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Chinese Equity Market Pricing and Loan Sales Discount in US Banking

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Dedication

I deeply thank to Dr. Zhou lizhi's (Professor at Xi'an Jiao Tong University Management Department) generosity and corporation both on data and suggestions.

I sincerely thank to my academic adviser Dr. Mohammad Kabir Hassan who has offered tremendous encouragement during the past four years of my doctoral program, I believe that without his help I cannot hold all the trophies and achievements. Dr. Selma Izadi who has provided irreplaceable hard work is another important role in my first research. Also, I deeply thank to Dr. Ali Ashraf who has provided remarkable suggestions and ideas is a remarkable co-author in my second research. Again, without the hardcore co-authors, I do not believe the good job can be done very well.

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Abstract

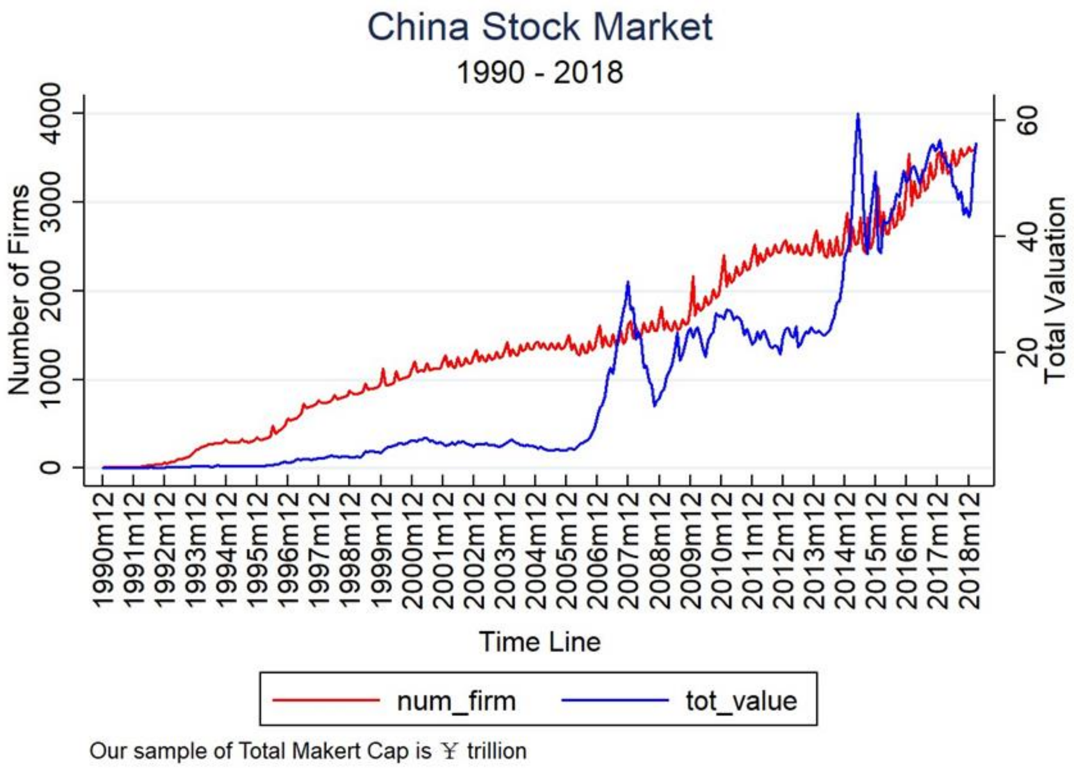
In the recent decades, the Fama–French three-factor (1992, 1993, 1996) and five-factor (2015) models become the most widely used asset pricing models in the world. The U.S. (i.e., developed financial market) country-specific 2 additional factors in the 5-factor model, RMW and CMA or profitability and investment premium, empirically cannot further capture the return variation of the classic three-factor/characteristic in China's stock market (i.e., developing financial markets). In China, based on our result, therefore, the classic three-factor outperforms the five-factor model. We do not presume that firms in different countries share the same features. Following Liu, Stambaugh, and Yuan (2019), we replaced the price-to-book ratio (PB) with the earnings-price ratio (EP). By using Shanghai and Shenzhen exchange stocks, we suggested that the explanatory uncertainty of HML only exists in the five-factor model. In the Fama MacBeth regression, the SMB and HML are significant factors in the three-factor model, explaining the return variation in China. Surprisingly, though the size effect is impressively persistent in both models, the ratio effect has limited explanatory power.

JEL Codes: C5, G1, G2
JEL Keywords: Fama-French Factors; Asset Pricing; Chinese Stock Market

1. Introduction

What are the determinants of factor in explaining the expected stock return in nowadays? This is the researchers' enduring question, and it is a prominent issue in the study of asset pricing. Banz (1981) proposed that there is a negative relation between average stock return and size (market capitalization), hence we predict that the smaller the firm, the higher the average return. DeBondt and Thaler (1985) and Fama and French (1992) present the value effect, which we call the ratio effect: that stocks or firms with higher book-to-market (BM) or book-to-price (BP) ratios are more likely to have higher-than-average returns. At the year end of 2019, China's total equity market capitalization, the world's second largest, is around 59.29 trillion China yuan; the U.S. stock market capitalization, in turn, is about $37.68 trillion U.S. dollars, nearly 300 trillion China yuan. Figure 1.1 presents the uptrend of Chinese published firms' valuation, along with that of the Shanghai and Shenzhen A share class and Second-board markets.

Figure 1.1 The Overview of China Stock Market, Dec. 1990 – Dec. 2018



To some extent, the empirical experience of the stock market and relevant analysis of transaction or trading data enlarges and improves the asset pricing theory. In the last few decades, accordingly, researchers have not only focused on theoretical asset pricing but also on enormous empirical works in the field. Moreover, the excess return of investment strategies has motivated professionals to continuously investigate theoretical systems of pricing in order to push up the pricing efficiency of the capital market and enhance trading strategies.

Jack Treynor (1961, 1962), William F. Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) independently purposed the Capital Asset Pricing Model (CAPM). However, CAMP’s single factor cannot satisfy the real and modern exchange market any longer. There are many frictional trading transactions, such as tax and other costs, in addition, the market portfolio is hard to be hold for diversifying out risk. CAPM should include more factors for explaining the real modern market. Ross (1976, 2013) first presented the Arbitrage Theory of Capital Asset Pricing (APT) in the multi-factor’s asset pricing liner-regression model. APT extends CAPM to multiple factors. Based on the framework of CAPM and APT, Fama and French first conclusively introduced the three and five-factor models in 1992, 1993 and 2015, respectively. Arbitrage pricing theory indicates that the behavior of arbitrage is a determining factor in the formation of modern efficient markets (market equilibrium pricing).

Griffin (2002) supported the claim that there is no benefit to use the Fama and French three-factor model in a worldwide range. Fama and French (2012) analyzed the application of five-factor model in North America, Europe, Japan, and Asia Pacific. Except in Japan, they found the same conclusion that they had found before, in the U.S. Moreover, they found out the return momentum for all the countries except Japan. In addition, Fama and French (2016) found that in North America, Europe, and Asia Pacific, the expected returns positively related to B/M and negatively related to investment. However, their conclusion and expectation did not explain the Japanese market. Both three- and five-factor models have been the most famous and extensively used asset pricing (investment) models, whether theoretically or empirically.

The localized factors or characteristics model has not received enough concern and development. Based on U.S. data, Fama and French created common factors to explain expected return anomalies. However, instead of creating another country-specific “factors or characteristics zoo,” our paper bases on the framework of the Fama–French three/five-factor model and Liu, Stambaugh, and Yuan (2019), hereafter LSY (2019), and mainly focuses on the empirical performance of factor model in the China stock market. Moreover, the emerging China stock market is not the case of the developed U.S. equity market. Investors in the developing market are separate and youth player, compared to sophisticated investors in developed financial markets. Many papers found out the serious herding, lottery, and speculative participant in investment behavior. For example, uninformed investors are likely chasing hot and discarding cold. According to LSY (2019) and Lee, Qu, and Shen (2017), hereafter LQS (2017), pre-enrolled-IPO firms face an extremely long inspection process and high costs, therefore, these companies passby and purchase “nearly bankruptcy or bad performance public firm” – the common part of these firms is small size and low ratio – for achieving the indirect Initial Public Offering. We can see the indirect-IPO throughout the last 20 years in China’s stock market. Until the end of 2013, the China Securities Regulatory Commission (CSRC) implemented its IPO Standards in the Audit of Reverse Mergers for regulating and managing requirements of indirect-IPO firms. In September 2019, CSRC revised the previous acts and detailed the processes of the inspection. The typical outperformance of indirect-IPO firms is extremely obvious after a success onboard. In addition, the outperformance attracts entire market attention. The anomalies of indirect-IPO should be considered in the empirical asset pricing playfield.

Based on the three-factor model, Fama and French (2015) provided the five-factor model, which included the profitability factor RMW and the investment factor CMA. They also confirmed the validity of the five-factor model with more than 50 years of U.S. market data. However, Zhao et al. (2016) indicate that the Chinese stock market rejects RMW and CMA due to their table evidence of coefficients of RMW and CMA. Hu et al. (2019), our evidence consistent with their paper is that the size effect has a huge weight in explaining the average return. However, our paper differed from the existing literature in its use of the ratio of EP, which outperforms BM in explaining average returns. Our paper considers the indirect-IPO to decline the possibility of mispricing. Therefore, according to LQS (2017) and LYS (2019), we have followed the step that 30% of small size stocks in each period are eliminated as a corrective for related potential mispricing.

