.000175	0.000175	0.0017	0.0017
N	497682	497682	498909	498909
Rsquare	0.816	0.816	0.706	0.706
hasbank	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes
QoYFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes

Notes: All entries are the sum of all lagged 4 quarter estimates.The variables size*MPU and transdep*MPU represent sum of all lagged 4 quarter estimates for interaction between logarithm of MPU and size, logarithm of transaction deposits respectively. The column hasbank indicates whether the regression specification has bank-specific variables (size, ROA, capitalization and efficiency) and BankFE, QoYFE and YearFE indicate whether the regression specification has bank-, quarter-of-year and year fixed effects. All standard errors are in parentheses.+, *, ** and *** denote 10, 5, 1 and 0.1 percent significance level

TABLE VIII: SIZE INTERACTION WITH MPU: SECURITY RETURNS AND FEDERAL FUNDS BORROWING COSTS

dependent variable:	intfedinc	intfedinc	inttreas	inttreas	intmbs	intmbs	intfedexp	intfedexp
proxy	BBD	RSH	BBD	RSH	BBD	RSH	BBD	RSH
size*MPU	0.014	0.013	0.027***	0.029***	0.034***	0.034***	-0.031	-0.03
	(0.0329)	(0.0247)	(0.00438)	(0.00491)	(0.00669)	(0.00669)	(0.0236)	(0.02)
N	246518	246518	216579	216579	209687	209687	123199	123199
Rsquare	0.396	0.396	0.908	0.908	0.802	0.802	0.603	0.603
hasbank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
QoYFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
proxy	BBD	RSH	BBD	RSH	BBD	RSH	BBD	RSH
size*MPU	-0.003	0.011	0.03***	0.036***	0.028***	0.028***	-0.061*	-0.026
	(0.0352)	(0.0268)	(0.00508)	(0.0056)	(0.00796)	(0.00796)	(0.0267)	(0.023)
trandep*MPU	-0.011**	-0.011**	0	0	-0.001	-0.001	-0.006*	-0.006*
	0.00407	0.00407	0.000547	0.000547	0.00076	0.00076	0.00251	0.00251
N	226495	226495	201444	201444	195856	195856	118062	118062
Rsquare	0.393	0.393	0.907	0.907	0.801	0.801	0.602	0.602
hasbank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
QoYFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All entries are the sum of all lagged 4 quarter estimates.The variables size*MPU and transdep*MPU represent sum of all lagged 4 quarter estimates for interaction between logarithm of MPU and size, logarithm of transaction deposits respectively. The column hasbank indicates whether the regression specification has bank-specific variables (size, ROA, capitalization and efficiency) and BankFE, QoYFE and YearFE indicate whether the regression specification has bank-, quarter-of-year and year fixed effects. All standard errors are in parentheses.+, *, ** and *** denote 10, 5, 1 and 0.1 percent significance level

The regression results in the intermediate variables provide some hints on the heterogeneous response to the MPU shocks. Larger banks incur lower credit losses as seen in the first two column results in table VII. As per the model, this implies a smaller leftward shift of the credit demand shift, which is consistent with the results in table VI. Meanwhile, I have also seen larger liquidity risks (more unused commitments) and higher security returns (higher gains from treasuries and MBS) among larger banks. However, neither of these results are consistent with the asset allocation and loan rate movement in table VI since these findings would predict larger loan drops and higher rise in loan rates among larger-sized banks. In other words, the differential change in credit risk is dominant in explaining the heterogeneous response to MPU shocks among banks with different sizes, although my current results also admit explanations from other channels. Again, adding the interaction term with transaction deposits has little impact on the size interaction term. I find that banks with higher deposit financing have fewer commitment contracts initiated and lower borrowing costs from fed funds market under more uncertain monetary policies.

1.6 Concluding remarks

This paper studies the links between monetary policy uncertainty and banks' asset allocation. I found that banks increase their liquid assets holdings in the face of more uncertain monetary policies. Loans portfolios shrink and interests on loans rise, implying a dominant supply-side response. The finding on interest rate is arguably consistent with my conjecture that since commercial banks are actively involved in the fed funds market (especially before the crisis) and fed funds rate is one of the major policy levers, response in the supply side of credits (banks) would dominate that from the demand side (borrowers).

As per my theoretical model, there are fmy pass-throughs where the effects on asset allocation and loan rate are realized: the credit risk, the liquidity risk, security return and the borrowing cost. The empirical analysis has mixed findings on the credit risk, where estimates on loan loss reserves are of ambiguous signs. On the other hand, I find positive correlation between unused commitments and MPU, suggesting that there is either an increase in demand (borrowers' need to hedge against borrowing rate uncertainty) or supply (suppliers' strategy to substitute drop in spot loans). Either way, rise in loan commitments are consistent with the direction of asset reallocation, as per the findings of Berrospide (2012). The returns among the most liquid securities (Treasury, fed funds, MBS) have seen positively related with MPU. This is likely due to rise in demand for safe assets. Borrowing cost in fed funds also increases, which might add to the loan rate and explain my finding of the positive correlation between MPU and loan rate.

Size heterogeneity is another topic of my interest. I find that large banks have smaller adjustments in their portfolios and the change in their loan rates reflect more on the response of demand-side. I associate this with smaller changes in credit risk among large banks. On the other hand, I find heavy transaction deposits financing also reduce the impact of MPU. I argue that my finding in the size heterogeneity is somehow comparable to Kashyap and Stein (2000), who finds that monetary policy (first moment of MP) matters more for smaller-sized banks.

Findings in this paper have implications on the real effects of MPU. Previous literature relates MPU with volatility of the stock markets (Kaminska and Roberts-Sklar (2018); Kurov and Stan (2018)) whereas my findings suggest that MPU might have a more persistent impact on the economy via the contractual bank loans. In fact, I have documented the response of the credit market by quantitatively assessing how bank reallocates his assets under uncertain MP. Although other more real variables (e.g. employment, inflation) still remains unknown on how they relate with MPU, I see my work as first step towards investigating the real effects of MPU.

2 Annual report sentiment and accounting conservatism: evidence from US bank level data

2.1 Introduction

There has been increasing attention on the information content of annual report-measured sentiment. Part of the driver under this recent trend comes from the moral hazard behind financial reporting. Gandhi et al. (2019) argue that firm managers are highly incentivized to "window dress" financial ratios under scrutiny by regulators and investors. On the other hand, they think that annual reports-based sentiment, when under the concerns of litigation risk and reputation, has provided a more "reliable" reflection of the "true" operation results of the firm. However, I find this argument lacks direct empirical supports. This paper intends to shed some lights on this line of research by linking the textual measurement with one of financial reporting behavior, the accounting conservatism.

Accounting conservatism is a financial reporting phenomenon where higher verification of gains is required than losses. This asymmetry in verification has been thought to be influential. For one example, implied in Watts (2003), higher verification that underlies accounting conservatism can serve as a counter force against managerial discretion to inflate distressed assets values. Another study carried out by Huizinga and Laeven (2012) has found that such managerial discretion is seen over the mortgage crisis, which might provide misleading signals to investors. However, the seminal paper by Watts (2003) has focused more on the downside of accounting conservatism. One major criticism, mainly raised by standard-setters and regulators is that although net asset values are understated due to higher verification imposed on gains, overstatement might come subsequently as a result of current period understatement.

The purpose of this research is to address the argument raised in Gandhi et al. (2019), that is to see if textual measurement is indeed "better". Since "better" is too vague a term, I would claim the textual sentiment is only better when its information content contains the future information of financial reporting behavior. In other words, I am trying to answer, if textual measure is to dominate accounting measure in terms of reflecting firms' financial status, can annual reports sentiment future changes in accounting conservatism?

Note that both subjects in this research question are difficult to quantify. In measuring the annual report sentiment, I refer to two mostly used methods in existing literature: dictionary-based and machine learning-based. The dictionary is the word list compiled by Loughran and McDonald (2011b). The word list categorizes words into positive/negative/uncertain categories. The dictionary-based method uses the frequency of different categorical words as proxies of the sentiment of the whole annual report. Although this method is computationally efficient, the underlying oversimplification might fail to capture the complex sentiment. The machine learning-based method accounts for the shortcomings of the dictionary method and makes use of the sophisticated computational linguistic models in uncovering the data generating process of natural languages. However, the method is challenged by the subjectivity in training samples and measurement error based on computational linguistic model, apart from the high computing time. In all, there's no commonly agreed view on which of the methods provide overwhelming accurate results. That's why I measure annual report sentiment using both methods, so a more comprehensive view of textual assessment is provided.

Measuring accounting conservatism is also challenging. I refer to the seminal research carried by Basu (1997) and Khan and Watts (2009). Khan and Watts (2009) propose a regression-based method to assign a score of accounting conservatism to each firm. Before I explore the link between conservatism score and textual sentiment, I start by showing the link between annual report sentiment and income (loss) recognition asymmetry. The next exercise then tests the correlation between the regression-based conservatism score and textual measure. The results show that negative tone predicts higher conservative score, or more negative sentiment is correlated with more accounting conservatism.

This paper is organized as follows in the coming sections: section 2.2 reviews related papers; in section 2.3. I introduce a theoretical model based on the contracting explanations of accounting conservatism; section 2.4 focuses the data and mainly methods in complying sentiment measurement; section 2.5 includes the major empirical results and I conclude in section 2.8.

2.2 Related literature

This paper is attributed to several lines of existing literature. The first primary source of researches is a list of burgeoning papers on the information contents of text-based financial documents. These documents, as summarized by Kearney and Liu (2014), mainly include corporate reports, media news and internet messages. While this paper is based solely on the annually released 10-K reports, I also review studies on latter two financial documents. Tetlock (2007) is among the earliest to explore the link between media source-based sentiment and stock price. Employing a principal component analysis, or PCA method, the constructed measure of market level pessimism in his study has been found highly correlated with downward pressure of the DJIA (Don Jones industrial average). In a subsequent study, Tetlock et al. (2008) explores informativeness of the firm-specific news stories and find that higher frequency of negative words in news stories predicts lower return. As for the internet messages, existing studies manage to conduct their analysis on large samples of textual messages from online sources. As highlighted by Kearney and Liu (2014), the research by Antweiler and Frank (2004) use Internet messages (e.g. Yahoo! Finance and Raging Bull) and find that more disagreement among these messages is associated with higher trading volatility.

While media and internet source messages better reflect sentiment among investors and analysts, corporate released files provide more insights from the firm side. Feldman et al. (2008) conducts a comparison between two major sources of corporate files, the MD&A (management discussion and analysis) in 10-K reports under SEC requirement and earnings announcement. They find that larger portfolio return is observed in the time windows of the SEC filing dates and conclude that MD&As could be more informative. Using the 10-K reports, Loughran and McDonald (2011a) examine whether Barron's phrase, a set of phrases said to be correlated with financial distress, can imply poor performance. In another study, Loughran and McDonald (2011b) find that several widely used dictionaries (e.g. Harvard Dictionary) have misclassification problem among a large fraction of words. Therefore, they contribute by proposing new word lists that apply specifically to financial documents. Li (2010) takes this exercise to a further step. He examines a subset of the 10-K report content, the forward-looking statements (FLS) among MD&A sections and find that tones among FLS are predictive on future earnings. Moreover, they find that the mispricing of accruals is smaller, or lower association of accruals with future returns, when FLS "warns" about future performance.

Except for the difference in text sources, this line of researches can also be categorized based on their content analysis method they adopt. Methodology-wise, two methods are used in extracting textual sentiment: dictionary-based and machine learning-based. As early as Li (2010) and Loughran and McDonald (2016), researchers have made detailed comparisons on these two methods. Although several drawbacks of these two methods have already been modified in my opinion, it's still worth noting that: 1. The dictionary method has advantages over reduction of subjectivity ("once the dictionary is selected, researcher subjectivity is avoided", Loughran and McDonald (2016)), computation efficiency, and ease of replication of existing studies. The review by Loughran and McDonald (2016) has devoted to illustrating the merits of this method and in fact they list several commonly used dictionaries (Harvard's GI, Loughran and McDonald (2011b)). 2. The survey by Li (2010), however, favors the machine learning method. He points out several shortcomings including failure in capturing the context and lack of publicly acknowledged dictionaries. He believes models developed by computation linguists can overcome such weaknesses. Even though I can hardly draw any conclusion on which method strictly dominate the other, discussions made in these papers provide insightful guidance in the content analysis.

I also review a list of papers using the above two methods. Under the dictionary-based sentiment, ratios of negative words in annual reports have found to be correlated with higher trading volatility (Frank, 2004), lower future earnings (Huan, Teoh and Zhang, 2011), smaller litigation risks (Rogers, Van Buskirk and Zechman, 2011) and higher delisting probabilities (Gandhi et al , 2018). These papers differ on the choice of dictionaries. However, since Loughran and McDonald (2011b), their proposed word list "has become predominant in more recent studies" (Kearney and Liu (2014); Loughran and McDonald (2016)).

While the process of conducting a dictionary-based method has been more standardized (see a summary by Kearney and Liu (2014)), there're relatively more variants in the line of machine learning papers, thanks to new development pioneered by computer scientists. Early literature has done extensive research work based on Naïve Bayes classification (NBC) algorithm. Antweiler and Frank (2004) have once referred to it as "the most successful natural language algorithms". A more influential study by Li (2010) study not only the determinants of the machine-learning extracted sentiment, but also show the robust predictive power on future earnings. More recent studies in this line use more advanced statistical linguist models and claim higher accuracy is achieved. Azimi and Agrawl (2018) employ an RNN (recurrent neural networks) model and find over 90% in-sample accuracy. The extracted sentiment also shares high predictive power on future earnings, similar to other aforementioned papers.

A second major category of literature is on accounting conservatism. Basu (1997) is among the earliest to find the asymmetry in financial reporting. He finds timeliness of negative news is higher, evidenced by higher sensitivity of earnings to negative stock returns. Following Basu (1997), Khan and Watts (2003) devise a firm-specific measurement of accounting conservatism. In short, they assume that their measurement, also known as C_score, is a linear function of size, market-to-book ratio and leverage. These two papers constitute the fundamentals in this line of literature.

Ever since Basu (1997) and Khan and Watts (2003), researchers are devoted to studying empirically the determinants/ consequences of accounting conservatism. Conceptually, Watts (2003) propose four possible explanations: contracting, litigation, regulation and taxation. Qiang (2007) has provided empirical evidence that all of four causes are likely associated with either conditional/ unconditional conservatism. In the determinants side, studies have found that national culture (Kanagaretnam et al. (2013)) and managerial optimism (Ahmed and Duellman (2013)). This paper also falls into this category and therefore follows similar steps in conducting empirical analysis.

Equally many efforts are devoted to studying the consequences. A few theoretical papers to be mentioned below argues that a conservative financial reporting system helps reduce information asymmetry. One of the empirical papers in this topic is from Ahmed et al. (2002), who find that accounting conservatism lowers the conflicts between debt holders and stake holders. Extending on that, ongoing researchers find desirable outcomes such as lower bankruptcy risks (Biddle et al. (2013)), reduced chances of stock price crash (Kim and Zhang (2016)). In the context of banking, Beatty and Liao (2011) find that banks that delay losses reduce less lending during recession. Andreou et al (2017), similar to Kim and Zhang (2016), find that crash risk decreases when banks exhibit higher degrees of accounting conservatism. A cross county study by Akins et al. (2017) finds that higher accounting conservatism has negative effects on the expansion of bank credits. These studies help us understand the significance of accounting conservatism and provide strong motivation to this paper.

The empirical researches, apart from uncovering the cause/impact of accounting conservatism, have also guided us in measuring the conservatism in financial reporting. Except for C_score method developed by Khan and Watts (2009); I have also come through several alternatives in measuring the asymmetry in gains/loss recognition against good/bad news (e.g. conditional conservatism): Ha (2018), instead of using the asymmetry in income recognition, she also argue that asymmetry in recognizing loan loss provision can be used to measure conservatism in the context of banking studies. On the other hand, conditional conservatism is measured using accruals and earnings metrics. For example, Givoly et al. (2007) use skewness of incomes and Ahmed et al. (2000) propose deflated accruals before depreciation as proxies.

Theoretical researches on accounting conservatism have been relatively rare. As early as Watts (2003), he has made comprehensive explanations on the rise of accounting conservatism. Among several possible causes, he argues that the contracting explanation is the most critical one. In his contracting explanation, higher verification of gains is one major instrument of debt holders to constrain managers from such practice as dividend payments that reduces net asset value. The contracting explanation reveals the conflict of interests among parties within the firm and takes accounting conservatism as one solution to the moral hazard by debt holders. Interpretation of conservatism, according to Watts (2003), is usually a timelier fashion of loss recognition than gains, which is beneficial for the sake of welfare. However, one counter argument raised by Gigler et al (2009) claim that the untimeliness in gains recognition could also lead to loss of welfare. Other papers also contribute to more discussions of the origins of accounting conservatism. For one example, Raith (2009) thinks conservatism in accrual accounting also provides a solution to the moral hazard between managers and the firm. In his theory, optimal accrual accounting also incentivizes managers. Some other theoretical researches study the consequence of accounting conservatism. Guay and Verrecchia (2017) find that timely report of bad news results in higher firm values.

2.3 The model

2.3.1 Basic setup

While the existing theoretical literature has done a comprehensive review into the causes of accounting conservatism, the model in this paper mainly aims to incorporate textual information and shed lights on the later empirical sections. Therefore, unlike the existing papers that focus on the sources of accounting conservatism, I take this phenomenon as given and define:

Definition 2.1 *if a firm is conservative in its accounting, then it holds that*

$$\frac{\partial X_{it}}{\partial R_{it}}|_{R_{it}<0} > \frac{\partial X_{it}}{\partial R_{it}}|_{R_{it}>0} > 0 \tag{2.4.1}$$

where X_{it}, R_{it} are earning/loss metrics of interests (e.g. net income, loan loss provision or earning before provision) and return respectively.

The sign of stock return is a proxy of good/bad news. The definition claims that given the same change in stock return, changes in net income in the face of bad news are in greater magnitudes than that of good news since costs of verifying gains are higher when accountants are conservative.

I further assume that NI is linear with R conditional on the signs. That's both sides of the equation 2.4.1 corresponds to a constant. Let $\delta_1 + \pi =$

$\frac{\partial X_{it}}{\partial R_{it}}|_{R_{it}<0}, \delta_1 = \frac{\partial X_{it}}{\partial R_{it}}|_{R_{it}>0}$. Accounting conservatism implies that $\pi > 0$ from the following specification:

$$X_{it} = \delta_0 + \delta_1 R_{it} + \delta_2 D_{it} + \pi R_{it} D_{it} + \theta_i + \gamma_t + \epsilon_{it} \tag{2.4.2}$$

Where D_{it} is a dummy variable that indicates $R_{it} < 0$.

2.3.2 The informativeness of textual sentiment

Let $Sentiment_{it}$ be some textual measurement of sentiment. I argue that the textual sentiment is informative on accounting conservatism when $\frac{\partial \pi}{\partial Sentiment_{it}} \neq 0$. Applying a linear assumption where $\pi = \beta_0 + \beta_1 Sentiment_{it}$, the null hypothesis of interests is then:

$$H_0 : \beta_1 = 0$$

Meanwhile, plugging $\pi = \beta_0 + \beta_1 Sentiment_{it}$ into equation 2.4.2, I derive the empirical specification[3]:

$$\begin{aligned} X_{it} = \delta_0 + \delta_1 R_{it} + \delta_2 D_{it} + \beta_0 R_{it} D_{it} + \beta_1 R_{it} D_{it} Sentiment_{it-1} \\ + Other\,Terms + \theta_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{2.4.3}$$

An alternative approach is to devise a firm specific score of accounting conservatism. It starts by assuming that there's some relationship between conservatism and such fundamentals as size, MTB and leverage, or $\pi_{it} = \pi\left(size_{it}, MTB_{it}, lev_{it}\right)$. I can then explore the effect of textual sentiment by directly regressing the conservatism score against sentiment. I will detail more about this method in the empirical analysis.

2.4 The data

2.4.1 The financial data

To testify the predictive power of texts on accounting conservatism, I supplement the financial/accounting data with annual report texts. As for the financial/accounting data, I obtain most of the balance sheet information (e.g. total assets, loan loss provision, etc.) from the quarterly filed regulatory

[3]The Other terms include the stand-alone terms like size, MTB, leverage, Sentiment as well as the interaction terms of the return dummy and return with the stand alone terms.

documents FR Y9C by bank holding companies (BHC). Each of BHC is identified by a unique RSSD ID in this data source (see row 1 in table IX). Then I merge the RSSD ID with other external sources, namely the CRSP RSSD-PERMCO link and compustat PERMCO-CIK link, to acquire the corresponding PERMCO and then CIK number (see row 2 and 3 in table IX). I proceed to use the CIK number to merge with Loughran and McDonald's annual report database to acquire a subset of BHCs whose annual report is available. By joining with Loughran and McDonald's database, I also acquire the frequency of negative/positive/uncertain words for each of the BHC. The CIK number is also used to derive the market data (e.g. long-term debt from compustat, year-end stock price from CRSP, etc.). Finally, the dataset contains 7,851 bank-year observations, very close to a similar study by Gandhi et al. (2019).

TABLE IX: SAMPLE CONSTRUCTION

	total obs	key required
FR Y9C year end samples	179607	
join with CRSP rssd permco link	13888	rssd
wrds permco cusip cik link	11167	permco
LM text database	8599	cik
drop if stock price data missing	7851	cik

Notes: The table highlights the key data sources and steps in getting the samples ready. The number in the first column is the toal bank-year observations after performing the sample selection steps to the left. And the second column is the key used in merging the tables.

The construction of machine learning based sentiment, however, takes more efforts. In the coming section, I detail more about the methodology and results.

2.4.2 The machine learning based sentiment

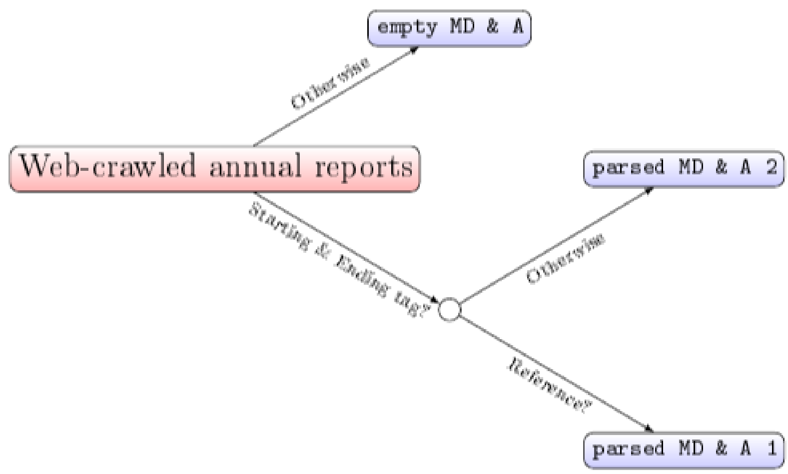
Sample selection and web-crawling annual reports The Loughran and McDonald database provides the web links of SEC 10-K reports. Although they also provide an already-parsed 10-K reports online and following researchers have developed sophisticated codes to extract the MD&A sections in these reports (e.g. see R package, edgar), I still find significant amounts of documents where only a small fraction of MD&A sentences has been extracted. In fact, of all the extracted 10-K reports from R, over one third of them have one sentence or less. Therefore, I redo the web-crawl and extracting MD&A steps, before I compare the parsed documents with Loughran and McDonald (2011b).

Using the link prepared by Loughran and McDonald (2011b), I web-crawl the 10-K reports using Python module BeautifulSoup. Since the major focus is a subsection of 10-K report, the Item 7 Management's Discussion and Analysis (MD&A), the next step following the web-crawling procedure is to parse the MD&A. In each of the 10-K reports, I search for the header "ITEM 7" and use the texts following the header the beginning of MD&A.

I then search for the header “ITEM 7A” or “ITEM 8” and use it as a flag of the MD&A ending. The texts between these two headers are results of MD&A. However, even under this method, I are still seeing a large amount of MD&A missing. Some MD&A, although with valid starting (“ITEM 7”) and ending (“ITEM 8” or “ITEM 7A”) flag, contains “invalid” components. One common example comes from the annual report of Amsouth Bancorp in 2000 that “management’s discussion and analysis of financial condition and results of operations the section entitled management’s discussion and analysis of financial condition and results of operations of amsouth’s 1999 annual report to shareholders is hereby incorporated herein by reference”. In this case I need extra methods to search the reference part of annual reports to parse the containing MD&A. The proposed method is very similar to the one mentioned above, I parse the reference using the valid starting and end labels. I summarize the parsing logics using below decision trees and under this method, I manage to parse 7,645 out of the 7,851 documents.

Naïve Bayes Classifier on forward looking statements (FLS) The Naïve Bayes classifier (NBC) is among the most successful algorithm in textual sentiment analysis. One of the examples can be seen in Li (2010). In classifying 30,000 FLS, the NBC built in his article achieved roughly 60% of accuracy. I follow the methodology in Li (2010). First, I randomly select 2,000 FLS out of 861,692 FLS from 7,851 MD&A. Then I manually classify the randomly selected 2,000 samples into 4 categories based on their senti-

Figure 4: A decision tree to parse the MD&A documents



mental content: positive, negative, neutral and uncertain. One noteworthy among my choice of categorization is the uncertain category. Following Li (2010), the uncertain category does convey negative sentiments, although in a less explicit way than the negative category. I further compare the distribution of tones with that in Li (2010) and find they are similar.

The 2000 sample sentences are then divided into two sets: training and testing set. The training set sentences are used to calibrate the machine learning model and then the testing sets are used to validate the calibrated model. Words in the training set are organized in a way called "bag of words". The bag of words is essentially the frequency table of words. Although it might be more straightforward to measure the frequency of words using raw counts, re-

TABLE X: DISTRIBUTION OF TONES

	Li (2010)	This paper
positive	19.59	25.2
neutral	39.97	39.8
negative	17.82	15.1
uncertain	22.55	19.9
Total sample size	30,000	2,000

Notes: The table compares the distribution of different sentiment FLS. I find similar proportion in the sample FLS where neutral FLS take up the majority with Li (2010), although samples in this paper might have higher fractions in positive FLS.

searchers have developed different weighting schemes in accounting for word frequency (for one example, see Jegadeesh and Wu (2013)). I adapt one commonly used weighting scheme, term frequency inverse document frequency (TFIDF). To be more specific, the TFIDF frequency of word is computed as:

$$tfidf = tf \times idf$$

where tf is the raw counts and $idf = \log \frac{N}{|\{s' \in S, w \in s'\}|}$ is the inverse document frequency. The numerator N is the total number of sentences in a 10-K MD&A and the denominator is the number of sentences where word w is contained. Instead of a single sentence, the TFIDF also accounts for the occurrence in the whole documents and assigns more weights toward "rare" words.

There are three parameters in composing bag of words: the upper/lower limit of the frequency and the number of grams in the words of the bag (e.g. a 2-gram, or bigram, bag of words means that 2-word phrase like "liquidity risks", "commercial bank" will also be included in the bag). I will later introduce a fourth parameter in the NBC and then proceed to a grid search method to find the optimal classifier.

In the NBC, a set of conditional probability is computed, $P\left(w_i|cat\right) = \frac{P(w_i,cat)}{\sum_{w_j \in W} P(w_i,cat)}, w_i \in W, cat \in Cats$ where $W, Cats$ is the word in the bag and all possible sentiments. $P\left(w_i|cat\right)$ measures the occurrence of word w_i in sentimental category samples cat (e.g. the occurrences of the word "risk" among sentences categorized as uncertain). Such probabilities are available when words are organized under a method called "bag-of-words". Once the probabilities are prepared, I assign a predicted category cat^* to an out-of-sample testing sentence s if it satisfies the following condition, using Li (2010) notation,

$$
\begin{gathered}
cat^* = \underset{cat \in Cat}{\arg\max} P\left(cat|w_1, w_2, \cdots, w_n\right) \\
= \underset{cat \in Cat}{\arg\max} \frac{\Pi_{i=1}^{n} P(w_i|cat) P(cat)}{\Pi_{i=1}^{n} P(w_i)} = \underset{cat \in Cat}{\arg\max} \Pi_{i=1}^{n} P\left(w_i|cat\right) P\left(cat\right)
\end{gathered}
$$

Supposed the words $w_1, w_2, \cdots, w_n$ are contained in s . The NBC finds the optimal category for s by computing the ex post probability given the training set derived (the first equality). The second equality holds when I assume distribution of words are mutually independent. Note that since the denominator of equality 2 doesn't change by cat . Getting rid of the denominator, I derive a more simplified form in the last equality.

The smoothing parameter is added to account for words out of the bag. Under the previous method $P(w_i|cat) = \frac{P(w_i,cat)}{\sum_{w_j \in W} P(w_i,cat)}$, the conditional probability $P(w_i|cat) = 0$. Thus, by computing the joint probability is also zero, regardless of conditional probability from other words. Therefore, the smoothing parameter α is added as follows:

$P(w_i|cat) = \frac{P(w_i,cat)+\alpha}{\sum_{w_j \in W} P(w_i,cat)+n\alpha}$, where n is the number of words in the bag.

Under the new method of computing conditional probability, all out-of-bag words have the same probability $\frac{1}{n}$. However, the conditional probability of in-bag word could also be affected depending on the values of α , which is the last parameter in finding the optimal NBC. I search for the optimal NBC based on the following set of parameters.