We contribute to the existing literature in several aspects. First, we investigated the models' adoption by using Chinese stock market data and found that the three-factor model is more applicable than the five-factor. Second, this question of adoption rarely has been asked in the literature, more specifically, by using China stock market, we investigate this model adoption issue. Third, the evidence suggests that the asset pricing theory in the field of factor model has the endemicity. Fourth, the localized factor model is needed.

2. Literature review

In the 1960s, Jack Treynor (1961, 1962), William F. Sharpe (1964), John Lintner (1965), and Jan Mossin (1966) independently purposed CAPM. Since then, the model has developed rapidly. Fama and MacBeth (1973), for example, used the cross-section regression method to further test the CAPM model empirically.

However, CAPM is a single-factor model interpreting stock return in market risk premium (market retune minus risk free rate). It does not incorporate listed companies' features and characteristics—size effect, book-to-market ratio (Fama and French 1992, 1993, 1996), momentum factor (Jegadeesh and Titman, 1993), and liquidity factor (Pástor and Stambaugh, 2003). In addition, Banz et al. (1981) and Stattman (1980) found that in the US market, there are two famous factors, the firm capitalization (market cap or size effect) and book to market ratio (BM or ratio effect). Fama and French (1993) combined the CAPM, size and BM together, purpose an asset pricing model in three factors: market risk premium, size effect, and book-to-market ratio. It is their classic 1993 paper that directed researchers' focus to empirical asset pricing model.

Based on the FF three-factor model, Jegadeesh and Titman (1993) and Carhart (1997) further incorporates the momentum factor and claims the four-factor model. In the most recent, the authors of three-factor model, Fama and French (2015), purpose the five-factors model by adding in the profitability factor (RMW) and the investment factor (CMA). By using China stock market data, our paper mainly investigates an adoption issue that the model equally explains China stock return in both 3 and 5 factors. Namely, which model is more adaptive (FF3 or FF5)? There are many significant differences between the US and China stock markets, for example, the way of regulation, the mechanism of initial public offering and stock delisting, the report of financial statement and so on. FF3 and FF5 are country-specific three- and five-factor model, respectively. It is necessary to fit China-specific data in the FF model framework to see the difference. However, we barely see the paper in this area. According to our empirical result, the FF3 outperforms the FF5 in China.

Fama and French applies BM to sort stock portfolios, but in this article, we replace it with the reciprocal of EP. According to Liu, Stambaugh and Yuan, LSY (2019), the evidence strongly supports the approval of EP ratio because of advanced model explanation in most reported anomalies. As we know, the size effect is embodied by BM and the ratio effect is reflected by EP in FF papers. In addition, the "B" accounts for the book value; "M" represents the firm's market value; E stands for earning per share and P is the stock price. According to Fama and French (1996) and professor Kenneth R. French's website: SMB (Small Minus Big) is the average return on small portfolios minus the average return on big portfolios, while HML (High Minus Low) is the average return on high EP portfolios minus the average return on low EP portfolios. In 1992 Fama and French issued a paper that elaborated on the common risk factors in the returns on stocks and bonds. Their evidence clearly points out that three factors affect the average return on stocks, the overall market factor, firm size factor, and BM-equity factor. Fama and French (1996) showed that the three-factor model solves problems that CAPM cannot fix.

In addition, some papers point out the models' acclimatized issues in many countries. Unfortunately, the model cannot solve anomalies across all countries (see, Griffin (2002), Fama and French (2012), Fama and French (2016), LSY (2019)). The three-factor model holds the outperformance in China. The reason of the five-factor model underperformance could be complex. However, we know that there are many differences in the US and Chinese stock markets. For capturing the expected excess return, firm features that based on U.S. market may not equally explain the China stocks. Moreover, we know not only that the size effect and ratio effect work well but also that, for the left-hand side variable, expected excess return, the size effect holds persistent explanatory power. According to Lee, Qu, and Shen (2017), LQS (2017), there is a unique spot in China stock market, that is, the longtime and tight IPO processes cause a bypass, so called indirect-IPO. Unlike the US stock market, the Chinese stock market, was established 30 years ago, in 1990s. It is developing rapidly since 2006. Some researchers have confirmed the size effect and ratio effect; others, however, have not. Stock trading in emerging markets is fraught with speculation, opaque information disclosure, information distortion, and other market-specific characteristics. The factor model is based on features inherent in developed capital markets. Thus, the investigation in model adoption becomes an urgent topic in China capital market. We find limited papers focused on the three- or five-factors model in specific China.

Because of Fama and French (2015), investment and profit factors become famous characteristics in the asset pricing playfield. The current research on the company's profitability and investment level become the main direction of the asset pricing model, but research on emerging markets combined with profitability and investment factor is still rare, especially in China's stock market.

Therefore, this article bases on the factor pricing model to study whether the profitability and investment factors in the Chinese stock market can equally explain average return. By using China data, we follow the exact same way to create the CMA and RMW. The role of the factor pricing model varies from market to market; this paper complements existing research in this area.

In the rest of article, the data section is in the next chapter, and then we sort the China listed stocks using methodology of Fama and French (1994, 1995, 2015). In the methodology section, the three-factor model is adapted to China A-class and small-medium share stock markets. We suggest that the five-factor model cannot be fit in China A-class.

3. Data and Methodology

We use the China Stock Market & Accounting Research (CSMAR) Database and investigate the adoption of the factor models. Our analysis includes monthly stock return and considers monthly cash dividend reinvestment (the accounting regulation and definition are obviously differently). The frequency of return is monthly. Risk-free rate is the three-month fixed-time deposited rate and the quarterly financial reports (the most of researchers in China consider the three-month fixed-time deposited rate as the risk-free rate). The full sample is the period beginning January 2003 and ending December 2018. Because the classic methodology required value-weighted stock return (VWRET) data to construct the portfolios, we then compute it by monthly frequency. We have three main markets: first, the A-Class shares of the Shanghai stock exchange; second, the A-class shares of the Shenzhen stock exchange; and third, the Second Board Market.

The regression methodology is time-series regression, or "Fama and French regression." Fama and French (1996, 2015) applied the same methodology in their paper. The cross-sectional loadings, b_i , s_i , h_i , r_i and c_i, are estimated from equation 1 and 2, three and five factor model respectively. The monthly value-weighted return on mimicking size and other explanatory independent variables showing on the right-hand side. According to LSY(2019) and LQS (2017), there are several filters for processing data (a) Stocks within 15 days in the previous month or that have less than 120 days in the last year are dropped for decreasing the targets of potential indirect-IPO. LSY (2019) indicated that the rank of bottom 30% market-cap should be deleted to sidestep step the potential indirect-IPO. (b) The poorly performance firms are eliminated for the same reason, such as the prefix contained *S and PT. (c) Financial firms were excluded. (d) We smooth the 1% on each tail. (e) we use A Class share from the Shanghai and Shenzhen stock exchanges to form the story, such as, the first two digits "00" "60" and "30." (f) According to Zhao el al. (2016), the date before 2003 is quite noisy. Therefore, the start date is January 2003, and the end date is December 2018; the maximum period is 192 months. The total number of companies in December 2018 is approximately 3800; after all the requirements, our sample contains around 2400 firms and 290,000 observations.

Regression model:

$$R_{\mathrm{it}} - R_{\mathrm{Ft}} = a_i + b_i(R_{\mathrm{Mt}} - R_{\mathrm{Ft}}) + s_i\mathrm{SMB}_t + h_i\mathrm{HML}_t + e_{\mathrm{it}} \quad (1)$$

$$R_{\mathrm{it}} - R_{\mathrm{Ft}} = a_i + b_i(R_{\mathrm{Mt}} - R_{\mathrm{Ft}}) + s_i\mathrm{SMB}_t + h_i\mathrm{HML}_t + r_i\mathrm{RMW}_t + c_i\mathrm{CMA}_t + e_{\mathrm{it}} \quad (2)$$

Rit, the return of the portfolio "i" on time t, RFt is the risk-free rate, therefore, the LHS is the excess return. RMt is the monthly value weighted market return, so, the excess return is difference between the value weighted market return and risk free rate; SMB (small mines big) is the diversified return difference between the low market-cap portfolio and the high market-cap portfolio (market-value equals to the total share times the stock price) on time t, HML (high mines low) is the diversified return difference between the high of reciprocal of price-to-earnings ratio (P/E ratio) portfolio and the low reciprocal of price-to-earnings ratio (P/E ratio) portfolio on time t, e_{it} is the zero-mean residual. Monthly Value-weighted was calculated for constructing S/L, S/N, SH, B/L, B/N and B/H and these components formed SMB and HML. For ranking the excess portfolio return, we use the same method and cut the EP and size into 5 groups (1 stands for smallest and 5 stands for biggest) respectively, thus, intersectional 25 monthly value-weighted portfolios formed the whole picture. On the second equation, according to Fama and French (2015), RMW_t (robust mines weak) is the diversified return difference between the robust profitability portfolio and weak profitability portfolio. Because of the difference in accounting regulation, we calculate the profitability by using revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. CMA_t (conservative mines aggressive) is the diversified return difference between the conservative profitability portfolio and aggressive profitability portfolio. To measure the investment level, we use ratio of the change in total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by t-2 total assets.