The performance of the classifier is evaluated based on a 10-fold cross-validation. Conceptually, the sample of 2000 sentences are equally divided into 10 folds. And the NBC will be trained for 10 times. In each of the

TABLE XI: NBC PARAMETER CANDIDATES

uppper limits	0.5, 0.75, 1
lower limits	0.005, 0.01, 0.05, 0.1
n-gram	1, 2, 3
smoothing parameter	0.0001, 0.001, 0.01, 0.1, 1

Notes: The table lists all candidate parameters in the grid search for the best NBC.The upper/lower limits are the maximum/minimum of frequency of the elements of bag of words. The n-gram is the maximum of words in each element in the bag of words.

training epoch, two of the folds is used as testing sample and the remaining ones are used for training. The average accuracy, the percentage of NBC predictions, is then taken as the performance metrics for the NBC under given parameters. I find that below parameters yield the highest accuracy.

TABLE XII: NBC PERFORMANCE

Panel A: performance metrics	precision	recall	f1-score
negative	0.48	0.29	0.36
neutral	0.59	0.72	0.65
positive	0.43	0.53	0.47
uncertain	0.67	0.45	0.54
Panel B: Accruacy by methods			
overall accruacy (NBC)	0.543		

Notes: The table summarizes the performance of NBC.

The overall accuracy of the classifier is very close to that in Li (2010), who has achieved 59%. I attribute the better performance of their classifier to a larger training sample with more human auditing inputs. In panel A of table 4 I present the detail performance metrics of the classifier. One noteworthy in the table is that the model has relatively poor performance in classifying negative FLS. The precision of negative FLS is 48% (first column and first row), meaning that roughly half of predicted negative labels are correct. Worse even, the recall is 29%, or I only classify 29% of the negative FLS into the right category. As mentioned in latter sections and shown in many relevant literatures, the fraction of negative texts is more informative. The relatively poor performance of the classifier might cast concerns over the measurement error in the corresponding variables.

Meanwhile, even if performance of the machine learning results is worrisome, I still find that the machine learning has higher overall accuracy than the dictionary method. Although the machine learning has higher accuracy, dictionary-based sentiment measure is also constructed to provide better overview of the predictive power of textual measurement. For each bank's annual report, I use the percentage of negative/positive/uncertain words, as defined by Loughran and McDonald (2011), as proxies of the according sentiment.

I proceed to apply the above classifier to the whole FLS sample. As parallel to the dictionary-based sentiment variables, I use the percentage of positive/negative/neutral sentences in the whole MD&A section as proxies of the 10-K report sentiment.

Sentiment extraction using neural network (NN) The low recall in negative sentiment FLS being a major concern of the NB classifier, I turn to alternative machine learning algorithms. The research carried by Azimi and Agrawal (2018) has proven the power of NN on classifying financial document sentiments. The inputs to the NN model are very similar to the NB classification model (same bag of words processed by TFIDF method). Due to the high computation costs involved, I limit the number of features to 1,000. Then I train a NN with 1,000 input nodes, one hidden layer with relu activation function with four intermediate nodes and the output layer with softmax function. Likewise, I perform 10-fold cross validation. Below table summarizes the performance of the NN model in table XIII.

I find better performance of the NN model. The NN model has dominated performance over NB model in terms of precision and recall. The overall accuracy is over 90 percent, very close to the results from Azimi and Agrawal (2018). In future sections, I keep all three textual measurements to better compare these measurements and access the potential measurement error within each of them.

TABLE XIII: NN PERFORMANCE

Panel A: performance metrics			
	precision	recall	f1-score
negative	0.85	0.79	0.81
neutral	0.76	0.74	0.75
positive	0.81	0.85	0.83
uncertain	0.78	0.78	0.77
Panel B: Accruacy by methods			
overall accruacy (NN)	0.901		

Notes: The table summarizes the performance of NN.

Time series variation of sentiment Figure 5 and 6 present the time series variation of both positive and negative sentiment under different textual analysis methods. At the first glimpse we see that the three methods generate very similar trends among both sentiment (which is also seen later summary statistics in the correlation). On the other hand, we see that the negative sentiment among banks' annual reports have seen a major rise after the crisis (also a major drop of the positive sentiment), which is consistent with our prior conjecture of a more uncertain macroeconomic envrionment and stricter regulations.

Measures of accounting conservatism Following the existing literature, the accounting conservatism is measured via regression of earnings against

Figure 5: Time series variation of negative sentiment

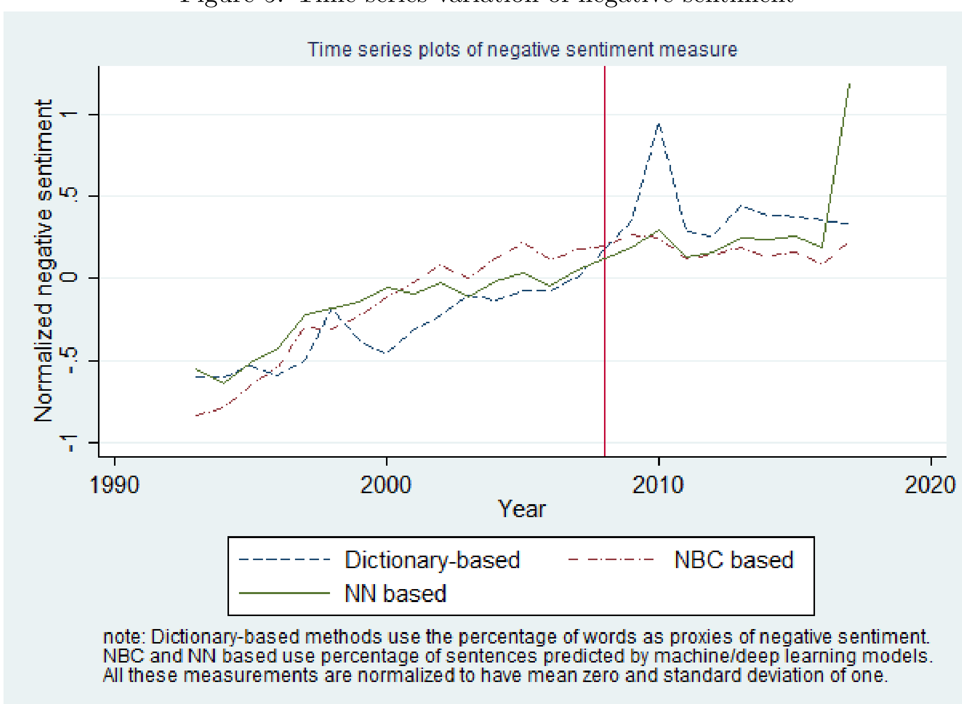
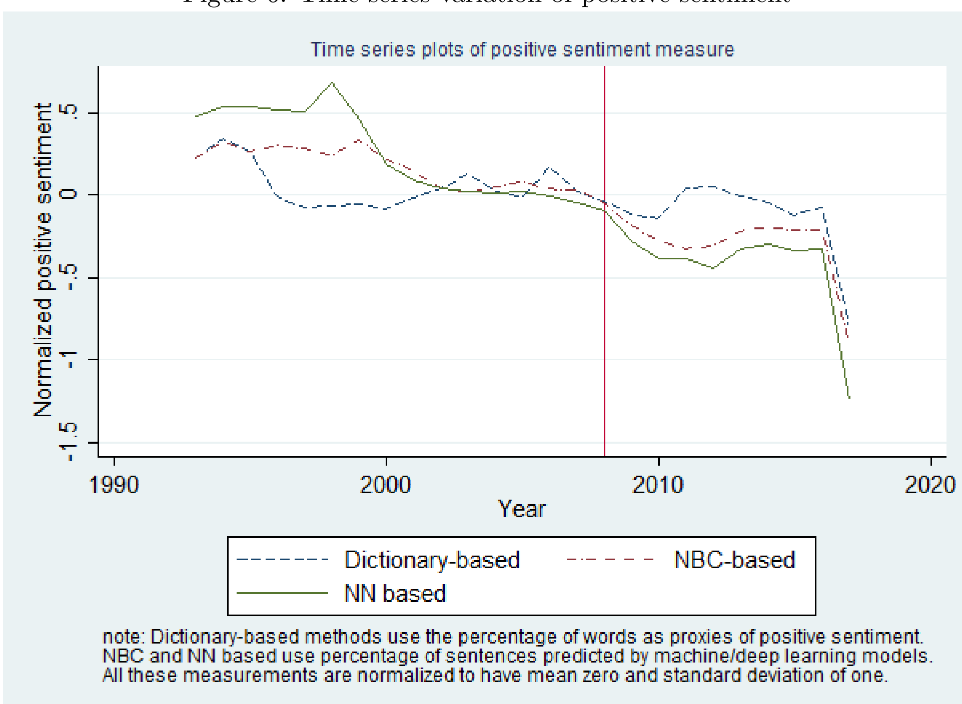


Figure 6: Time series variation of positive sentiment



news. As in Khan and Watts (2009) , the derived measured requires performing the following regression:

$$X_{it} = \delta_0 + \delta_1 D_{it} + \delta_2 R_{it} + \delta_3 D_{it} R_{it} + \delta_4 D_{it} R_{it} size_{it}$$
$$+ \delta_5 D_{it} R_{it} MTB_{it} + \delta_6 D_{it} R_{it} Lev_{it} + \alpha_i + \beta_t + \epsilon_{it}$$

Where X_{it}, D_{it}, R_{it} are the accounting items of interest (e.g. net income, loan loss allowance, earnings before provision, etc), a dummy of negative stock return and stock return of firm i in the financial report period t. The stock return is the hold-and-sell return starting from 3rd month to year end to exclude the announcement effect of annual report at the beginning financial year. The C-score of firm i at the reporting period t is based on the regression results of the above specification:

$$C - Score_{it} = \delta_3 + \delta_4 size_{it} + \delta_5 MTB_{it} + \delta_6 Lev_{it}$$

A higher C-score indicates more changes in the face of "bad" news, or timelier accounting. Following Ha (2018), I devise three versions of C_score based on the dependent variables , the net income (NI), loan loss provisions (LLP) and earnings before provision (EBP).

Below are the regression results from the Khan and Watts (2009) specification. To better compare the results with previous studies, in the fourth column I also include Khan and Watts (2009) coefficients. I find that the coefficients on the double interaction term is much higher in the above regressions. That implies that the C_score in this paper has a larger constant. Apart from the double interaction term, the estimated coefficients for the triple interaction term are also larger in magnitudes (see results in column 1 and 4). Even though so, the signs of estimates are quite consistent with Khan and Watts (2009). Also note that the signs are consistent with another loss metrics (LLP) and income metrics (EBP).

I would want to add more comments on the signs. The following arguments are mostly based on Khan and Watts (2009). Larger size is associated with lower conservatism. The major course is that larger size reduces informational asymmetry and tax liability. The MTB, which is a proxy of growth options, is also affecting conservatism mainly via the informational channel. They argue that higher MTB (growth options) levels up the agency costs, which calls for higher conservatism to counteract. Meanwhile, higher MTB is very likely associated with higher stock volatility, leading to greater chances of litigation. However, although these two major channels are suggesting a positive correlation, it's rarely proven in empirics due to the "buffer problem". The "buffer problem" happens when "over a short horizon beginning M/B (of the year) is negatively correlated with conservatism flows due to prior unrecognized increases in asset values reducing the necessity to recognize asset value losses" (Khan and Watts (2009)). In their paper, they

TABLE XIV: REGRESSION RESULTS

	NI	LLP	EBP	NI(KW, 2009)
$D_{it}R_{it}$	3.756***	-0.014	0.0178**	0.237***
	(0.799)	(0.828)	(0.68)	(0.022)
$D_{it}R_{it}size_{it}$	-0.164**	-0.000562	-0.00037	-0.033***
	(0.0537)	(0.0556)	(0.0457)	(0.004)
$D_{it}R_{it}MTB_{it}$	-0.458***	0.00179*	-0.00156**	-0.006
	(0.0675)	(0.0699)	(0.0575)	(0.007)
$D_{it}R_{it}Lev_{it}$	0.368***	0.0000361	-0.00027	0.033*
	(0.0232)	(0.024)	(0.0197)	(0.018)
N	7373	7367	7373	115516
R sq	0.554	0.45	0.149	0.24

Notes: The table includes the regression results of the timeliness regression. I compare the above results with that in Khan and Watts (2009) in column 4. The major difference is the sample period and the makeup of samples. Khan and Watts (2009) include firms of all industries from 1963 to 2005, while I only include banking frims from 1994 to 2017. Meanwhile, apart from net income, I also include loan loss provision (LLP) and earnings before provision (EBP) as dependent variables of the timeliness regression in column 2 and 3.

identify a negative insignificant correlation which they have attributed to the buffer problem. The buffer problem seems more pronounced in the banking business as seen in the results. Finally, higher leverage implies higher bargaining power from the debt holders, leading to higher contracting demands of conservatism.

Summary statistics and pair-wise correlation Below table includes the summary statistics of the variables to be used in empirics.

TABLE XV: SUMMARY STATISTCS

Variable	Obs	Mean	Std. Dev	Min	Max
timeliness & c_score					
nic	7,183	-0.01	0.56	-6.22	0.25
llp	7,183	0.006	0.009	-0.006	0.064
ebp	7,183	0.012	0.007	-0.023	0.043
mtb	7,183	1.61	0.78	0.17	4.92
lev	7,183	0.74	1.47	0.00	13.06
return	7,183	0.09	0.35	-0.69	2.59
ni_cscore	7,183	-2.88	0.81	-5.02	2.25
llp_cscore	7,183	-0.01	0.00	-0.01	0.00
ebp_cscore	7,183	-0.01	0.00	-0.01	-0.01
dictionary-based sentiment					
neg	7,183	1.90	0.70	0.00	4.20
pos	7,183	0.71	0.32	0.00	2.03
NB-based sentiment					
neg_s	7,183	17.27	8.34	0.00	46.43
pos_s	7,183	22.42	10.39	0.00	62.90
NN-based sentiment					
nn_neg_s	7,183	29.52	8.69	0.00	56.52
nn_pos_s	7,183	25.64	8.99	0.00	60.00
other variables					
roa	7,183	0.80	0.98	-5.94	3.32
size	7,183	14.74	1.60	12.21	21.12
cap	7,183	0.09	0.03	0.03	0.22
eff	7,183	1.34	0.19	0.71	2.03

Notes: The table includes all variables used in the empirical regressions. Note that from here on, the negative category under different linguist models is a sum of both negative and uncertain words/sentences from previous dictionary and machine learning sections.

I include four types of variables in table 6. Variables in panel A are used mainly in estimation of earning timeliness and C_score. In Panel B, C and D, I include the fraction of positive and negative sentiment words/sentences. From here on, when I refer to the negative sentiment, it's the sum of both "negative" and "uncertain" labels (Li, 2010). I find that under the dictionary-based method, the fraction of negative words is higher than that of the positive one, which is also seen in the neural network-based sentiment extraction. However, the NB predicts otherwise, which points out my previous concern of measurement error underlying negative sentiment. In the last four rows of table XV, I include the summary statistics of other variables of the regression.

Meanwhile, as preliminary exploration of casual links, I also find the correlation among these variables:

table XVI presents the pairwise pearson correlation of several selected variables. The correlation among the C_scores are mainly due to the correlation among the C_score factors (size, MTB and leverage) and the corresponding coefficients. I find correlation of income C_scores (NI_cscore and EBP_cscore) are positive and correlation between income and loss C_scores are negative (see row 1, 2 and 3). As for correlations among the textual sentiment, I find that they are correlated in expected ways. For example, the correlation between negative sentence (both NB and NN based) fraction is positively correlated with negative words percentage. Similar corre-

TABLE XVI: PAIR-WISE CORRELATION

	ni_cscore	llp_cscore	ebp_cscore	size	mtb	lev	neg	pos	neg_s	pos_s	nn_neg_s	nn_pos_s
ni_cscore	1.0000											
llp_cscore	-0.4072	1.0000										
ebp_cscore	0.5146	-0.4530	1.0000									
size	-0.3788	-0.4597	-0.5249	1.0000								
mtb	-0.7209	0.8226	-0.8223	0.1192	1.0000							
lev	0.8227	-0.2769	-0.0375	-0.0047	-0.3514	1.0000						
neg	0.1192	-0.1713	0.0888	0.0495	-0.1620	0.0945	1.0000					
pos	0.0312	-0.0167	-0.0035	0.0079	-0.0129	0.0395	-0.0805	1.0000				
neg_s	0.1257	0.0061	0.1299	-0.1538	-0.0916	0.0525	0.3105	-0.0554	1.0000			
pos_s	0.0005	0.1269	-0.0029	-0.1166	0.0680	-0.0122	-0.1739	0.3477	-0.0439	1.0000		
nn_neg_s	0.1329	-0.0271	0.1208	-0.1188	-0.1069	0.0701	0.3186	-0.0616	0.6473	-0.0575	1.0000	
nn_pos_s	-0.0717	0.1540	-0.0832	-0.0541	0.1372	-0.0419	-0.2312	0.2939	-0.2208	0.6449	-0.3560	1.0000

Notes: The table includes the pairwise correlation of several selected variables.The selected variables include C_score and its components, all annual reprot sentiment measures.

lation is also found among the positive ones. Meanwhile, the correlation between annual report sentiment and C_score is confounding. For instance, the dictionary-based negative sentiment is negatively correlated with net income C_score but the machine learning based have opposite signs. Nevertheless, these metrics only very preliminary univariate relations. More insights of how annual report sentiment interacts with accounting conservatism should be found in the regression framework.

2.5 The empirics

Ahmed et al (2013) has provided an approach for the reference to study the determinants of the accounting conservatism. In their paper, relationships between both measures of conditional conservatism and managerial optimism are tested. They find that firms with more confident CEOs have lower conservatism and stronger monitoring tends to mitigate this link. I follow similar methods and organize the results by exploring the timeliness and then the C_scores.

2.6 Timeliness of net income recognition and C_score

Like several other papers that study determinants of conservatism (e.g. corporate governance (Leventis, 2013), national culture (Kiridaran et al, 2013)), I start by following the regression specification in by Ahmed and

Duellman (2013)[4]:

$$X_{it} = \delta_0 + \delta_1 D_{it} + \delta_2 R_{it} + \delta_3 D_{it} R_{it} + \delta_4 D_{it} R_{it} size_{it} + \delta_5 D_{it} R_{it} MTB_{it}$$
$$+\delta_6 D_{it} R_{it} Lev_{it} + \sum_{j=1}^{n} \pi_j D_{it} R_{it} Sentiment_{it-1}^{j} + Other\,Terms + \alpha_i + \beta_t + \epsilon_{it}$$

Where $Sentiment_{it}^{j}$ is the j th textual measure (positive, negative, etc) under different methods (dictionary, NBC, NN). I use three sets of textual: one based on the dictionary method and the two other on machine learning (ML) and neural network (NN) method. The parameters of interests are π_js. A non-zero implies that the corresponding sentiment predicts higher asymmetry. When π_j is positive (negative), it means that the associated sentiment increases (decreases) future accounting conservatism.

I have found that negative sentiment in previous year annual report is increasing in more future accounting conservatism. The argument is supported by the regression estimates using dictionary-based and NN-based sentiment (see column 1 and 7 in table XVII). However, this result is expected given the measurement error underlying the NB performance. The dictionary and NN based estimates imply that given the same drop in stock price, one standard deviation of negative words and sentences are associated with 0.339 and 0.116 percent of write-down in income (in terms of firm size). Similar results

[4]The Other terms include the stand-alone terms like size, MTB, leverage, Sentiment as well as the interaction terms of the return dummy and return with the stand alone terms.

TABLE XVII: TIMELINESS AS MEASURES OF ACCOUNTING CONSERVATISM

	dictionary based			machine learning based			neural network based		
	NI	LLP	EBP	NI	LLP	EBP	NI	LLP	EBP
$D_{it}R_{it}size_{it}$	-0.172***	-0.00141*	-0.00061	-0.173***	-0.00127*	-0.00068	-0.176***	-0.00134*	-0.00072
	(0.033)	(0.000605)	(0.000474)	(0.0337)	(0.000615)	(0.000482)	(0.0332)	(0.000608)	(0.000476)
$D_{it}R_{it}MTB_{it}$	-0.215**	0.00774***	-0.00129	-0.274***	0.00831***	-0.00151	-0.219***	0.00777***	-0.00089
	(0.0655)	(0.0012)	(0.000941)	(0.0655)	(0.0012)	(0.000937)	(0.0657)	(0.0012)	(0.000943)
$D_{it}R_{it}lev_{it}$	0.515***	-0.000844*	0.000643*	0.525***	-0.000999*	0.000614+	0.522***	-0.000999*	0.000535+
	(0.022)	(0.000403)	(0.000316)	(0.022)	(0.000402)	(0.000315)	(0.0219)	(0.000401)	(0.000314)
$D_{it}R_{it}neg_{it-1}$	0.272***	-0.00439***	0.0012	-0.0184	-0.00111	0.00077	0.0426	-0.0006	0.00205*
	(0.0535)	(0.00098)	(0.000768)	(0.0577)	(0.00105)	(0.000825)	(0.0594)	(0.00109)	(0.000852)
$D_{it}R_{it}pos_{it-1}$	-0.0452	0.00146	0.00184*	-0.0249	0.00263**	0.000142	-0.219***	0.00365**	-0.00200*
	(0.0509)	(0.000932)	(0.00073)	(0.0547)	(0.000999)	(0.000783)	(0.0625)	(0.00115)	(0.000897)
N	6188	6188	6188	6188	6188	6188	6188	6188	6188
R-sq	0.591	0.515	0.189	0.589	0.514	0.188	0.591	0.514	0.189

Notes: The table includes results from the timeliness regression. All three measurements of sentiment are normalized.+, *, ** and *** denote 10, 5, 1 and 0.1 percent significance level.

are seen when the accounting measures become loan loss provision (LLP) and earnings before provision (see column 2 and 3, 8 and 9 in table XVII). Banks with more negative sentiment write up(down) more LLP (EBP) in the face of bad news.

As supplements to the market-based regressions, alternative methods construct the C_scores and explores their determinants. I have illustrated my methods in constructing the firm-level C_scores. As mentioned in previous sections, a higher (lower) income (losses) C_score is associated with higher levels of conservatism in accounting. For that purpose, below regression specifications are performed:

$$C - Score_{it} = \delta_0 + \sum_{j=1}^{n} Sentiment_{it-1}^{j} + \alpha_i + \beta_t + \epsilon_{it}$$

The above regressions explore the predictive power of textual sentiment (positive, negative under either methods). Taking other factors into account, I control for profitability, efficiency and capitalization in the following regressions. These factors are chosen following the specification in Ahmed and Duellman (2013).

$$C - Score_{it} = \delta_0 + \delta_1 ROA_{it-1} + \delta_2 Eff_{it-1} + \delta_3 Cap_{it-1} + \sum_{j=1}^{n} \pi_j Sentiment_{it-1}^{j} + \alpha_i + \beta_t + \epsilon_{it}$$

TABLE XVIII: C_SCORE AS MEASURES OF ACCOUNTING CONSERVATISM

	ni_cscore	ni_cscore	llp_cscore	llp_cscore	ebp_cscore	ebp_cscore
			Panel A: dictionary-based			
neg_{it-1}	0.0293**	0.0247**	-0.0000423*	-0.0000330*	0.0000265+	0.000021
	(0.0102)	(0.00897)	(0.0000179)	(0.0000163)	(0.0000145)	(0.0000141)
pos_{it-1}	0.00607	-0.0056	-0.0000332+	-0.0000193	0.000029	0.0000216
	(0.0159)	(0.0135)	(0.0000194)	(0.0000179)	(0.0000179)	(0.0000173)
N	6188	6188	6188	6188	6188	6188
r2	0.326	0.398	0.556	0.601	0.329	0.34
			Panel B: machine learning based			
neg_{it-1}	0.0251*	0.0239*	0.0000181	0.00000226	-0.0000162	-0.0000115
	(0.0126)	(0.0117)	(0.0000212)	(0.0000189)	(0.0000195)	(0.000019)
pos_{it-1}	0.0175	0.0101	-0.0000436+	-0.0000384+	0.0000241	0.0000271
	(0.0137)	(0.0122)	(0.0000231)	(0.0000198)	(0.0000197)	(0.000019)
N	6188	6188	6188	6188	6188	6188
r2	0.325	0.398	0.556	0.601	0.328	0.34
			Panel C: neural network based			
neg_{it-1}	0.0143	0.00798	0.0000102	0.00000658	-0.0000104	-0.0000108
	(0.0132)	(0.0114)	(0.0000221)	(0.0000193)	(0.0000193)	(0.000019)
pos_{it-1}	-0.0017	-0.00463	-0.0000372+	-0.0000134	0.00000601	0.00000648
	(0.0128)	(0.0115)	(0.000022)	(0.0000196)	(0.0000201)	(0.000019)
N	6188	6188	6188	6188	6188	6188
r2	0.324	0.397	0.555	0.6	0.328	0.34
bankFE	YES	YES	YES	YES	YES	YES
YearFE	YES	YES	YES	YES	YES	YES
bankctrl	NO	YES	NO	YES	NO	YES

Notes: The table includes results from the C_score regression. All three measurements of sentiment are normalized.+, *, ** and *** denote 10, 5, 1 and 0.1 percent significance level.

I find that negative words/sentences are more likely in predicting higher NI C_score, or more conservatism in accounting in the future, results of which are consistent with market-based regressions. In panel A of table XVIII, I find that one standard deviation rise in negative words is associated with roughly 0.03 rise of NI C_score. This result is significant even bank-specific factors are controlled. Similar results are seen in the panel B when sentiment is extracted from the NB model. Again even under the positive significant results, it's noteworthy that the underlying measurement error is casting concerns over the validity of these estimates. In panel C, I do see the NN-based sentiment is also positively correlated with future C_score. However, these results lack statistical power to support its validity. As for the C_score of LLP, negative words seem to predict lower score, consistent with the NI C_score results. The negative correlation can hardly be seen in NB and NN based sentiment. Similar patterns are seen in the EBP C_score.

To conclude in the empirics, I see a positive correlation between negative words/sentences and accounting conservatism. Most of the empirical results support the argument. However, there's some remaining puzzles underlying these results. First, I still have yet to find the underlying mechanism that connects textual sentiment with accounting conservatism. Second, some of the results, although not contradicting that of other proxies, lack statistical power (e.g. NN-based results in C_score regression). I hope to address these two problems in the regression analysis of different factors (size, MTB and leverage) against the sentiment measure. From the regression result of each these factors, I hope to find out which of these channels are the most contributing in linking textual sentiment to accounting conservatism.

2.7 C_score decomposition

In this session, I perform a regression analysis of how the three factors in C_score is correlated with textual sentiment. The estimates in these regressions are helpful in discovering through which channel C_score is affected by textual sentiment.

My analysis focuses on the NI C_score is affected. Recall that the magnitude of estimated coefficients in the NI C_score is (from large to small) MTB, leverage and size. For the factor of MTB, I see that the coefficients of MTB are relatively close across three proxies of textual sentiment (see column 3 and 4 across three panels in table XIX), although the coefficients of NN based sentiment is smaller. All of these coefficients are positive, with differing levels of significance, implying that negative sentiment is predicting higher future MTB. Meanwhile, the effects of textual sentiment on future size are also similar, especially when bank-specific control variables are added. The coefficients are all negative, implying that negative sentiment predicts smaller size in the coming period. I think that this finding is consistent with the finding in MTB. It could be the case that market value is dropping by

TABLE XIX: C_SCORE AS MEASURES OF ACCOUNTING CONSERVATISM

	size	size	MTB	MTB	Lev	Lev
			Panel A: dictionary-based			
neg_{it-1}	-0.00179	-0.00262	0.0482*	0.0422*	-0.0252**	-0.0199*
	(0.00631)	(0.00207)	(0.0219)	(0.0195)	(0.00892)	(0.00839)
pos_{it-1}	0.000138	0.00195	-0.00677	-0.0262	-0.0193+	-0.0104
	(0.00714)	(0.00242)	(0.0381)	(0.0324)	(0.0104)	(0.00986)
N	6188	6188	6188	6188	6188	6188
r2	0.697	0.937	0.181	0.262	0.515	0.541
			Panel B: machine learning based			
neg_{it-1}	-0.0202*	-0.00752**	0.0613*	0.0572*	0.00148	-0.00372
	(0.01)	(0.00284)	(0.0294)	(0.0275)	(0.0112)	(0.0107)
pos_{it-1}	0.00916	0.00664*	0.0217	0.00344	-0.0224+	-0.0202+
	(0.0109)	(0.00259)	(0.0311)	(0.0281)	(0.0119)	(0.0111)
N	6188	6188	6188	6188	6188	6188
r2	0.699	0.937	0.181	0.262	0.514	0.541
			Panel C: neural network based			
neg_{it-1}	-0.0123	-0.00335	0.0382	0.0265	0.00159	0.00246
	(0.0088)	(0.00253)	(0.0297)	(0.0259)	(0.0117)	(0.0109)
pos_{it-1}	0.0294*	0.00682*	-0.00421	-0.0141	-0.0124	-0.00584
	(0.0123)	(0.00276)	(0.0277)	(0.0253)	(0.0118)	(0.0111)
N	6188	6188	6188	6188	6188	6188
r2	0.7	0.937	0.18	0.261	0.513	0.54
bankFE	YES	YES	YES	YES	YES	YES
YearFE	YES	YES	YES	YES	YES	YES
bankctrl	NO	YES	NO	YES	NO	YES

Notes: The table includes results from the three factors of C_score regression. All three measurements of sentiment are normalized.+, *, ** and *** denote 10, 5, 1 and 0.1 percent significance level.

smaller amounts to the size, which leads to higher MTB as I have observed. The estimates on leverage, however, differ greatly. I find that leverage is decreasing in the dictionary-based sentiment while these estimates became insignificantly close to zero. The difference in its effect on MTB and leverage cannot be the leading reason in explaining the differences of C_score regression, since if that was the case, the dictionary-based sentiment should have a more negative estimates instead of a more positive one. Therefore, I conclude that it was the difference associated with size that leads to differences among various textual sentiment proxies.