Figure 3.2 The Factor Construction

five-factor construction		
Sort	Breakpoint	Construction
Size and E/P, or Size and OP, or Size and Inv	Size: median E/P: 30th and 70th OP: 30th and 70th Inv: 30th and 70th On percentiles	$SMB_{E/P}$ = (SL+SN+SH)/3 – (BL+BN+BH)/3 SMB_{op} = (SR+SN+SW)/3 – (BR+BN+BW)/3 SMB_{Inv} = (SC+SN+SA)/3 – (BC+BN+BA)/3 thus, SMB = ($SMB_{E/P}$ + SMB_{op} + SMB_{Inv})/3 HML=(SH+BH)/2 – (SL+BL)/2 RMW=(SR +BR)/2 – (SW+BW)/2 CMA=(SC+BC)/2 – (SA+BA)/2
three-factor construction		
Sort	Breakpoint	Construction
Size and E/P	Size: median E/P: 30th and 70th	SMB=(SL+SN+SH)/3 – (BL+BN+BH)/2 HML=(SH+BH)/2 – (SL+BL)/2

In summary, if the model performs protectively well, the expected return can be fully captured by b_i, s_i, h_i, r_i and c_i. Thus, the R-squares must be high, and the pricing error must be low, while all the intercepts must be statistically insignificant. However, the level of market efficiency and self-regulation can be a very important precondition for explaining anomalies. The grafting model is questionable; it is necessary to develop the unique version of China's stock market.

In fact, both accounting and regulation are very different between USA and China. Factor consideration/filtration do impact on the result. Based on the Chinese listed companies, some researchers found that the BM factor is redundant. Other researchers in China, in turn, found that BM is unexplanatory and replaced it, for example, with PB when they analyze the three-factor model in many China research paper. One of a major school use the reciprocal of PB as a substitution for BM. However, Liu, Stambaugh and Yuan (2019) supportive proved the performance of earning to price ratio (EP) by using China stock market data.

There are three main types of separation used in constructing the five-factor model (2X3, 2X2 and 2X2X2X2). In this paper, 2X3 separation is the only methodology.

4. The empirical results

By size, value, and other factors, we sorted the stocks into 25 portfolios. The difference between low ratios and high ratios represents the incremental level of earning to pricing ratio. The difference between small and big size represents the incremental level of firms' market capitalization (total share outstanding times the month end price). We run the time-series regression for estimating the loading in each return portfolio, for instance, the intercept/α, coefficients of market premium/Coff. RP, size premium/Coff. SMB and value premium/Coff. HML. t(α), t(RP)， t(SMB) and t(HML) are the corresponding t-statistics, respectively. Residuals are the time-series regression of each 25 portfolio. On another side of coin, we focus on the coefficients of investment premium/Coff. CMA, profitability premium/Coff. RMW. t(CMA) and t(RMW) are the corresponding t-statistics, respectively.

Table 4.1 shows the coefficients on 25 portfolios of value-weighted stocks. According to Fama and French (1996), the small-sized firms are more likely to have higher returns than the large-sized firms, while the high-ratio stocks are more likely to have higher returns than the low-ratio stocks. Our sample supports this same pattern.

Table 4.1 The Empirical Result of Three Factor Model

R_{it} is the stock return on portfolio-based return i for month t, R_{Ft} is the three-month deposit rate, R_{Mt} is the return on value weight market portfolio; SMB_t is a diversified return on portfolio of the difference between small stocks and big stocks on month t. HML_t is the diversified return on portfolio of the different between high ratio firms and low ratio firms. e_{it} is the potential zero-mean residual. In June of each year, we firstly separate list firms into 2 groups (small or big, S or B) by median market capitalization (total shares outstanding times the month end stock price) and reform the rank in June of year t+1. Based on EP, the earning to price ratio, in the year of t -1, we then separate list firms into 3 segments by 30th and 70th quintiles, so, we have the low ratio(L), middle ratio (N)and high ratio groups(H).
Thus, we intersectional hold 6 grouped value-weighted return portfolios, such as, SL, SN, SH, BL, BN and BH, to construct SMB and HML at each time t. In the whole paper, monthly value weighted returns were calculated in each portfolio. The market risk premium was the difference between value weighted market return and three month fixed deposited rate. We use the same methodology to construct 25 portfolios by size (5 groups) and EP (5 groups).

α						t(α)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small	-0.0342	-0.0239	-0.0116	-0.0098	-0.0125	Small	-2.79	-1.90	-0.85	-0.70	-0.91
2	-0.0204	-0.0177	-0.0035	-0.0049	-0.0065	2	-1.83	-1.54	-0.30	-0.51	-0.82
3	-0.0088	-0.0025	0.0110	0.0115	0.0053	3	-1.09	-0.29	1.33	1.29	0.86
4	0.0030	0.0019	0.0114	0.0074	0.0116	4	0.31	0.26	1.33	0.85	1.92
Big Size	-0.0109	-0.0173	-0.0107	-0.0100	0.0046	Big	-1.72	-3.63	-1.64	-2.08	0.75
Coff. RP						t(RP)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small	0.768	0.812	0.874	0.882	0.874	Small Size	15.21	16.10	17.38	17.46	16.88

<*Table 4.1 cont.*>

2	0.850	0.864	0.937	0.909	0.917	2	20.05	18.29	21.00	23.33	28.23
3	0.921	0.944	0.993	1.015	0.979	3	28.63	25.06	31.50	29.52	40.60
4	0.988	0.971	1.009	0.989	1.011	4	26.32	34.77	28.41	31.07	45.70
Big	0.926	0.886	0.922	0.918	0.993	Big	26.34	29.92	30.89	44.38	34.52
Coff. SMB						t(SMB)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small	0.498	0.508	0.487	0.473	0.344	Small	8.88	8.27	7.37	7.52	5.82
2	0.488	0.580	0.519	0.434	0.349	2	7.91	9.64	8.25	7.03	9.75
3	0.300	0.338	0.307	0.311	0.183	3	3.35	5.85	5.26	6.76	3.32
4	-0.065	-0.013	0.021	-0.029	-0.047	4	-1.35	-0.40	0.52	-0.60	-2.05
Big	-0.147	-0.095	-0.032	-0.068	-0.076	Big	-4.32	-2.78	-0.92	-2.56	-1.67
Coff. HML						t(HML)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small	-0.396	-0.329	-0.168	-0.005	0.144	Small	-8.69	-5.57	-4.29	-0.11	5.44
2	-0.400	-0.355	-0.119	0.079	0.155	2	-6.88	-5.20	-5.49	4.43	5.73
3	-0.335	-0.277	-0.082	0.047	0.119	3	-8.67	-6.51	-4.81	2.88	6.00
4	-0.289	-0.224	-0.058	0.016	0.096	4	-7.69	-9.05	-2.98	0.83	4.75
Big	-0.136	-0.132	-0.044	0.005	0.073	Big	-2.79	-2.25	-2.69	0.31	3.41
R square (Time-series regression)						Residual 【stander deviation】					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small Size	84%	85%	85%	83%	84%	Small Size	4.96%	5.07%	4.98%	5.38%	5.25%
2	85%	86%	87%	86%	90%	2	5.32%	4.97%	4.61%	4.64%	4.05%
3	87%	86%	86%	88%	90%	3	4.79%	4.68%	4.37%	4.05%	3.73%
4	86%	86%	86%	83%	91%	4	5.09%	4.61%	4.62%	4.81%	3.50%
Big Size	80%	88%	88%	91%	92%	Big Size	5.46%	4.00%	3.84%	3.28%	3.24%

Table 4.1 presents the estimated loadings of three factor in time-series regression. Unsurprisingly, we find out that almost all of the intercepts are insignificant expect for the portfolio of stocks in the smallest size and lowest EP section, that almost all of the t statistics of SMB and HML are significant, and that, thus, these two factors provide significant explanatory power for the left-hand side variable, average excess return. LSY (2019) propose that EP performs better in capturing the anomalies of the Chinese stock market, in addition, LQS (2017) point out that the indirect-IPO leaves arouses substantial noise in the market. Therefore, we follow the methodology of LSY (2019) and eliminate the bottom 30% of small market-cap firms to reduce to this noise.

Table 4.2 the Empirical Result of Five Factor Model

R_{it} is the stock return on portfolio-based return i for month t, R_{Ft} is the three-month deposit rate, R_{Mt} is the return on value weight market portfolio; SMB_t is a diversified return on portfolio of the difference between small stocks and big stocks on month t. HML_t is the diversified return on portfolio of the different between high ratio firms and low ratio firms. e_{it} is the residual. In June of year t, we firstly separate list firms into 2 groups (small or big, S or B) by median market capitalization (total shares outstanding times the month end stock price) and reform the rank in July of year t+1. Based on EP, the earning to price ratio, in the year of t -1, we then separate

list firms into 3 segments by 30th and 70th quintiles, we have the low ratio(L), middle ratio (N)and high ratio groups(H). Thus, we intersectional have 6 grouped portfolios, such as, SL, SN, SH, BL, BN and BH, to construct SMB and HML. In the whole paper, monthly value weighted returns were calculated in each portfolio. The market risk premium was the difference between value weighted market return and three month fixed deposited rate.