Given results in this section, the attempted conclusion is that size and market value information embedded in the annual report sentiment provide hints on future accounting conservatism.

2.8 Conclusion

This paper examines the predictive power of annual report sentiment on accounting conservatism. The intended testing hypothesis is that if the textual measurement does dominate accounting information in terms of fewer manipulation, then underlying tones in annual reports shall be able to foresee financial reporting behavior.

The financial reporting behavior metric is proxy by accounting conservatism. By definition, financial reporting is more conservative when accounting managers impose higher restrictions in recognizing gains. The significance of this topic is widely acknowledged in a long list of literature since Basu (1997). And I haven't found any other similar researches in connecting annual report sentiment with accounting conservatism.

I start from constructing textual sentiment measurement. The construction of these measurements is largely consistent with existing literature (Loughran and McDonald (2011b); Li, 2010). And in constructing the machine learning sentiment, I achieve similar accuracy using the same textual analysis algorithm. However, although the overall accuracy is close to Li (2010), I remained concern in my forecasts in some categories of sentiment. I also apply an NN based method to classifying the sentences as Amizi and Agrawal (2018). The NN based method achieves higher accuracy. In the empirical section, I examine the forecasting power of all three measurements of sentiment (dictionary, NB, NN based).

Carrying these measurements to the empirics, I perform regression analysis on accounting conservatism against these textual sentiments. Amid the market-based regression results of timeliness, I do see robust positive predictive power of negative sentiment on accounting conservatism. In other words, higher fraction of negative words/sentences in historical annual reports might imply higher levels of conservatism being implemented in the current fiscal year.

The negative correlation is consistent with later findings in C_score. I find that higher fraction of negative words/sentences are associated with higher C_score. Among the three factors in C_score, stronger predictive power is seen among size and MTB. Therefore, the empirical results suggest that the informativeness of historical annual report sentiment on accounting conservatism is very likely gained by its power on predicting future sizes and MTB, or growth options. Firms with smaller size and more growth options tend to include more negative messages in their reports on one hand, while they are also more conservative in recognizing gains on the other hand. Such behavior pattern could then establish the links that I observe in the empirics.

3 CEO optimism and Net interest margin: evidence from US bank level data

3.1 Introduction

Is there a "reward" to being optimistic in the banking business? Do managerial personal characteristics play a role in banks' profitability? If they do, through what channels? In this paper, I attempt to answer these questions by relating the net interest margin (NIM) with stock option-based optimism measures. By exploring the links, the contributions of this paper are at least twofold:

First this study shed lights on the behavioral perspectives of the Net Interest Margin (NIM). Early studies on NIM emphasize more the interaction between risk taking as Ill as other market imperfection factors and NIM (Angbazo (1997)), whereas little attention is paid to how the managerial sentiment is reflected in NIM. Even though the corporate decision process could be complicated and sometimes hinges heavily on group thinking, especially among large companies, individual characteristics from major executives have been shown to correlate with risk-taking, investments and other major corporate operations (Malmendier and Tate (2005)). The study of NIM provides hints not only on whether the levels of NIM have any behavioral implications, but also on how optimism is "priced" in terms of interest rate spread.

This study also highlights the channels through which optimism is connected to NIM. As mentioned above, existing research has linked optimism with multiple corporate operations, most of which are also related with profitability. Even if I find evidence of optimism affecting NIM, the exact mechanism may remain unclear. Identifying the major channels gives us better sense and this part of this paper has arguably regulatory implications. Supposed I find, for example, that optimistic CEO charges higher NIM by taking excessive risks, then tougher regulation on banks' risk management could Iaken the pass-through and leads to greater homogeneity of NIM.

The reminder of this paper is organized as follows: in section **??** I list relevant literature on either CEO optimism or NIM; in section 3.3 I reiterate the model by Ho and Saunders (1981) and relate the parameters with CEO optimism, where I derive several predictions; I illustrate the data used in section 3.4 and I put the theoretical predictions to test in section 3.5. Empirical results are concluded in section 3.6.

3.2 Related literature

This paper is inspired by two board categories of literature. The first one relates to the study of determinants of NIM. This line of literature usually cites the theoretical model proposed by Ho and Saunders (1981) as seminal work of commercial banks' NIM. In Ho and Saunders (1981), the NIM is determined by bankers who set up the optimal fees on deposits and loans, solving the profit maximization under uncertain arrival of deposit supply and loan demand. The Ho and Saunders (HS, hereafter) model is later extended by Allen (1988). Allen (1988) finds that under loan heterogeneity, the diversification among loan products reduced NIM. Zarruk and Madura (1992) studies how NIM interacts with regulatory parameters, such as capital requirement and deposit insurance. They find that under the risk aversion of bankers, both factors are negatively correlated with interest margins. Angbazo (1997) specifies the risks in the HS model in the model as interest rate and liquidity risk. In the meantime, Angbazo (1997) is the first paper that applies HS model to empirics. Using the US call report data, Angbazo (1997) identifies several key determinants of the NIM among US banks. Starting from Angbazo (1997), more work is devoted to identifying NIM determinants. The work of Angbazo (1997) has direct impacts on ours since I find many of the literature follow his work in determining bank-specific risks in the empirical specification. Since I see NIM as the price of major products from banks, I will later refer to Angbazo's regression as the "pricing model" and the associated coefficients with each risk in the pricing model as "pricing factor".

Later work following Angbazo (1997) focuses on NIM of banking in other countries. For example, the factors identified in Angbazo (1997) are included in the regression analysis of the determinants of NIM in banking industry of European countries (Maudos and De Guevara (2004)). The regression of Maudos and De Guevara (2004) also emphasizes the role of competition in determining the optimal spread between deposit and loan rates. In fact, they find negative correlation between competition and NIM, the main channel of which is that competition reduces risk factors of NIM. In another paper, Maudos and Solis (2009) also highlights the role of market power in NIM. In the study of Mexican banking industry, they find that market competition accounts for the major fall and rise of NIMs during different sub-periods (e.g. sale of banking to the private sector in 1993-1994 or reconstruction of banking system in 1996-1999). The factors in Angbazo (1997) are also validated in the studies of other countries (Southeast Asia, Doliente (2005); China, Zhou and Wong (2008); Tunisia, Ben Naceur and Goaied (2008)).

The aforementioned empirical researches (e.g. Angbazo (1997); Maudos and De Guevara (2004); Maudos and Solís (2009)) have paid more of their attention to identifying the bank-specific factors (although the latter two papers introduce competition as one key determinants of NIM). Other researches emphasize the role of macro factors. López-Espinosa et al. (2011) make a remark on how different accounting standards are related with interest margins. To be more specific, they find that the implementation of International financial reporting standards (IFRSs) is associated with lower variations in NIM. A more recent paper by Claessens, Coleman and Donnelly (2018) provides some quantitative assessment between policy rate and interest margins under cross-country samples. Although macro factors are not the research focus, this line of literature deepens the current understanding on the formation of NIM.

The second group of papers relate broadly to the impacts of CEO optimism on corporate behavior. Researchers have found evidence that company-level capital structure and financing decision (Heaton (2002); Malmendier and Tate (2005)a), investment in innovations (Hirshleifer et al. (2012)), CEO selection (Banerjee et al. (2006)), forced turnover (Campbell et al. (2011)) are all functions of individual optimism. Different focus as they are, the above papers share similar logics in depicting the behavioral characteristics of an optimistic CEO: he tends to overestimate the return of his investments and thus be aggressive in investing. Of the growing literature, I are specifically interested in two questions: are there any established and widely acknowledged measurements of optimism? And is there any existing work that focuses mainly on banking firms?

As for the first question of measurements, the stock option-based optimism is widely used. This measure is first proposed by Malmendier and Tate (2005a) and later modified by Campbell et al. (2011). Since the timeliness of exercising an option is embedded in the future outlooks of the underlying assets, delays in exercising in-the-money options are generally seen as confidence in the company' s future performance. Campbell et al. (2011) finds that the modified proxies of optimism produce qualitatively similar results.

Malmendier and Tate (2015) have also commented on other three measures of CEO optimism. The earnings forecasts are also be seen in some other recent “promising” researches (Otto (2014)). The forecast-based optimism is later found to be positively correlated with option-based one. A second alternative measure comes from press portray data. One of these examples can be found in Niu et al. (2010), where he finds optimism among bank CEOs reduced risk taking. The last source of optimism measure relates to specific survey. Duke University has conducted a 10-year survey into CFOs in US, the information of which is used in Ben-David et al. (2013) as a proxy of managerial overconfidence. Although these measurements are not adapted in this paper due to its availability, it does point out one direction where the results could be tested.

Banking firms are somehow special in terms of their roles in intermediate financing and the regulatory environment they face. Thus, it’s also of interest to see the impact of bank CEOs’ optimism. Two more recent papers study are noteworthy. The 2008 Global financial crisis (GFC) had led to many criticisms on banks’ failure in risk management, which managerial bias could be responsible for. Inspired by this, Ho et al. (2016) provides evidence that banks with overconfident CEOs have lower lending standard and experience aggressive growth in loans, along with higher default probability and poorer performance. The work of Huang et al. (2018) somehow reiterates the upside of the links of optimism and lending from Ho et al. (2016). Huang et al. (2018)

finds that higher optimism is associated with more liquidity creation. This paper can be seen as closely linked to this line of literature where banking firms are taken as the research subjects and inferences are drawn upon the supply of loans.

3.3 The theoretical model and hypothesis development

The model is from the seminal work by Ho and Saunders (1981) and Angbazo (1997). In their model, banks set optimal spread between deposit rate and loan rate based on their conjecture of the random arrivals of loan demand and deposit supply. Also, in their model, other factors like risk aversion, portfolio risk characteristics are also determinants of net interest margins. I see their model as foundation in exploring how NIM is priced given certain characteristics. In the coming sections, I refer to these characteristics as "factors" and coefficients associated with these factors as "price" of factors. For this purpose, I argue that optimism is correlated with all these factors. To start, I give a brief introduction of the Ho-Saunders (HS) model:

The bank holds two types of assets: net inventory (difference between deposits and loans) and cash, denoted as Y_0, I_0, C_0 respectively, where the net credit inventory is $I_0 = L_0 - D_0$. The total wealth of the bank is a sum of these three components, and over the course of time, the three assets increment values as:

$$I_T = (1 + r_I + z_I)\, I_0$$

$$C_T = (1 + r_C + z_C)\, C_0$$

The subscript 0, T indicate the initial and period-end respectively. Therefore, the period-end wealth is $W_T = (1 + r_W)\, W_0 + z_I I_0 + z_C C_0$, where $W_0 = Y_0 + I_0 + C_0, r_W = r_Y \frac{Y_0}{W_0} + r_I \frac{I_0}{W_0} + r_C \frac{C_0}{W_0}$. I assume that the return to I_0, C_0 is uncertain. The uncertainty component is mean-zero, with variance and covariance $\sigma_Y^2, \sigma_I^2, \sigma_{YI}$.

The expected utility of the bank, under risk aversion, is given as:

$$E\left(u\left(\tilde{W}\right)\right) = u\left(\overline{W}\right) + \frac{1}{2} u''\left(\overline{W}\right)\left(\sigma_C^2 C_0^2 + \sigma_I^2 I_0^2 + \sigma_{CI} C_0 I_0\right) \tag{3.4.1}$$

where $\overline{W} = (1 + r_W)\, W_0$.

Another assumption of the HS model is that banks have monopoly power in converting cash deposits to lending. Also, I assume that each loan transaction has the same size as the deposit, Q. Under the monopoly assumption, banks set the deposit and lending rate based on the risk-free return as $r^D = r - a, r^L = r + b$.

Under one deposit transaction, the net credit inventory increases by size Q and cash decreases by the corresponding size, with charge $r^L Q$. Therefore, the end-of-period wealth is:

$$W_T = (1 + r_I + z_I)\, I_0 - \left(1 + r^D + z_I\right) Q + (1 + r + z_C)\,(C_0 + Q)$$

Or

$$W_T = \overline{W} + aQ + z_I\,(I_0 - Q) + z_C\,(C_0 + Q) \tag{3.4.2}$$

Note that W_T is comprised of several terms: aQ is the return due to the spread of lower deposit rate. The term $z_I\,(I_0 - Q)$ reflects a lower variance due to reduction in net credit inventory because of the deposit transaction. Accordingly, variance in cash component rises, as seen in the last component $z_C\,(C_0 + Q)$.

Changes in expected utility under one loan transaction is

$$E\,(\Delta W_T | one\, transdeposit) =$$
$$u'\left(\overline{W}\right) aQ + \tfrac{1}{2} u''\left(\overline{W}\right) \left[(aQ)^2 + (Q - 2I_0)\, Q\sigma_I^2 + (Q + 2C_0)\, Q\sigma_C^2 + 2\,(C_0 - Q - I_0)\, Q\sigma_{CL}\right] \tag{3.4.3}$$

Similarly, changes in expected utility under one loan transaction is

$$E\,(\Delta W_T | one\, loan) =$$
$$u'\left(\overline{W}\right) bQ + \tfrac{1}{2} u''\left(\overline{W}\right) \left[(bQ)^2 + (Q + 2I_0)\, Q\sigma_I^2 + (Q - 2C_0)\, Q\sigma_C^2 + 2\,(C_0 - Q - I_0)\, Q\sigma_{CL}\right] \tag{3.4.4}$$

I assume a passion distributed arrival of the loan demand and deposit supply, where the distribution is a function of the fee a, b. The distribution functions λ_a, λ_b are $\lambda_a = \alpha - \beta a, \lambda_b = \alpha - \beta b$. Given that the expected utility function under uncertain demand for loans and supply of deposits are written as:

$$Eu\left(\Delta W_T\right) = \lambda_a E\left(\Delta W_T | one\, transdeposit\right) + \lambda_b E\left(\Delta W_T | one\, loan\right)$$

Following Ho and Saunders (1981), I further assume that the effects of second moment aQ^2, bQ^2 are negligible. Maximizing the above utility with respect to , I derive two first order conditions:

$$\begin{aligned} a^* &= \tfrac{\alpha}{2\beta} - \tfrac{u''}{4u'}\left[\left(Q - 2I_0\right)\sigma_I^2 + \left(Q + 2C_0\right)\sigma_C^2 + 2\left(C_0 - Q - I_0\right)\sigma_{CL}\right] \\ b^* &= \tfrac{\alpha}{2\beta} - \tfrac{u''}{4u'}\left[\left(Q + 2I_0\right)\sigma_I^2 + \left(Q - 2C_0\right)\sigma_C^2 + 2\left(C_0 - Q - I_0\right)Q\sigma_{CL}\right] \end{aligned}$$

Or

$$\begin{aligned} a^* &= \tfrac{\alpha}{2\beta} - \tfrac{u''}{4u'}\left[\left(Q - 2I_0\right)\sigma_I^2 + \left(Q + 2C_0\right)\sigma_C^2 + 2\left(C_0 - Q - I_0\right)\sigma_{CL}\right] \\ b^* &= \tfrac{\alpha}{2\beta} - \tfrac{u''}{4u'}\left[\left(Q + 2I_0\right)\sigma_I^2 + \left(Q - 2C_0\right)\sigma_C^2 + 2\left(C_0 - Q - I_0\right)Q\sigma_{CL}\right] \end{aligned} \tag{3.4.5}$$

Therefore, combining equations in 3.4.5, I derive the optimal NIM,

$$s^* = a^* + b^* = \frac{\alpha}{\beta} - \frac{u''}{u'}\left[Q\sigma_I^2 + Q\sigma_C^2 + 2\left(C_0 - Q - I_0\right)\sigma_{CL}\right] \tag{3.4.6}$$

Let $A = -\frac{u''}{u'}$ be the risk aversion of the banks. I find that the optimal NIM is a function of the following factors:

$$s^* = f(\overset{+}{A}, \overset{+}{\sigma^2})$$

I simplify the NIM as a function of a risk factor σ^2 and the price of the factor A . Let o be the optimism. I propose following propositions:

Proposition 3.1 *A is decreasing in o.*

Proposition 3.2 *σ^2 is increasing in o.*

The multiplicative form in A, σ^2 implies that the return to risk, measured by NIM, are increasing and decreasing respectively.

The regression scheme is mostly based on the model predictions. Note that according to the previous assumptions,o is positively correlated via the channels of σ^2, but negatively correlated if the risk aversion channel A is dominant. Therefore, the first regression (see below) tests the correlation between optimism and NIM, trying to validate whether the risk aversion channel is dominant.

$$NIM_{it} = \theta_0 + \theta_1 optimism_{it} + other_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{3.4.7}$$

I frame the above argument into the following hypothesis:

Hypothesis 3.1 *if proposition 3.1 represents the dominant channel on how optimism affects NIM, then* $\theta_1 < 0$*. Otherwise, if proposition 3.2 is the dominant channel, it holds that* $\theta_1 > 0$ *.*

Next, I attempt to verify proposition 1 and 2 via the following regression specification:

$$NIM_{it} = \pi_0 + \pi_1 risk_{it} + \pi_2 optimism * risk_{it} + other_{it} + \alpha_i + \gamma_t + \epsilon_{it} \quad (3.4.8)$$

Where $risk_{it}$ are risk proxies. The estimated coefficients π_2 are negative. Also by testing the signs of π_2 , I also provide evidence against the following hypothesis:

Hypothesis 3.2 *if proposition 1 is true, then* $\pi_2 < 0$*.*

Note that the regression above provides little direct hints on proposition 3.2. To examine the below hypothesis, I can perform the following regression specification to validate these two assumptions.

$$risk_{it} = \psi_0 + \psi_1 optimism_{it} + other_{it} + \alpha_i + \gamma_t + \epsilon_{it} \quad (3.4.9)$$

Hypothesis 3.3 *if proposition 3.2 is true, then* $\psi_1 < 0$*.*

3.4 Data

I examine the previous theory using data from the quarterly filed regulatory data from FH-Y9C and the annual Execucomp. Both data sources are available through the Wharton Research Database (WRDs). To start, I only keep the year-end (fourth quarter) data of FH Y9C. The FH-Y9C data, which contains detailed financial data in the bank holding company (BHC) level, is first merged with a list of RSSDID-PERMCO code available from the Federal reserve Ibsite. The PERMCO code in the merged dataset is then matched with the WRDs data to acquire the cusip code for each BHC-year observation. Finally, each BHC with matching cusip code is joined to managerial information in the Execucomp.

One variable I add to the regression analysis is the deposit share in local markets. As a comparison of the pricing model in Angbazo (1997), he controls for the branching limitation. Neither the FH-Y9C nor Execucomp contains relevant information. Instead the market share is derived from the annual report of Summary of deposits (SoD). The SoD contains information on deposits for each branch under the same commercial bank (RSSD9001). To start, I aggregate each branch to the same commercial bank within the same county. Then I compute the deposit share of the bank for each county. To derive the market power for a bank, I aggregate the market share in each county where bank operates, weighted by the number of deposits to the bank level. As a final step, I perform another aggregation of bank-level market share into each BHC, using deposits as weights. Same method can be seen in Berger and Roman (2015). Merging all these datasets yields roughly 2000 BHC year observations. Below are the steps I take to construct the samples. The total bank-year observations I end up is 1,990. As a comparison, Ho et al. (2016) has 990 samples in their regression analysis. In their paper, they only include depository institutions.

TABLE XX: SAMPLE CONSTRUCTION

	total obs	key required
FR Y9C year end samples	179,607	
join with CRSP rssd permco link	13,888	rssd
wrds permco cusip cik link	11,167	permco
Execcomp	2,264	cusip
CRSP stock price	2,215	cusip
SOD data	1,990	RSSD9001

Notes: The table highlights the key data sources and steps in getting the samples ready. The number in the first column is the total bank-year observations after performing the sample selection steps to the left. And the second column is the key used in merging the tables.

Another important variable in the regression analysis is the measurement of optimism. The construction methodology can be found in many existing literature (Malmedier and Tate, 2005; Campbell et al, 2010; Ho et al, 2016;

Huang et al, 2017). The key to constructing these measurements is estimating the moneyness of the options held by CEOs. The construction makes use of two variables in the Execomp dataset: OPT_UNEX_EXER_EST_VAL and OPT_UNEX_EXER_NUM, which represent the estimated realizable value and the total number of the exercisable options. Dividing the former by the latter yields the estimated realizable value per option. Then I derive the strike price by taking difference between the year-end stock price and, based on CRSP database, and the estimated realizable value per option. The moneyness is just the ratio of estimated realizable value per option and strike price.

The general practice is having two thresholds to define an "in-the-money" option: whether moneyness exceeds 100% or 67% (Huang et al, 2017). I follow these practices and assign 1 to those CEO-year observation whose options are in the money. To be more specific, if the year-end options are in the money, or the dummy is 1 for some CEO in a year, then it clearly indicates the CEO delays exercising the in-the-money options. A CEO is defined as optimistic if he is observed to delay exercising his in-the-money options at least twice during his tenure. In other words, if a CEO turns optimistic in some year, he would always remain the same status until the end of his tenure.

Although the option-based optimism is used in many published studies, it still raises some concerns of measurement error. One of the major concerns is that the optimism label hinges on whether the CEO has a chance to delay the in-the-money option. In other words, if the stock price is always below the strike price, then even if the CEO is optimistic by nature, this measurement would fail to capture that. In other words, I argue that the option-based measure is very likely affected by the market condition. Other than that, Malmendier and Tate (2015) have also pointed out the correlation between option-based optimism and market condition can also come from the makeup compensation package. In an upturn of markets, companies tend to compensate the CEOs with more stock options. Noting all these caveats, the time trend somehow attests the previous conjecture. There are several observed periods: before 2000, between 2000 and 2008 and 2008 onwards. These periods also mark the up- and down- turns of US stock markets. The correlation with market conditions might pose challenges in the identification. However, this problem has yet to be addressed in current literature.

Below are the summary statistics of all the variables to be used in the regression analysis. All data are winsorized at 1%.

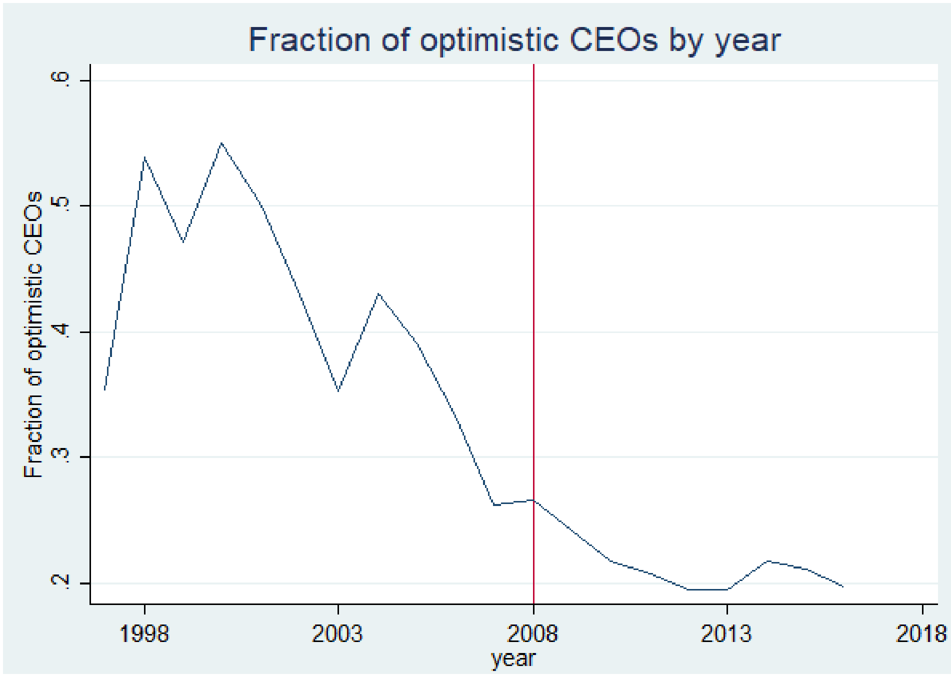
In the datasets summarized by table XXI, the average NIM is roughly 3.5%. The BHCs have average 15.46% in weighted deposit market share. BHCs in the sample generate a ROA of 1.03 percent over the sample periods and have 0.76 percent of LLP in terms of their total loan portfolios. Under the defined measure of optimism, 32% of BHCs are optimistic under the 100% moneyness (as seen in the row “holder100”) threshold and 40% more BHCs

TABLE XXI: SUMMARY STATISTICS

Variable	Obs	Mean	Std.dev	Min	Max	definition
nim	1,526	3.50	0.96	0.41	7.04	(interest income - interest expense)/interest earning assets
liquid	1,526	28.57	14.32	5.67	90.09	liquid assets /total assets
rgap	1,526	18.17	17.58	-26.36	68.79	net assets repriced or mature in one year/total assets
implicit	1,526	1.12	1.95	-16.56	4.74	total net non-interes payment/total assets
magm	1,526	1.41	0.21	0.77	2.15	total income/total expense
depsh	1,526	15.45	10.78	0.11	72.02	weighted deposit share
roa	1,526	1.03	1.46	-5.46	12.36	total income/total assets
size	1,526	16.75	1.66	13.69	21.52	logarithm of total assets
cap	1,526	10.48	6.48	4.21	67.62	equity capital/total assets
llp	1,526	0.76	1.17	-0.51	7.90	loan loss provision/total loans
nonbear	1,526	2.43	1.64	0.23	10.94	non interest bearing assets/total assets
holder100	1,526	0.32	0.47	0.00	1.00	optimism dummy under 100% moneyness
holder67	1,526	0.40	0.49	0.00	1.00	optimism dummy under 67% moneyness
age	1,526	56.80	6.50	32.00	80.00	CEO age

Notes: The table summarizes the statistics (mean, standard deviation, max and min) of all variables used in the empirical section.

Figure 7: Fraction of optimistic CEOs by year



are classified as optimistic under the looser 67% threshold (as seen in the row "holder67"). These CEOs are on average of their late 50s. One last key takeaway from the table is that I use LLP instead of NCO (net charge-offs) as proxy of credit risk since I think LLP is better reflection of banks' conjecture on default probability of their current loan contracts, whereas NCO more likely captures the historical aspect of it.

In table XXI, I also list other variables included in the later analysis. These variables include: a set of risks to be priced in the NIM: credit risk, proxy by the net charge-offs, normalized by total assets; liquidity risks, proxy by liquid assets to total assets ratio; and interest rate risk, proxy by the difference of short-maturity net assets. These variables are chosen according to the regression specification in Angbazo (1997) and Sinkey and Carter (1998). A set of bank characteristics correlated with banks' risk-taking: size, capitalization and profitability, proxy by ROA (Laeven and Levine, 2009). One last set of variables relates bank-specific costs associated with management, non-interest operations and reserves: high management quality might be critical when it comes to whether the managers can select the optimal portfolios. As argued by Angbazo (1997), high NIM might be mirrored in high implicit payments among non-interest operations. Also, the cost of reserves, proxy by the fraction of non-interest-bearing assets might add to the NIM charged. All these factors are taken into account and to alleviate the impacts from outliers (possibly due to abnormal business operations like mergers and acquisitions), I winsorize the data at 1% level.

Below table presents another set of summary statistic, grouped by the optimism status under the 100% moneyness criteria. I find that on average banks with optimistic CEOs are having higher NIM. Under the criteria of 100% moneyness, the difference of NIM is 0.14%, with significance level of 0.01. As for other risk proxies, optimistic CEOs are more likely to be associated with higher interest risk, lower credit risk, lower implicit interest costs, higher management efficiency, lower deposit market share, higher non interest-bear assets allocation. Also, these banks tend to have higher profitability, more capitalized and more aged.

TABLE XXII: SUMMARY STATISTICS BY GROUP OF OPTIMISM

Variable	holder100 = 1	holder100 = 0	difference	std err
nim	3.6	3.46	0.14**	0.05
liquid	29.79	28.01	1.78**	0.79
rgap	17.25	18.59	-1.33	0.97
implicit	0.69	1.31	-0.62***	0.11
magm	1.43	1.4	0.025**	0.01
depsh	13.85	16.18	-2.33***	0.6
roa	1.39	0.86	-0.52***	0.08
size	16.64	16.8	-0.16+	0.09
cap	11.34	10.09	1.25***	0.36
llp	0.67	0.8	-0.14**	0.06
nonbear	2.97	2.18	0.78***	0.09
age	56.33	57.84	1.51***	0.36

Notes: The above table summarizes the statistics by group of banks depending on the overconfidence of CEO in the third and fourth column I include the difference in mean and the standard error of the difference. +, *, **, *** indicate significance at the 10%, 5%, 1% and 0.1% level, respectively.

I also include more details on how these proxies relate to NIM based on Angbazo (1997). Note that not all these proxies are increasing in risks. For all those variables positively/negatively correlated with risk, if proposition 1 is true, the interaction term should be negative/positive.