We use the profitability (revenues minus cost of goods sold, minus selling, operating, and administrative expenses, minus account expense all divided by book equity) in end of year t-1 to divide sample into 3 groups by 30th (Robust) and 70th (Weak) percentiles. Based on the change ratios in the last two years, the investment was calculated by the total asset change ratio, then we separate them into 3 groups by 30th (Conservative) and 70th (Aggressive) percentiles. Again, we intersectional have 6 portfolios by size (2 groups) and profitability (3 groups), and 6 group portfolios by size (2 groups) and investment (3 groups). Then, we have the RMW (Robust Minus Weak) and CMA (Conservative Minus Aggressive)

We use the same methodology to construct 25 portfolios by size (5 groups) and EP (5 groups) at each month.

α						t(α)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small	0.0056	0.0075	0.0082	0.0059	0.0078	Small	1.13	1.47	1.44	1.16	1.88
2	0.0068	0.0087	0.0055	0.0094	0.0084	2	1.31	1.44	1.22	2.18	2.55
3	0.0101	0.0096	0.0124	0.0084	0.0101	3	1.95	2.13	3.23	2.28	3.34
4	0.0099	0.0099	0.0099	0.0093	0.0103	4	2.28	2.17	2.46	2.16	4.26
Big Size	0.0021	0.0007	-0.0017	-0.0013	0.0029	Big	0.87	0.31	-0.46	-0.45	1.64
Coff. HML						t(H)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small	-0.179	-0.215	-0.025	0.060	0.200	Small Size	-6.06	-5.21	-1.32	1.08	4.61
2	-0.174	-0.187	0.010	0.094	0.138	2	-3.91	-4.26	0.21	3.29	5.33
3	-0.163	-0.133	-0.041	0.017	0.060	3	-4.07	-3.51	-1.79	0.85	2.12
4	-0.095	-0.146	-0.046	0.001	0.063	4	-1.61	-7.72	-3.70	0.04	1.85
Big	-0.085	-0.162	-0.059	0.020	0.026	Big	-1.31	-3.54	-2.68	1.60	1.09
Coff. RMW						t(R)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small	-0.040	-0.050	-0.092	0.001	-0.025	Small	-2.01	-3.68	-4.66	0.05	-2.05
2	-0.079	-0.029	-0.090	-0.059	-0.007	2	-3.56	-2.23	-4.07	-5.65	-1.69
3	-0.080	-0.035	-0.051	-0.058	-0.018	3	-5.83	-3.54	-3.06	-3.68	-1.48
4	-0.042	-0.051	-0.086	-0.065	-0.011	4	-3.82	-3.02	-6.96	-2.95	-1.37
Big	-0.033	-0.054	-0.046	-0.025	0.052	Big	-0.82	-4.10	-4.12	-2.91	4.21
Coff. CMA						t(c)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small	0.038	-0.016	-0.172	-0.206	-0.070	Small	1.18	-0.71	-5.27	-3.92	-1.72
2	0.016	-0.051	-0.122	-0.112	-0.094	2	0.25	-3.01	-4.79	-2.93	-5.37
3	0.108	-0.023	-0.061	-0.076	-0.024	3	2.26	-1.80	-3.25	-4.92	-1.66
4	-0.019	-0.041	-0.084	-0.123	-0.057	4	-0.52	-1.64	-2.74	-3.23	-2.52
Big	0.088	-0.018	-0.126	-0.078	0.083	Big	3.91	-0.80	-4.30	-2.86	4.73

<Table 4.2 cont.>

Coff. SMB						t(s)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small	0.728	0.714	0.671	0.743	0.505	Small	8.92	8.09	6.69	8.79	6.61
2	0.663	0.752	0.599	0.535	0.448	2	8.00	8.03	8.00	6.10	11.48
3	0.502	0.464	0.394	0.337	0.245	3	4.35	6.22	5.19	6.63	3.67
4	0.097	0.119	0.095	0.034	-0.022	4	1.31	3.65	3.25	0.73	-1.10
Big	-0.182	-0.164	-0.241	-0.308	-0.207	Big	-3.20	-5.38	-6.15	-5.53	-5.50
Coff. RP						T(RP)					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small Size	0.668	0.701	0.740	0.659	0.734	Small Size	9.99	8.75	8.84	9.16	12.99
2	0.870	0.875	0.891	0.841	0.876	2	14.64	9.18	13.97	14.08	21.79
3	1.066	1.049	1.015	1.026	1.015	3	17.92	18.98	29.14	27.12	26.29
4	1.172	1.079	1.044	1.014	1.045	4	26.75	33.62	21.46	22.84	34.68
Big Size	0.945	0.832	0.720	0.688	0.881	Big Size	17.40	21.77	14.65	15.96	29.96
R square (Fama - French regression)						Residual 【stander deviation】					
	Low Ratio	2	3	4	High Ratio		Low Ratio	2	3	4	High Ratio
Small Size	80%	81%	82%	80%	82%	Small Size	5.00%	5.03%	4.88%	5.01%	4.74%
2	81%	80%	84%	84%	87%	2	5.11%	5.35%	4.48%	4.32%	4.05%
3	81%	82%	83%	84%	87%	3	5.12%	4.67%	4.29%	4.10%	3.62%
4	80%	81%	81%	77%	88%	4	5.37%	4.68%	4.57%	4.84%	3.38%
Big Size	72%	82%	84%	87%	89%	Big Size	6.00%	4.16%	3.66%	3.18%	3.09%

The comparison between the three and five factor model indicates that the empirical evidence supports the outromance of three factor model instead of five factor model. The insignificant intercepts in FF3 (EP instead of BM) obviously dominate the insignificant intercepts in FF5, while in FF3 the average R-square is nearly 87% and the average standard deviation of residuals is around 4.5%. However, there are 11 significant intercepts in FF5 (EP instead of BM), and the average R-square in FF5 is almost 4% lower than the average R-square of FF3. The average of residuals is around 4.5%. Empirically, therefore, we support that the performance of FF3 is better than that of FF5. The difference of China and U.S. stock market is a possible explanation in the gap between FF3 and FF5, investment and profitability premium are constructed by the common features of public companies, in addition, China individuals normally focus on the underestimated stock in equity market instead of looking for potential growth target, thus the investment and profitability could be automatically omitted. Investors significantly focus on short term return or fast money, for example, it is very common to see that individuals chase the hottest one and discard the coldest stock in order to harvest benefit. Moreover, the system of information disclosure is not as developed as the system in U.S., investor do not put too much weight on evaluating financial statement. The huge gap between informed and uninformed investor directs the herding movement obviously.

CMA and RMW, two additional factors in FF3, cannot fit in the emerging China stock market. On the opposite, the revised classic Fama and French three-factor model constructed by size (market capitalization) and EP hold the advantage in analyzing average stock return.

Our findings, finally, are inconsistent with papers that the FF5 is better than the FF3 in U.S. equity market, are consistent with claims that FF3 is better than the FF5 in China stock market.

5. Fama and MacBeth Regression

According to Fama and French (1993), in each June, we separated the firms' market capitalization into six equal-sized groups. We applied the individual stock's exposures to the market factor (MRK), size effect (SMB) and ratio effect (HML) for the pre-ranking betas. The pre-ranking betas are estimated from the previous 24 to 36 month's returns. Because of the high correlation between the size and size-betas, Fama and French (1993) point out that the problem of using size and size-betas is high correlation issue. To account for this problem, then, in the basis of pre-ranking CAPM betas, we sub-separated the six size groups into six more group, thus we have 36 portfolios which is sorted by the intersection between betas and size. Hu et al. (2019) utilities similar method but different problem. Moreover, we calculated the portfolios' monthly return for the next 15 months, starting in July of each year. Then, the post-ranking betas (full sample) are estimated by the calculated monthly return on 36 portfolios constructed on size and CAPM betas, MRK, SMB and HML. In the second pass of the Fama and MacBeth regression, we used post-ranking betas on each factor to estimate the exposures.

Table 5.3 The Fama MacBeth Regression for Three Factor

In the first step of Fama MacBeth regression, by past 36 (min 24) months, we estimate pre-ranking betas for individual stocks. 36 intersections between size and CAMP betas portfolios were formed for estimating post-ranking betas. We calculated the monthly returns on portfolios for the next 15 months, then we have post-ranking average return on 36 portfolios formed on size and pre-ranking CAMP betas. Finally, we use full sample period to estimate post-ranking betas by all the value weighted portfolios of stocks. In the end, these betas were used in the second step of Fama MacBeth cross-sectional regression in each time point for individual stocks. Note: the MRK, SMB and HML are the coefficients of independent variable. For example, SMB in this table represent the coefficient of size effect.

	1	2	3	4	5
	ALL	SMB+HML	SMB+MRK	HML+MRK	MRK
MRK	-0.014		-0.011	-0.001	0.007
	(-0.62)		(-0.47)	(-0.01)	-0.360
SMB	-0.029*	-0.027*	-0.034*		
	(-2.03)	(-2.31)	(-2.33)		
HML	0.044*	0.044*		0.053**	
	2.540	2.520		2.960	
cons	-0.004	-0.005	-0.004	-0.005	-0.005
	(-0.59)	(-0.61)	(-0.59)	(-0.67)	(-0.69)
r2	0.007	0.005	0.006	0.004	0.002

t statistics in Parentheses

* p<0.05, ** p<0.01 *** p<0.001

We compute exposures in Fama MacBeth regression. These estimates are provided to filter out which independent variable has non-zero expected premiums. In Table 5.3, we can clearly see all the time series average of coefficients of month by month cross-sectional regression on size, beta, and other factors. The size and ratio play a consistently important role in explaining the average stock returns. The persistent negative (positive) sign and significant level on SMB (HML) form models 1 to 4 is supportive evidence that the size and value effect explain cross-sectional average stock returns significantly.