TABLE XXIII: PREDICTED SIGNS FROM Angbazo (1997)

factor	proxy	signs of coeff	rationale
default risk	nco	positive	nco $\uparrow \rightarrow$ default risk $\uparrow \rightarrow$ default premium $\uparrow$
deposit share	depsh	negative	depsh $\uparrow \rightarrow$ scale economies $\uparrow \rightarrow$ margins $\uparrow$
implicit interest payments	implicit	positive	implicit $\uparrow \rightarrow$ cost $\uparrow \rightarrow$ margins $\uparrow$
interest rate risk	rgap	negative	rgap $\uparrow \rightarrow$ int rate risk $\downarrow \rightarrow$ int risk premium $\downarrow$
leverage	cap	negative	cap $\uparrow \rightarrow$ costs of funds $\downarrow \rightarrow$ margins $\downarrow$
liquidity risk	liquid	negative	liquid $\uparrow \rightarrow$ liquidity risk $\downarrow \rightarrow$ liquid premium $\downarrow$
management efficiency	magm	positive	magm $\uparrow \rightarrow$ revenues $\uparrow \rightarrow$ margins $\uparrow$
opportunity costs	nonbear	positive	nonbear $\uparrow \rightarrow$ costs $\uparrow \rightarrow$ margins $\uparrow$

Notes: The above table is from Angbazo (1997). In this table I includes the predicted relations between all the factors and NIM. Some differences exist in how I proxy deposit share and leverage.

3.5 The regression analysis

3.5.1 The instrumented optimism

To start, I follow the current literature (Ho et al 2016; Huang et al, 2017) by instrumenting the optimism using the age of CEO. The underlying concern of endogeneity comes from the selection of CEO, that is, banks with varying performance might be prone to hire CEOs with corresponding characteristics. In the first stage, I perform a logit regression on the optimism dummy on the age, along with other control variables as follows:

$$Pr\left(optimism = 1|age_{it}, X_{it-1}\right) = L\left(\delta_0 + \delta_1 age_{it} + X_{it-1}\psi + \eta_i + \pi_t\right) \tag{3.4.10}$$

The independent variables age_{it} are the CEO age of bank holding company i at year t. According to Ho et al. (2016), elderly adults tend to be more overconfident in a demanding task like CEO. Below is the first stage result under the two different proxies:

I find positive correlation between CEO ages and option-based optimism as in Ho et al. (2016). Meanwhile, signs of other estimates in size and ROA are largely the same as their papers. Note that their paper uses the change in sizes and ROA in the first stage regression whereas I didn't use the first differenced variables as they did. Using the levels variable, I maintain a con-

TABLE XXIV: FIRST STAGE REGRESSION RESULTS

	This paper		Ho et al. (2016)	
	holder100	holder67	holder100	holder100
age	0.480***	0.369***	0.15***	0.09***
	(0.0575)	(0.0448)	(0.04)	(0.045)
size	-0.246	-0.432	-0.9*	-0.24
	(0.563)	(0.545)	(0.48)	(0.26)
ROA	-0.560***	-0.193+	1.89***	0.13**
	(0.124)	(0.103)	(0.38)	(0.063)
capitalization	0.822***	0.528**	0.14**	0.07*
(leverage)	(0.213)	(0.195)	(0.06)	(0.04)
samples	All BHC	All BHC	depository	add IB
N	563	626	910	1186
BankCtrl	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes

Notes: The above table reports the results from the logistic regressions of overconfidence dummy against age. The third and fourth columns are the estimated coefficients from Ho et al. (2016). +, *, **, *** indicate significance at the 10%, 5%, 1% and 0.1% level, respectively.

sistent specification over the whole paper. In the proxies of capitalization, I use the ratio of equity capital to total assets whereas they use the leverage. Although their paper doesn't provide detailed explanations on other variables then CEO ages, I believe that the positive(negative) estimates in size (capitalization) are possibly affecting the optimism via the regulatory channel. Larger or better capitalized firms are mostly reasons or results of stricter regulations, which limits the optimism in managerial executives. That's when banks are larger in size (or more capitalized), this can be a signal of banks facing more regulatory pressure, which discourages the optimism of the management.

3.5.2 NIM and CEO optimism

I start by testing the direct correlation of optimism and NIM:

$$NIM_{it} = \alpha_0 + \alpha_1 optimism_{it} + X_{it-1}\upsilon + \beta_i + \gamma_t + \epsilon_{it} \tag{3.4.11}$$

Where I add the bank-specific controls X_{it-1} which includes size, profitability and capitalization. Below is the regression result:

The regression shows that banks with more optimistic CEOs are associated with higher NIM. The range of the positive difference is between 0.06-0.09 while the instrumented variables yield higher estimates, roughly 0.2-0.3.

TABLE XXV: DIRECT EFFECT OF OPTIMISM ON NIM

Panel A: all BHCs

	holder100	holder67	holder100_p	holder67_p
optimism	0.0932	0.0678	0.293	0.204
	(0.0914)	(0.0721)	(0.189)	(0.183)
N	1291	1291	1291	1291
Rsquare	0.241	0.24	0.248	0.243

Panel B: Year before 2007 (Pre-crisis)

	holder100	holder67	holder100_p	holder67_p
optimism	-0.00323	-0.017	0.167	0.156
	(0.0782)	(0.0592)	(0.161)	(0.182)
N	526	526	526	526
Rsquare	0.225	0.225	0.229	0.228

Notes: The above table reports the results of the univariate regression analysis of NIM on optimism. +, *, **, *** indicate significance at the 10%, 5%, 1% and 0.1% level, respectively. Each column represents a regression specification using different proxies of optimism (e.g. the column under holder100, holder67, holder100_p, holder67_p correspond to regressions of NIM against these proxies). Banks size, ROA and capitalization are also controlled in these regressions. I include results of different subsamples in different panels.Meanwhile I also add bank fixed effect and year fixed effect.

Moreover, I find that estimates using stricter criteria (holder100) in identifying optimism are associated with higher estimates (see row 1 versus row 2 or row 3 versus row 4 of table XXV). This is consistent with intuition since the holder100 adapts higher standards and thus the comparison group is less optimistic under the setup. However, none of these estimates are endowed with statistical power to support any valid inferences.

One of the concerns in panel A is that the sample periods cover some of the extreme scenarios, namely the 2008 Global Financial crisis (GFC). I argue that the periods segmented by GFC represent very different norms, in terms of regulatory environments. Thus I conduct separate regression analysis into the periods before the crisis. In panel B, I find the estimated effects of optimism on NIM is smaller in magnitudes around 0. However, these results also lack statistical power to support the validity. In the coming sections, the regression focuses more on how the marginal difference comes into being.

3.5.3 Risk pricing and CEO optimism

I propose to perform the following regression specification to find the optimism effect on factor pricing:

$$NIM_{it} = \alpha_0 + \Sigma_{j=1}^{5} \beta_j risk_{it-1}^{j} + \Sigma_{j=1}^{5} \theta_j optimism_{it} * risk_{it-1}^{j} + X_{it-1}\tau + \alpha_i + \gamma_t + \epsilon_{it} \tag{3.4.12}$$

I control for four risk proxies, where $risk_{it-1} = \{liquid_{it-1}, llp_{it-1}, rgap_{it-1}, nonbear_{it-1}, cap_{it-1}\}$, and $\theta^j, \beta^j, j = 1...5$ are the estimated coefficients associated with each of the risks and interaction of risks with optimism. Note that I are not including all the eight factors in the model of Angbazo (1997). But instead I narrow down to the five factors since I think these five factors are more risk-related and thus the associated coefficients are more risk pricing related. I argue that higher optimism reduces risk aversion and thus affect the pricing each factor in NIM. The regression results would tell us which of the factor prices is more likely affected by managerial optimism.

I have found that over the whole sample periods, optimism bankers price credit risk lower than their counterparts. As seen from row 5 in panel A of table **??**, the price factor is lower than 0.06 units, although the instrumented estimates are somewhat smaller, and there's no more statistical significance to support the validity of these estimates. The instrumented estimates on the price of capitalization also conflicts with their counterparts. With the instrumented optimism, I find optimistic bankers are pricing capitalization 0.1 units higher (see column 3 and 4 in panel A) whereas the estimates in column 1 and 2 implies otherwise. With the non-instrumented proxies, the price of capitalization factor is lower by roughly 0.03 units. The higher price in the capitalization might be attributed to changes after the crisis, which I will detail in the analysis to follow.

TABLE XXVI: EFFECTS OF OPTIMISM ON FACTOR PRICING

	Panel A: All BHCs				Panel B: Year before 2007			
	holder100	holder67	holder100_p	holder67_p	holder100	holder67	holder100_p	holder67_p
liquidity*optimism	0.00211	0.000962	0.00105	0.00149	0.00371	-0.00046	0.0147+	0.00939
	(0.00436)	(0.00419)	(0.00687)	(0.00748)	(0.00419)	(0.00368)	(0.00797)	(0.00809)
rgap*optimism	-7.5E-05	0.000163	0.00391	0.0029	0.00326	0.0039	-0.00232	0.000103
	(0.00222)	(0.00215)	(0.00308)	(0.00297)	(0.00222)	(0.00269)	(0.00522)	(0.00494)
nonbear*optimism	-0.00199	-0.0279	-0.0392	-0.0724	0.0365	-0.0148	0.112	0.0405
	(0.0329)	(0.0297)	(0.0406)	(0.046)	(0.0386)	(0.0196)	(0.0705)	(0.0611)
cap*optimism	0.0371**	0.0327*	-0.0972***	-0.0986**	-0.011	-0.0325	0.0222	0.00249
	(0.0126)	(0.0133)	(0.0199)	(0.0313)	(0.022)	(0.0276)	(0.0454)	(0.0347)
llp*optimism	-0.0587+	-0.0626*	-0.0346	-0.056	-0.190*	-0.149+	-0.226*	-0.17
	(0.0313)	(0.029)	(0.0373)	(0.038)	(0.0855)	(0.0773)	(0.112)	(0.128)
optimism	-0.334	-0.207	1.123**	1.177**	-0.127	0.291	-0.725	-0.282
	(0.245)	(0.188)	(0.34)	(0.441)	(0.324)	(0.262)	(0.658)	(0.519)
N	1291	1291	1291	1291	526	526	526	526
Rsquare	0.455	0.453	0.484	0.468	0.369	0.364	0.382	0.359
BankCtrl	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The above table includes the results of optimism interacting with different NIM factors. In panel A and B, results from all the BHC and those with HHI larger than 1800 are shown. +, *, **, *** indicate significance at the 10%, 5%, 1% and 0.1% level, respectively.Each column represents a regression specification using different proxies of optimism (e.g. the column under holder100, holder67, holder100_p, holder67_p correspond to regressions of NIM against these proxies). Banks size, ROA and capitalization are also controlled in these regressions. I include results of different subsamples in different panels.Meanwhile I also add bank fixed effect and year fixed effect.

I find significantly lower price of credit risk before the crisis (see row 5 of panel B). The price estimates of credit risk are negative and significant, ranging from 0.15 to 0.23. For results not present in this section, price of credit risk remains significantly lower during the crisis, one finding consistent with Huang et al (2017).

Overall, the lower price in credit risk might contribute to lower NIM among optimistic bankers. However, as from table XXV, the weakly significant higher NIM implies that there's another force balancing the effect of lower credit risk pricing, which I will explore in the risk-taking section.

3.5.4 Risk taking and CEO optimism

Note that factor pricing is not the only channel where NIM is affected by CEO optimism. More optimistic CEOs might engage in more risk-taking behavior and thus record higher risks, which might level up NIM even given the pricing constant.

I perform another regression analysis into the above five risk factors identified in section 3.5. I find a statistically significant relationship between interest risk and CEO optimism. In words, more optimistic CEOs are more likely to have their portfolio exposed to short term interest risks. The more active interest risk taking is seen by a drop of net assets ratio maturing or repricing in one year. The drop is between 2-7 percent based on different proxies. As can be seen from the regression results, the optimism proxies reduce the net interest assets ratio significantly. The reduction in net interest assets ratio might lead to rise in NIM, despite of its statistical insignificance.

The following table also risk-taking behavior before the crisis, which represents periods with less changes in regulatory environment. In the pre-crisis period, I find that optimistic CEOs also tend to take more interest risks (Table XXVII panel A, column 3), estimates of which have close magnitudes to that in the whole sample period. However, this finding loses statistical significance under optimism is measured with stricter criteria. Overall, I would conclude that the weakly higher NIM among optimistic banks are a balance between higher interest rate risk taking and lower price of credit risk. I have also found that capitalization level is lower among banks with optimistic CEOs before the crisis. The average difference is around 0.2-0.4 percent. However, the difference lacks statistical power to support its validity.

The pre-crisis period presents a similar pattern to the whole period. In both samples, I first see the NIM difference is insignificant. Regression analysis that follows attributes the margin difference to a balance between lower price in credit risks and higher interest risk taking. Findings in empirics are consistent with the theoretical model in section 3.3.

TABLE XXVII: EFFECTS OF OPTIMISM ON RISK-TAKING BY PERIODS

Panel A:All BHCs

	liquidity	llp	rgap	nonbear	cap
holder100	0.611	0.00752	-2.678	0.209	-0.139
	(1.007)	(0.101)	(1.984)	(0.173)	(0.105)
holder67	0.232	0.0123	-3.525*	0.253+	-0.077
	(0.897)	(0.1)	(1.72)	(0.147)	(0.0931)
holder100_p	-0.242	0.153	-5.397	0.387	0.244
	(1.624)	(0.154)	(3.772)	(0.28)	(0.198)
holder67_p	-0.78	0.117	-7.477*	0.379	0.374+
	(1.762)	(0.161)	(3.434)	(0.323)	(0.212)

Panel B: Year before 2007 (Pre-crisis)

holder100	1.779+	-0.124+	-1.55	0.216	-0.31
	(0.996)	(0.0681)	(2.274)	(0.136)	(0.188)
holder67	1.752	-0.131	-3.712	0.0835	-0.247
	(1.077)	(0.0819)	(2.404)	(0.128)	(0.154)
holder100_p	2.812	-0.174	-5.732*	0.252	-0.378
	(1.826)	(0.195)	(2.859)	(0.21)	(0.291)
holder67_p	1.039	-0.4	-9.792**	0.0445	-0.452
	(2.239)	(0.248)	(3.377)	(0.279)	(0.359)

Notes: The above table includes the results of optimism affecting different factor loadings. In panel A and B, results from all the BHC and those with HHI larger than 1800 are shown. +, *, **, *** indicate significance at the 10%, 5%, 1% and 0.1% level, respectively. In each cell I include

3.6 Concluding remarks

In this paper I investigated how NIM is correlated with CEO optimism. I started by reiterating a seminar model by Ho and Saunders (1981) and argued that optimism can affect NIM via two channels: risk pricing and the risk taking, both of which raises NIM. In developing hypothesis, I argued that optimism might reduce the risk pricing and rise risk taking, leaving overall changes in NIM ambiguous. Next, I attempted to clarify the theoretical ambiguity using empirical regression. The table below summarizes our qualitative findings.