In Table 5.4, however, in the Fama and French five-factor model, the uncertain positive significant number on HML supports that the explanatory power of the ratio effect is not as pronounced as that of the size effect. Thus, in five model, our empirical evidence implies that the size effect acts the most meaningful explanatory power for the returns. This uncertainty of the ratio effect's explanatory power reflects the unique Chinese stock market, which is the reason it is necessary to develop a country-specific asset pricing model even as we consider the indirect-IPO. The consistent insignificant coefficients, CMA and RMW, reject that the investment and profitability factor can equally explain China stock return, moreover, this evidence reinforces our empirical findings in table 4.1 and 4.2 that the FF3 is better than the FF5.

Table 5.4 The Fama MacBeth Regression for Five Factor

In the first stage of Fama MacBeth regression, we separate sample into 6 groups by size (total share outstanding times monthly end stock price) on each June. The pre-ranking CAMP-bests were estimated by using the individual stocks and all value-weighted return portfolios and by past 36 (min 24) months. Then, we further separate each of the six-size group into 6 groups by using the pre-ranking CAMP-bests, thus we have 36 portfolios formed by size and CAMP-betas. We compute the equal-weighted return (post-ranking) on stock portfolios and run full sample (2003 - 2018) regression on market and other proxies for post-ranking betas. Note: the MRK, SMB, HML, CMA and RMW are the coefficients of independent variable. For example, HML in this table represent the coefficient of value effect.
In the second stage of Fama MacBeth regression, we cross-sectional estimate the time series average post-ranking betas on each of the time period.

	1	2	3	4	5	6	7
	ALL	S+R+C	H+R+C	R+C	S+H	S	H
MRK	0.007	0.004	0.004	0.002	-0.019	-0.024	-0.022
	0.400	0.230	0.230	0.100	(-0.81)	(-1.02)	(-0.96)
SMB	-0.037**	-0.034*			-0.036*	-0.032*	
	(-2.69)	(-2.54)			(-2.51)	(-2.41)	
HML	0.031*		0.024		0.031*		0.024
	2.130		1.730		2.040		1.700
RMW	-0.023	-0.018	-0.027	-0.022			
	(-1.66)	(-1.27)	(-1.88)	(-1.53)			
CMA	-0.033	-0.036	-0.031	-0.034			
	(-1.84)	(-1.95)	(-1.69)	(-1.82)			

<Table 5.4 cont.>

cons	-0.003	-0.003	-0.004	-0.004	-0.003	-0.002	-0.004
	(-0.40)	(-0.36)	(-0.52)	(-0.48)	(-0.35)	(-0.31)	(-0.47)
r2	0.015	0.012	0.012	0.010	0.010	0.007	0.007
t statistics	in parentheses						
* p<0.05, **	p<0.01, *** p<0.001						

In the empirical results, we found that the size effect has the strongest performance for both three- and five-factor models. It is surprising low that the difference between R-square of two factor (MRK and SMB) and R-square of three factors (MRK, SMB and HML), more specifically, this difference is around 5%. Table 5.4 provides the evidence to suggest that investment and profitability do not contribute to explain the average return. However, the HML, formed with EP, also does not provide persistent explanatory power.

In summary, the empirical result in table 4.1 and 4.2 indicate that the 3-factor model is better than the five model. Moreover, the evidence in table 5.3 and 5.4 enhance the empirical result. In table 5.4, one fact of insignificant coefficient in model 3 and 7 implies the uncertainty of EP ratio. However, no matter in 3 or 5 factor model, the size effect is consistently significant. Both empirical result and Fama MacBeth regression, none of investment and profitability provides any explanatory power on average return.

6. Conclusion

Many researches have investigated the Fama and French three- and five-factors models in developed markets, like G7 countries. However, we found limited studies that focused on the same issue in emerging markets, especially in China’s stock market. By using the earnings-to-price ratio (EP) instead of book-to-market ratio (BM) (see, Liu, Stambaugh, and Yuan (2019) and Lee, Qu, and Shen (2017)), we find out that the performance of the three-factor model empirically precede the five-factor model and our FF3 (revised classic FF3 because of application of EP ratio) model do provide better performance in explaining average return, also, in the tradition Fama MacBeth regression, the result strengthen the empirical findings. Consistent with Zhao, Yan, and Zhang (2016), the performance of both the RMW and CMA is neglectable.

As our results supported, because of features of emerging market, the localized multi-factors model needs to be developed in order to, in particular, fulfill the blank of China’s asset pricing field. Different stock markets have different feature and common, we may not use one rule to measure market difference. Moreover, in the five-factor model, the HML is an uncertain factor in China stock market. Also, this finding is consistent with other group of Chinese researchers.

Further studies may focus on the common factors of Chinese public companies. We see the feature of high volatility in Chinese stock market at short period of time, this is, it is easy to see the same positive and negative movement, again due to the supportive policy design, we may also see the abnormal benefits in stock market.. Thus, this homogenous movement must be investigated in further research.

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Abstract

We analyze Federal Deposit Insurance Corporation (FDIC) managed 4273 loan sales transactions between 1994 and 2019 that include two major financial crises of the modern times: the dot.com bubble of 2001, and the global financial crisis of 2008 and 2009. We find that loan sales discounts, asset quality, industry classifications, compositions and buyers interest vary significantly during financial recessions and non-recessionary periods. Industry classifications affect loan sales discount rates. Loan sales discounts are inversely related with asset quality. While the non-performing and lower quality loans are sold at higher discounts, the sub-performing and the performing loans are sold at lower discount. Our evidences backup Demsetz’ s (2000) hypotheses that banks with limited branches and high reputation are more likely participate in the secondary market in order to erode the loan origination problem and diversify the current loan portfolio.

JEL Codes: G210, G280

JEL Keywords: Banks; Depository Institutions; Financial Institutions and Services: Government Policy and Regulation; Bailout, FDIC.

8. Introduction

In the last several decades, sophisticated investor has locked considerable returns from the transaction of distressed real estate asset from underperforming banks. In a similar way, the FDIC-involved secondary market of loan sale provides a playfield in which seller banks sell out loans and buyer banks take in assets. Asset securitization and loan sales are two commonly used financing tools that the banks and financial institutions use to generate additional short-term fund from their long-term loan portfolios. During favorable economic situations, banks prefer to asset securitizations as the financial market has appetite for asset-backed-securities (ABS). However, during an unfavorable economic situation, banks and their investment banks find difficult to raise capital by issuing ABS, and loan sales transactions provide better way to generate capital. Both asset securitization and loan sales allow the issuing or selling bank to transfer the risks of the loan portfolio to the buying bank. Loan sales are generally sold at a discounted price and for the purchasing banks, loan sales provide excellent investment opportunity (Smith and Hall, 2010).

For bidders (prequalified banks), distress loan-sales originating from the underperformed banks are even more lucrative as the selling banks are more likely to accept a higher discount in selling their assets to generate capital. The Federal Deposit Insurance Corporation (FDIC) has provided the opportunity for buying and selling failed-banks' loan since 1990s. In the early stage, limited products were sold on the market, nowadays, according to our paper, in the last three decades FDIC has arranged 4273 loan sales transactions, for example, multiple loan-qualities (such as Mixed, Non-Performing, between Perform and Non Performing, Performing, and Sub-Performing) and various loan-classifications (such as Bank Charge-Off, Commercial, Consumer, Deficiency Bal, Installment, Judgment, Mixed, ORE Participation, Other, Real Estate Backed Commercial, Real Estate Backed Residential, Student).

Existing literature on loan sales provide various insights to implications of loan sales in terms of bank risk taking, bank performance, and corporate governance. Pennacchi (1988) provides theoretical explanations on how loan sales can provide a lower cost of financing loans for the selling banks in a competitive deposit market. Becketti and Morris (1987) analyze the increased interest in loans sales during late 1980's when Government National Mortgage Association (GNMA) initiated selling loan portfolios, that followed by banks selling various types of loan portfolios: their automobile loans, credit card and lease receivables, agricultural loans, etc. Becketti and Morris (1987) find that loan sales can enhance smoother functioning of short-term credit market. Demsetz (1993) finds that banks engage in loan sales transactions and loan syndications for several purposes: a) Leverage (acquisitions, Leverage Buyout LBO, recapitalization), b) Debt repayment, c) Specialty finance, and d) General Purposes. Demsetz (1993) shows that economic conditions play critical role in loan sales market. Loan sales by second-tier banks peaked from 1986 through the recessions in 1993; but during recessionary period, commercial and industrial loan sale origination declines for both second tier and first-tier banks. Weakness in borrowing conditions by corporations also plays a role in lower demand and creation of loan sales in post financial crisis period. Gorton and Pennacchi (1995) argue that if the selling bank gives no guarantees on loan sales, the share of loan sold is inversely affected by the spread between loan sales yield and the LIBOR.

Although, loan sale is a well-researched topic in banking literature, there is a caveat in loan sales research. Existing loan sale literature seldom provides any empirical evidence on the failed bank loan sales transactions. We contribute to the existing body of loan sales literature as one of the early papers to analyze the FDIC structured loan transactions. When an FDIC insured bank fails, the FDIC works as an intermediary and it conducts due diligence on the failed bank asset portfolio and make the available for sales to suitable investors, in addition, the purchasing banks can do the due diligence prior to the formal transaction. FDIC failed bank loan sales dataset consists of a total of 4273 loan sales transactions beginning from 1994 to 2019. The dataset also includes two financial crises of the recent times, the dot.com bubble of 2001, and the global financial crisis of 2008 and 2009, therefore, we claim that the discounted rate is extremely high in the crisis period. Although the FDIC channels out the loan sales from the failed banks, it does not provide any guarantee on the asset quality of the loan sales. Suitors or interested investors are provided opportunity to make their own judgement prior to the loan sale process. So, the asset quality of the loan sales remains a black box process, and investors are basically buying these loan sales based on their perceived asset quality.

We contribute to the existing loan sales literature by several important ways. First, we analyze whether the industry classification determine discount rates of the loan sales contracts. Second, we investigate asset quality definitions disclosed by FDIC database affect the loan sales discounts. Third, we analyze the impact of crisis period in discounted loan price. Fourth, we explore what factors affect the loan price. Fifth, we provide supportive evidences to comparative, diversification and reputation hypotheses and claim that banks with limited branches and high reputation are more likely participate in the secondary market in order to erode the loan origination problem and diversify the current loan portfolio.

9. Literature Review

Existing papers on loan sales focus on primary loan sales and secondary loan sales market, where selling banks or borrowers sale loan contracts through syndications, or directly to purchasers. We hardly see loan price investigation in the secondary loan sale market, our paper is one of the earliest one researches on the price of loan sale. According to Demsetz (2000), there are two main hypothetical theories in explaining the loan sale purchasing, comparative advantage and diversification hypothesis, for example, banks with advantages in originating loans more likely sell and banks with lack of abilities in diversifying loan portfolio buy, our evidences support these two main streams. As a typical credit shifting approaches, unlike the securitization, loan sale has no need to create new security. Loan sales and syndications allow a bank to sell off long-term loan assets from its balance sheet and generate short-term capital that bank re-invests in other investment opportunities. Bank loans have been circulated in the second market for almost three decades, the loan trading provides positive liquidity when the bank sector entirely desires credit transaction (Allen and Carletti, 2005).

1. Loan Sales Literature

Pennacchi (1988) is one of the earlier papers to put forward a theoretical framework for a financial firm and shows that loan sales can provide a lower cost of financing loans for the selling banks in a competitive deposit market. Borrowers might not like to see the loan sale unless they receive a portion of interest rate reduction, the loan origination banks save the cost of on balance sheet funding and obtain the benefit of increasing return on assets and equity, on another hand, the buyers receive more market exposure and potential gains (Gorton and Haubrich, 1990). Seller banks take the advantages via loan sale in various ways, for example, the transformation of credit risk rebalances capital structure on both side of buyer and seller, also, the active buyers and seller are more likely experiencing higher profits (Froot, Kenneth, and Stein, 1998).

Becketti & Morris (1987) analyze the increased interest in loans sales in late 1980's as Government National Mortgage Association started pooling mortgage loans and started selling loan portfolios, that followed with banks pooling their automobile loans, credit card and lease receivables, agricultural loans, and even pools of charged-off loans. Becketti & Morris (1987) find that increase of loan sales does not reduce the safety and soundness of banks; loan sales can be used as a tool for short-term credit and they can enhance smoother functioning of short-term credit market. The loan-related private information is a very sensitive topic in the transaction, in particular, the purchasing processes are involved many conditional agreements. Carlstrom and Sarnolyk (1995) point out that information asymmetries exist in the loan sale transaction and relatively facilitate the market. Moreover, the sale of loan indirectlly affect the underlying borrowers. Dahiya, Puri and Saunders (2003) document that the stock return of underlying borrowers is negatively related around the announcement of loan sale, the selling banks' equity returns are not impacted because of the selling action.

Demsetz (1993) finds that banks engage in loan sales transactions and loan syndications for several purposes: a) Leverage (acquisitions, Leverage Buyout LBO, recapitalization), b) Debt repayment, c) Specialty finance, and d) General Purposes. Economic conditions play critical role in loan sales market. Loan sales by second-tier banks peaked from 1986 through the recessions in 1993; but during recessionary period, commercial and industrial loan sale origination declines for both second-tier and first-tier banks. Weakness in borrowing conditions by corporations also plays a role in lower demand and creation of loan sales in post financial crisis period. Gorton and Pennacchi (1995) extend from Pennacchi (1988) model and present a theoretical model on bank and loan buyer behavior and use large bank loan sales data to calibrate their model. They find that if the selling bank gives no guarantees on loan sales, the share of loan sold is inversely affected by the spread between loan sales yield and the LIBOR. Haubrich and Thomson (1996) analyze the factors that drive some banks sale loan sales and other banks purchase loans. They find that discounts on loan sales are closely related with commercial papers rate and LIBOR. Loan sales is positively related with bank size as measured by total assets, but inversely related with bank's capital ratio. Higher the bank capital ratio, less like is to sell loans.

Demsetz (2000) finds empirical evidence supporting three alternate hypotheses, a) comparative advantage hypothesis: banks with relatively weak ability of originating loans are more likely to buy loan deriving from the banks with strong ability of originating loans; and b) diversification hypothesis: banks without sufficient opportunity to diversify internally loan portfolio are more likely buy loans from the multiple branches banks. c) reputation hypothesis: banks with higher reputation and goodwill are more likely participate in the loan market. We conjecture that the local banks or saving institutions with limited branches and higher business reputation or goodwill are the main buyers in the market. Bedendo and Bruno (2009) summarize that banks with more trouble loans portfolio are more likely involved loan sale market, also, their evidences support reputational hypothesis and claims that the banks size, loan portfolio and profitability can be the factors of loan sale involvement. Mokatsanyane, Muzindutsi and Viljoen (2017) indicate that in the south Africa market the total size of bank has a significant influence on capitalization. The banks' branches support the geographical diversification for a bank's multiple-branches in more than one state (Keil and Müller, 2020).

2. Bank Industry Literature

Several associated issues are originally built in the characteristics of loan sale. For instance, the increasing of systematic risk and latent ethics problem, loan sale could be a double-edged sword, in the financial pre-crisis period, the accumulated risks wait for a breakout, however, for an individual-bank, the stripping disposition positively improves balance-sheet performance. Drucker and Puri (2008) find that loan sales contracts contain additional restriction covenants for the sellers or the borrowing banks while they perceive the existence of agency problems and information asymmetry. In addition, adverse selection and moral hazard problems are potentially grievous not only because of declined incentive to monitor but also because of systematic risk rising, however, the limitation of loan sale enables banks to prudently conduct credit derivative business (Minton, Stulz and Williamson, 2009).

Because of credit transfer business, the systematic risk could be raised and the financial crisis could be happened. The proponents claim that the business supports the balance sheet and improves the buyers and sellers' liquidity. The loan-sale increases the liquidity of bank loan and fosters risk taking in primary markets, whereas the reduction of risky asset protectively improves bank's balance sheet by risk shifting, the improved loan liquidity could alleviate banks' risk (Wagner, 2007). Banks that have better abilities to sell out their risky assets are more likely to further hold a large portion of risky asset in their portfolio (Cebenoyan and Strahan, 2004). Purnanandam (2011) points out that the originate-to-distribute (OTD) secondary market was involved significantly poor-quality mortgages in the pre-financial crisis period. Beyhaghi, Massoud and Saunders (2016) provide evidence that banks with capital and liquidity constraints are more likely join in the loan sale secondary market.

Ivashina and Scharfstein (2008) point out that the new loan to large borrower drop 37% at the peak of financial crisis period. Ahn (2010) presents a theoretical model on loan sales in a competitive market that shows banks use loan sales as strategic tools to preserve informational advantage. Under information asymmetry where buying cannot identify low- and high-quality loans, both types of loan sales co-exist, and it eventually leads to growth of the loan sales market both in terms of quantity and quality. Chodorow-Reich (2012) clearly indicates that a health bank industry contributes a stable financial world and that the bank conducting with trouble banks in credit business may more likely has negative consequences. Irani and Meisenzahl (2017) document that in the crisis period banks with a heavily reliance on loan sale are more likely engage in the secondary market, we extend this issue in our paper and investigate the loan sold-price during the crisis period. By using the euro nonperforming loan transaction (NPL) data, Manz, Kiesel and Schiereck (2019) claim that the stripping of NPL actually do not provide any significant reduction on financial cost. The bank competition and entrepreneur directed search effectively decrease the interest rate on loans financed via on-balance-sheet activities, one reason of loan sale is the high competition in banking industry (Huang, Li and Sun, 2018).

Murfin and Petersen (2016) interestingly point the seasonal capital price theory, and claim that in the late spring and autumn firms are borrowing a little cheaper and raise 50% more funding than the summer and winter. In this paper, we are mainly address the widely accepted financial crisis in the history instead of seasonality or periodic problem.