TABLE XXVIII: ESTIMATED EFFECTS OF INCREASING OPTIMISM

sample period	pricing	effect on NIM	taking	effect on NIM	NIM effect
1994-2017	credit risk ↓	"-"	interest risk ↑	"+"	"+"
1994-2006	credit risk ↓	"-"	interest risk ↑	"+"	"+"

Notes: I summarize the findings in this paper using the table above. The first column indicates the sample periods where the empirical regressions are conducted.The second column selects the findings of pricing changes with significance given increasing optimism. The third column includes the marginal effect of the changes of second column. Likewise, the fourth column has the selected findings of risk taking with the marginal effect presented in column 5 of table XXVIII. The overall effect is in column 7, which is the summary of the reduced form regression in section 3.5.

The reduced form regression over the whole sample period has returned a statistically weakly positive correlation between NIM and optimism. Splitting the sample, I obtain similar findings in the pre-crisis periods.

I then investigated the driver of positive/negative correlations among the whole sample period and pre-crisis period. I found that during the whole period, optimistic CEOs tended to value less on credit risks, but they exposed their asset portfolio towards short-term interest risks. Similar patterns Ire observed in the pre-crisis periods. Noticing the dynamics of regulatory environments and macroeconomic conditions, I see that optimistic CEOs take fewer liquidity risks, although somehow counter-intuitive, leading to lower NIM. The positive association between optimism and liquid assets could be due to potential omitted variable problem, suggesting potential extensions to the current research.

References

Afonso, G., Armenter, R., and Lester, B. (2019). A model of the federal funds market: yesterday, today, and tomorrow. *Review of Economic Dynamics*.

Ahmed, A. S., Billings, B. K., Morton, R. M., and Stanford-Harris, M. (2002). The role of accounting conservatism in mitigating bondholder-shareholder conflicts over dividend policy and in reducing debt costs. *The Accounting Review*, 77(4):867–890.

Ahmed, A. S. and Duellman, S. (2013). Managerial overconfidence and accounting conservatism. *Journal of Accounting Research*, 51(1):1–30.

Ahmed, A. S., Morton, R. M., and Schaefer, T. F. (2000). Accounting conservatism and the valuation of accounting numbers: Evidence on the feltham-ohlson (1996) model. *Journal of Accounting, Auditing & Finance*, 15(3):271–292.

Akins, B., Dou, Y., and Ng, J. (2017). Corruption in bank lending: The role of timely loan loss recognition. *Journal of Accounting and Economics*, 63(2-3):454–478.

Angbazo, L. (1997). Commercial bank net interest margins, default risk, interest-rate risk, and off-balance sheet banking. *Journal of Banking & Finance*, 21(1):55–87.

Antweiler, W. and Frank, M. Z. (2004). Is all that talk just noise? the information content of internet stock message boards. *The Journal of finance*, 59(3):1259–1294.

Azimi, M. and Agrawal, A. (2018). Is the sentiment in corporate annual reports informative? evidence from deep learning. *Evidence from Deep Learning (November 1, 2018)*.

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

Banerjee, S., Gatchev, V. A., and Noe, T. H. (2006). Doom or gloom? ceo stock options after enron. *CEO Stock Options after Enron (February 1, 2008). AFA*.

Basu, S. (1997). The conservatism principle and the asymmetric timeliness of earnings1. *Journal of accounting and economics*, 24(1):3–37.

Bauer, M. D. et al. (2012). Monetary policy and interest rate uncertainty. *FRBSF Economic Letter*, 38:1–5.

Baum, C. F., Caglayan, M., and Ozkan, N. (2004). The second moments matter: The response of bank lending behavior to macroeconomic uncertainty.

Beatty, A. and Liao, S. (2011). Do delays in expected loss recognition affect banks' willingness to lend? *Journal of accounting and economics*, 52(1):1–20.

Belke, A. and Potrafke, N. (2012). Does government ideology matter in monetary policy? a panel data analysis for oecd countries. *Journal of International Money and Finance*, 31(5):1126–1139.

Ben-David, I., Graham, J. R., and Harvey, C. R. (2013). Managerial miscalibration. *The Quarterly Journal of Economics*, 128(4):1547–1584.

Ben Naceur, S. and Goaied, M. (2008). The determinants of commercial bank interest margin and profitability: evidence from tunisia. *Frontiers in Finance and Economics*, 5(1):106–130.

Berger, A. N., Guedhami, O., Kim, H. H., and Li, X. (2018). Economic policy uncertainty and bank liquidity hoarding. *Available at SSRN 3030489*.

Bernanke, B. and Blinder, A. S. (1992). The federal funds rate and the transmission of monetary policy. *American Economic Review*, 82(4):901–21.

Bernanke, B. S. and Gertler, M. (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic perspectives*, 9(4):27–48.

Berrospide, J. M. (2012). Bank liquidity hoarding and the financial crisis: An empirical evaluation.

Biddle, G. C., Ma, M. L., and Song, F. M. (2013). The risk management role of accounting conservatism for operating cash flows. *Available at SSRN 1695629*.

Blinder, A. S., Ehrmann, M., Fratzscher, M., De Haan, J., and Jansen, D.-J. (2008). Central bank communication and monetary policy: A survey of theory and evidence. *Journal of Economic Literature*, 46(4):910–45.

Boix, C. (2000). Partisan governments, the international economy, and macroeconomic policies in advanced nations, 1960–93. *World politics*, 53(1):38–73.

Bonaime, A., Gulen, H., and Ion, M. (2018). Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics*, 129(3):531–558.

Bordo, M. D., Duca, J. V., and Koch, C. (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level us evidence over several decades. *Journal of Financial Stability*, 26:90–106.

Calmes, C. and Théoret, R. (2014). Bank systemic risk and macroeconomic shocks: Canadian and us evidence. *Journal of Banking & Finance*, 40:388–402.

Campbell, T. C., Gallmeyer, M., Johnson, S. A., Rutherford, J., and Stanley, B. W. (2011). Ceo optimism and forced turnover. *Journal of Financial Economics*, 101(3):695–712.

Chang, B. Y., Feunou, B., et al. (2014). Measuring uncertainty in monetary policy using realized and implied volatility. *Bank of Canada Review*, 2014(Spring):32–41.

Craig, B. R. and Dinger, V. (2013). Deposit market competition, wholesale funding, and bank risk. *Journal of Banking & Finance*, 37(9):3605–3622.

Cukierman, A. and Meltzer, A. H. (1986). A theory of ambiguity, credibility, and inflation under discretion and asymmetric information. *Econometrica: journal of the econometric society*, pages 1099–1128.

Doliente, J. S. (2005). Determinants of bank net interest margins in southeast asia. *Applied Financial Economics Letters*, 1(1):53–57.

Feldman, R., Govindaraj, S., Livnat, J., and Segal, B. (2008). The incremental information content of tone change in management discussion and analysis.

Friedman, M. (1968). Dollars and deficits: inflation, monetary policy and the balance of payments. Technical report.

Gandhi, P., Loughran, T., and McDonald, B. (2019). Using annual report sentiment as a proxy for financial distress in us banks. *Journal of Behavioral Finance*, pages 1–13.

Givoly, D., Hayn, C. K., and Natarajan, A. (2007). Measuring reporting conservatism. *The Accounting Review*, 82(1):65–106.

Greenspan, A. (2004). Risk and uncertainty in monetary policy. *American Economic Review*, 94(2):33–40.

Guay, W. R. and Verrecchia, R. E. (2017). Conservative disclosure. *Available at SSRN 995562*.

Ha, J. (2018). Bank accounting conservatism and bank loan quality.

Heaton, J. B. (2002). Managerial optimism and corporate finance. *Financial management*, pages 33–45.

Higgs, R. (1997). Regime uncertainty: why the great depression lasted so long and why prosperity resumed after the war. *The Independent Review*, 1(4):561–590.

Hirshleifer, D., Low, A., and Teoh, S. H. (2012). Are overconfident ceos better innovators? *The journal of finance*, 67(4):1457–1498.

Ho, P.-H., Huang, C.-W., Lin, C.-Y., and Yen, J.-F. (2016). Ceo overconfidence and financial crisis: Evidence from bank lending and leverage. *Journal of Financial Economics*, 120(1):194–209.

Ho, T. S. and Saunders, A. (1981). The determinants of bank interest margins: theory and empirical evidence. *Journal of Financial and Quantitative analysis*, 16(4):581–600.

Huang, S.-C., Chen, W.-D., and Chen, Y. (2018). Bank liquidity creation and ceo optimism. *Journal of Financial Intermediation*, 36:101–117.

Huizinga, H. and Laeven, L. (2012). Bank valuation and accounting discretion during a financial crisis. *Journal of Financial Economics*, 106(3):614–634.

Ibrahim, M. H. and Shah, M. E. (2012). Bank lending, macroeconomic conditions and financial uncertainty: evidence from malaysia. *Review of Development Finance*, 2(3-4):156–164.

Jegadeesh, N. and Wu, D. (2013). Word power: A new approach for content analysis. *Journal of Financial Economics*, 110(3):712–729.

Jensen, H. (2002). Optimal degrees of transparency in monetary policymaking. *scandinavian Journal of Economics*, 104(3):399–422.

Jitmaneeroj, B., Lamla, M. J., and Wood, A. (2019). The implications of central bank transparency for uncertainty and disagreement. *Journal of International Money and Finance*, 90:222–240.

Kaminska, I. and Roberts-Sklar, M. (2018). Volatility in equity markets and monetary policy rate uncertainty. *Journal of Empirical Finance*, 45:68–83.

Kanagaretnam, K., Lim, C. Y., and Lobo, G. J. (2013). Influence of national culture on accounting conservatism and risk-taking in the banking industry. *The Accounting Review*, 89(3):1115–1149.

Kashyap, A. K. and Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3):407–428.

Kearney, C. and Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, 33:171–185.

Keister, T. and Bech, M. L. (2012). On the liquidity coverage ratio and monetary policy implementation. *BIS Quarterly Review December*.

Khan, M. and Watts, R. L. (2009). Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of accounting and Economics*, 48(2-3):132–150.

Kim, J.-B. and Zhang, L. (2016). Accounting conservatism and stock price crash risk: Firm-level evidence. *Contemporary Accounting Research*, 33(1):412–441.

Kurov, A. and Stan, R. (2018). Monetary policy uncertainty and the market reaction to macroeconomic news. *Journal of Banking & Finance*, 86:127–142.

Laeven, L. and Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of financial economics*, 93(2):259–275.

Li, F. (2010). The information content of forward-looking statements in corporate filings—a naïve bayesian machine learning approach. *Journal of Accounting Research*, 48(5):1049–1102.

López-Espinosa, G., Moreno, A., and de Gracia, F. P. (2011). Banks' net interest margin in the 2000s: A macro-accounting international perspective. *Journal of International Money and Finance*, 30(6):1214–1233.

Loughran, T. and McDonald, B. (2011a). Barron's red flags: Do they actually work? *Journal of Behavioral Finance*, 12(2):90–97.

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

Loughran, T. and McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, 54(4):1187–1230.

Malmendier, U. and Tate, G. (2005). Does overconfidence affect corporate investment? ceo overconfidence measures revisited. *European financial management*, 11(5):649–659.

Malmendier, U. and Tate, G. (2015). Behavioral ceos: The role of managerial overconfidence. *Journal of Economic Perspectives*, 29(4):37–60.

Maudos, J. and De Guevara, J. F. (2004). Factors explaining the interest margin in the banking sectors of the european union. *Journal of Banking & Finance*, 28(9):2259–2281.

Maudos, J. and Solís, L. (2009). The determinants of net interest income in the mexican banking system: An integrated model. *Journal of Banking & Finance*, 33(10):1920–1931.

Niu, J. et al. (2010). The effect of ceo overconfidence on bank risk taking. *Economics Bulletin*, 30(4):3288–3299.

Otto, C. A. (2014). Ceo optimism and incentive compensation. *Journal of Financial Economics*, 114(2):366–404.

Poole, W. (1968). Commercial bank reserve management in a stochastic model: implications for monetary policy. *The Journal of finance*, 23(5):769–791.

Qiang, X. (2007). The effects of contracting, litigation, regulation, and tax costs on conditional and unconditional conservatism: Cross-sectional evidence at the firm level. *The Accounting Review*, 82(3):759–796.

Raith, M. (2009). An agency theory of conservative accrual accounting.

Raunig, B., Scharler, J., and Sindermann, F. (2017). Do banks lend less in uncertain times? *Economica*, 84(336):682–711.

Rodnyansky, A. and Darmouni, O. M. (2017). The effects of quantitative easing on bank lending behavior. *The Review of Financial Studies*, 30(11):3858–3887.

Rogers, J. H., Sun, B., Husted, L. F., et al. (2016). Measuring monetary policy uncertainty: The federal reserve, january 1985-january 2016. Technical report, Board of Governors of the Federal Reserve System (US).

Sprenkle, C. M. (1987). Liability and asset uncertainty for banks. *Journal of Banking & Finance*, 11(1):147–159.

Stulz, R. (1986). Interest rates and monetary policy uncertainty. *Journal of Monetary Economics*, 17(3):331–347.

Talavera, O., Tsapin, A., and Zholud, O. (2012). Macroeconomic uncertainty and bank lending: the case of ukraine. *Economic systems*, 36(2):279–293.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of finance*, 62(3):1139–1168.

Tetlock, P. C., Saar-Tsechansky, M., and Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, 63(3):1437–1467.

Wang, X., Xu, W., and Zhong, Z. (2019). Economic policy uncertainty, cds spreads, and cds liquidity provision. *Journal of Futures Markets*, 39(4):461–480.

Watts, R. L. (2003). Conservatism in accounting part i: Explanations and implications. *Accounting horizons*, 17(3):207–221.

Wieland, V. (2000). Monetary policy, parameter uncertainty and optimal learning. *Journal of Monetary Economics*, 46(1):199–228.

Zhou, K. and Wong, M. C. (2008). The determinants of net interest margins of commercial banks in mainland china. *Emerging Markets Finance and Trade*, 44(5):41–53.

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Lecturer May, 2017 - Aug, 2017

Statistics for Economics, Summer 2017

Recitation Instructor/Teaching Assistant Sep, 2015 - May, 2017

Microeconomics theory, Spring 2017

Statistics for Economics, Fall 2016

Freakonomics, Fall 2015, Spring 2016

Professional Presentations

UIC Economics Research Lunch, 2018, 2019

Midwest Economics Association (MEA) annual conference, 2019

Illinois Economics Association (IEA) annual conference, 2018