In summary, the participators in the loan sale market are FDIC-insured banks and saving institutions, asset management firms, non-U. S-based banks, and nonbank firms. The business may reinforce the systematic risk; however, individual-banks still hold the interest on loan sale because of all the benefits. The discount rate could be affected, such as the size of bank total asset, commercial & Industrial (C&I) ratio, individual-bank's characteristic and reputation, combination of bank's loan portfolio, etc. Two main hypotheses, comparative advantage and diversification, explain the nature of loan sale. This research excludes financial entities that unnecessary provide any financial report to Federal Deposit Insurance

Corporation, for example, financial entities outside U.S.A, private firms and individual.

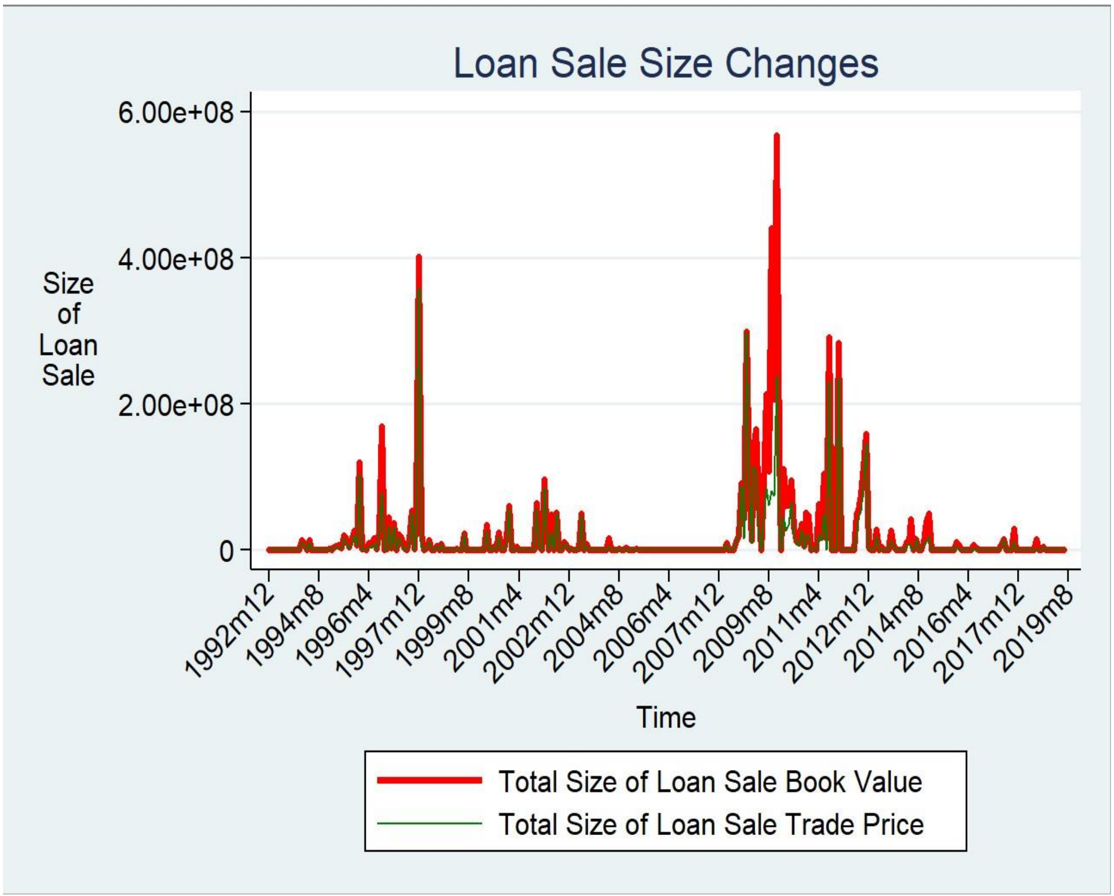
10. Data and Methodology

1. Data

We hand-collect the banks or saving institutions' financial reports and loan sale data from the FDIC official website. For example, we download the distressed loan sale data, then, we download and merge the financial reports with each of the corresponding loan sale transaction. In addition, Baker at el. (2016) develop an index of economic policy uncertainty (EPU), based on the FRED economic data, we deploy an economic policy uncertainty index in one of the independent variables. The incorporation of EPU is a way to shed the light on basic economic tone. The economic effects directly and indirectly influence the loan sale market, the higher risk economy is, the higher index banks face and the higher risk banks take, this uncertainty index provides country-wide level risk. For example, the figure 10.3 and 10.4 in this paper clearly present demonstration. We also see many papers include the macro- or micro- economic elements in their paper, one of the most famous paper is Demsetz (2000), the cross sectional statewide economic condition is considered as an attribution. Finally, we required every loan sale transaction can be traced from the financial report, thus, we find out almost three hundred involved-banks (those of banks or saving institution participate in distressed loan sale market) in our sample. Our full sample across 27 years and 16,542 financial institutions.

Figure 10.3 The Number if Loan Sale Transaction

Figure 10.4 The Loan Sale Size Changes



2. Methodology

In this section, we separately explain the independent variable and Left-Hand Side. The discounted loan sale rate, a ratio of selling price to book value and our LHS, is our main investigation and outcome variable throughout this article. The period of financial crisis located on 2008 and 2009, therefore, we create a dummy variable for these two years. Thus, we expect the positive and significant discount rate during the financial crisis, 2008-2009. The loan-quality and loan-type also affect discounted loan sale rate. Table 11.6 contains the color prism in presenting results, the dark green means the highest magnitude and the dark red means the lowest magnitude. We control fixed effect on individual, geopolitical state, loan type and loan quality. Our research mainly focuses on loan sale transaction in all states of the U.S.A. operated by active financial institutions, banks or saving institutions.

i. The Bank's Characteristics

The natural logarithm of asset in each time period is presented in many investigations, we utilize logarithmic asset (in thousand dollar) in the research. Demsetz (2000) claimed that the different size of asset provides contributions. We include the **goodwill** in account, banks' reputation in the market also drive the loan sale. Net gains (losses) on sales of loan, **Gain**, would attract or deter managerial decision in loan sale market, the active participator more likely to do the business again. **Deposit ratio**, a ratio of total deposited to total asset, is an important feature of bank loanable asset and also affect the acceptance of discount rate. The comparative hypothesis (Demsetz (2000)) claims that the ability of loan origination may affects banks' loan purchasing, more specifically, banks more likely sell loans when they sit on plenty of capital, in this article, we expect to see that banks with higher ratio are more likely to require a higher discount rate. In addition, deposit ratio is another commonly used indicator for analyzing banks' behavior. **Net income** impact on the discount rate, many researchers include bank profitability in their research for controlling or other purposes, for example, Drucker and Puri (2008) indicate that net income-to-Assets as an important variable, therefore we here use net income as a control. The dummy variable of interstate branch is **stmult** (A 'yes' or '1' indicates that an institution has branches that can accept FDIC-insured deposits in more than one state), the findings of Demsetz (2000) present that banks with extensive branches and access to diversified loan originations are less likely to engage in loan sells or purchases. Moreover, the number of offices owned by the bank is **num_office,** the diversification hypothesis predicts that banks with limited opportunities for diversified originations (attribute to size or limitations on geographical expansion) are most likely to participate in the secondary market.

ii. The Bank Loans' Relevant Ratio

The **sale ratio**, a ratio of loan held for sale to asset, could impact the discounted rate of loan sale, because the participation in the secondary loan sale market was embodied by the ratio. the **non-performing loan ratio**, a ratio of C&I loans in nonaccrual status plus C&I passed due 90+ days over the total asset, could affect managerial decision to meet the relevant financial achievements, moreover, the **net charge-off** works in the same logic and provide impaction on loan sale discount. Demsetz (2000) contains net charge-off ratio and non-performing loan ratio for explaining participation on the market, we use them for same purposes that these two ratios may prevent/force banks from the secondary market. More specifically, if a bank has observable bad loans in the first place, manager may focus on the discount rate. For measuring the funding constraints, we follow the most commonly used hot funds ratio (**Hot_fund**) which is the sum of brokered deposits, uninsured deposits and federal funds purchased, divided by assets.

iii. The Differences in Banks' Loan Type

We create some variables in the table 11.8 regression. The ratio of 1 – 4 family loan to total asset, **rfamily_loan**, the ratio of real estate loan to total asset, **rreal_ratio**, the credit card loan, **rcredit_laon** and farmland ratio, **rfarm_loan**. These ratios provide cross-sectional explanatory power on the discount loan-sale rate. Because the book value of each loan sale transaction may also affect the loan sale rate, we included, **rindivial_loan**, the ratio of individual loan to total asset. Because individual bank has the different structure of loan type, we assume that banks' loan structure tribute to some weights on loan-purchasing transaction. Managers or insiders detailly understand their bank's loan portfolios, thus the loan purchasing decisions somehow stem from the managerial or developmental strategy. For a bank, the main sources of loan portfolio are family loan (rfamily_loan), commercial and industrial loan (C&I), real estate loan (rreal_ratio), credit card loan, individual loan and farmland loan. Thus, to clearly understand the mechanism of discount rate, we add in banks' loan portfolio when we analyze the impaction of discount rate in loan type. In summary, the application of bank characteristics, bank loans' relevant ratio and the differences in banks' loan type variables could be the typical controls in the loan sale area, thus, in table 11.8, we include the loan portfolio ratios in the research.

3. Hypotheses Development and Modeling

Existing literature on loan sales also find that asset quality of loan sales determines their discount rates. While the investors or buyers in a structured loan sales or purchases get the opportunity to conduct proper due diligence, investors in a failed bank loan sales contract have limited access to do the same. Although the FDIC closes the failed banks and channels the loan contracts after doing due diligence, FDIC does not provide any guarantee on the quality of the loan. However, FDIC discloses ranking of asset quality for the loan contracts under the auctions. We argue that FDIC disclosed asset quality classification may affect the discount rates across the loan contracts.

Hypothesis 1: failed bank loan sales are discounted different rates based on disclosed asset quality rankings.

Becketti & Morris (1987) investigate loan sales across various industries and find that loan sales in different industries are discounted at different rates.

Hypothesis 2: Failed bank loan sales are discounted different rates across different industry classifications.

Demsetz (1993) identify that valuations of loan sales can vary during economic conditions. However, they do not analyze distress loan sales or failed bank loan sales. We argue that FDIC failed bank loan sales are affected by economic conditions, and discounts vary during recessionary periods and regular financial conditions. Accordingly, we hypothesize,

Hypothesis 3: Economic conditions affect loan sales, and failed bank loan sales during financial downturn are discounted at a higher rate.

For understanding the hypothesis 1, we include the equation 2 to 5 as the approval. The equation 1 is the composition of control variables. We use variables between b1 and b14 (coefficients of each control) as the controls in order to certify hypo 1 (Eq2 ~ Eq5) and apply the entire eq 1 to approve hypo 2 (Eq6 ~ Eq9). In addition, the hypothesis 3 is clarified in both Eq2~Eq5 and Eq6~Eq12. We expect to see the negative sign on b12 and b13 because they have more sources to originate funds and relatively less concern about the diversification issues. Thus, they may more likely buy small discounted product (good quality and higher price). We expect the positive b14 because buyers with interstate offices have better abilities to manage the risk fund and better risk tolerance.

$\mathbf{X} = b_1 \cdot \textit{sale\_ratio}_{i,t} + b_2 \cdot \textit{net\_charge-off}_{i,t} + b_3 \cdot \textit{Gain}_{i,t} + b_4 \cdot \textit{Log\_net\_income}_{i,t} + b_5 \cdot \textit{non\_performing\_ratio}_{i,t} + b_6 \cdot \textit{depoist\_ratio}_{i,t} + b_7 \cdot \textit{hot\_fund}_{i,t} + b_8 \cdot \textit{goodwill}_{i,t} + b_9 \cdot \textit{log\_uncertaintiy}_{i,t} + b_{10} \cdot \textit{log-asset}_{i,t} + b_{11} \cdot \textit{Year Dummy} + b_{12} \cdot \textit{STMULT} + b_{13} \cdot \textit{num\_office}_{i,t} + b_{14} \cdot \textit{STMULT} \cdot \textit{num\_office}_{i,t} + b_{15} \cdot \textit{family\_loan\_ratio}_{i,t} + b_{16} \cdot \textit{individual\_loan\_ratio}_{i,t} + b_{17} \cdot \textit{real\_estate\_ratio}_{i,t} + b_{18} \cdot \textit{credit\_card\_loan\_ratio}_{i,t}$ ***Eq(1)***

$\textbf{Discount rate}_{\textbf{it}} = a_0 + \mathbf{C_0} \cdot \textit{YEAR} + \mathbf{C_1} \cdot \text{non-performing}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(2)***

$\textbf{Discount rate}_{\textbf{it}} = a_1 + \mathbf{D_0} \cdot \textit{YEAR} + \mathbf{D_1} \cdot \text{performing/nonperforming}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(3)***

$\textbf{Discount rate}_{\textbf{it}} = a_2 + \mathbf{E_0} \cdot \textit{YEAR} + \mathbf{E_1} \cdot \text{performing}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(4)***

$\textbf{Discount rate}_{\textbf{it}} = a_3 + \mathbf{F_0} \cdot \textit{YEAR} + \mathbf{F_1} \cdot \text{sub-performing}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(5)***

X is a control variable composition, because our dataset is a panel data, thus, for example, Sale_ratioi,t , a ratio of loans held for sale over the total asset “i” at month “t”. εi,t represents error term. We conjecture that C0 to F0 have a strongly positive sign (+) due to the fact that financial crisis may push up the loan sale discount rate. More importantly, the non-performing loan quality may provide more budget space for buyers in the negotiation, we expect that C1 should have a strong positive sign (+) implying the non-performing loan positively impacts on the discount rate. In addition, the performing loan attracts qualifies buyers, thus, the good quality may drop down the discount significantly, we expect that E1 should have a negative sign (-). Moreover, the second-best quality loan (sub-performing) may provide a positive sign (+), the sign of performing/nonperforming is unpredictable because of the undefined quality.

For testifying the hypothesis 2, we include the equation 6 to 12 as the approval. For understanding the loan portfolio effect in loan purchasing, we further add several controls in the equation 1, such as family loan ratio, individual loan ratio, real estate loan ratio credit card loan ratio.

$\textbf{Discount rate}_{\textbf{it}} = a_4 + \mathbf{G_0} \cdot \textit{YEAR} + \mathbf{G_1} \cdot \text{Bank\_Chargeoff}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(6)***

$\textbf{Discount rate}_{\textbf{it}} = a_5 + \mathbf{H_0} \cdot \textit{YEAR} + \mathbf{H_1} \cdot \text{Commerial}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(7)***

$\textbf{Discount rate}_{\textbf{it}} = a_6 + \mathbf{I_0} \cdot \textit{YEAR} + \mathbf{I_1} \cdot \text{Installment}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(8)***

$\textbf{Discount rate}_{\textbf{it}} = a_7 + \mathbf{J_0} \cdot \textit{YEAR} + \mathbf{J_1} \cdot \text{Mixed}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(9)***

$\textbf{Discount rate}_{\textbf{it}} = a_8 + \mathbf{K_0} \cdot \textit{YEAR} + \mathbf{K_1} \cdot \text{Other}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(10)***

$\textbf{Discount rate}_{\textbf{it}} = a_9 + \mathbf{L_0} \cdot \textit{YEAR} + \mathbf{L_1} \cdot \text{RE\textbackslash comercial}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(11)***

$\textbf{Discount rate}_{\textbf{it}} = a_{10} + \mathbf{M_0} \cdot \textit{YEAR} + \mathbf{M_1} \cdot \text{RE\textbackslash residential}_{i,t} + \mathbf{X} + \mathbf{FE} + \varepsilon_{i,t}$ ***Eq(12)***

We exclude three loan type from our sample because of insufficient observations, such as student, deficiency, and ORE Participation. The financial crisis may lifts up the discount rate for promotional sale, we anticipate positive from G0 to M0 (+). The bank charge-off indicates that a delinquent asset of highly unlikely will be collected, we conjecture that this type of loan could lift up the discount rate, we might have a positive G1 (+). The complicated part is that the asset quality is unambiguous and predetermined, in the reality, good quality products always require the customer to pay more money, in the loan sale market, buyers also need to pay more because of FDIC-predetermined loans' good quality. However, the limitation of our research is that we cannot detail the purchasing motivation behind the selection of loan-classification, moreover, buyers may not easily distinguish the good or bad type. It is like a customer standing in front of a bunch of unknown fruit, he/her does not know which one is sweet or sour, thus, the best scenario for him/her is buying a mix-bag. Therefore, we might expect that the mix-type decline the discount rate, the J1 should be negative (-).

4. Descriptive methodology

We separately analyze data in several ways and present the description on tables as the following statement. Table 11.6 is a variable analysis, Table 11.7 and 11.8 are regression results.

HHI of loan type or **hhi_loan**, the Herfindahl-Hirschman Index (HHI) is a general measurement of market concentration and has been used to determine market competitiveness, we applied this variable in our analysis even though this one does not predict anything. However, for understanding the basic framework of a bank's loan type concentration, we simply calculate the HHI at each time period and conjecture the effective impaction on purchasing distressed loan sale. The components of calculating HHI here are, such as, residential 1-4 family construction, commercial and industrial loans, individual loan, and real-estate loan, etc., all of them are the main parts for an individual bank. The HHI is a resort for measuring concentrations. We use HHI as a resort for measuring individual bank's loan type concentrations, and might have some good findings crossing before, during, and after the loan purchasing. Moreover, for various reasons, banks deploy their loan-type demand and anticipate benefits form loan purchasing. Berger and Udell (1993), Demsetz (2000) provoke a very interesting description of the participation in loan sale secondary market. banks whose portfolios are concentration in other loan types are less likely to participate in secondary market, therefore, we would like to ask another question: Is there any change across concentration of banks' loan portfolio?

In table 11.6, we ranked all the variables into 10 equal size quantiles (1 is the smallest quantile and 10 is the highest quantile) and separate them into two groups (loan sale buyer and non-buyer). The purpose of table 11.6 is asking a question: is there any relevant increasing/decreasing relationship among the number of loan buyers-bank? ***Include*** means that these banks are loan-buyers in our sample and ***Exclude*** means that these banks are not loan buyers in our sample. For example, in the interstate branches panel, there are 16,114 banks do not have interstate branches and do not involve in the loan purchasing, in addition, there are 281 banks involved in the loan purchasing and do not have interstate branches, moreover, there are only 4 banks involved the loan purchasing and do have some interstate branches. Therefore, these evidences strongly support the comparative hypothesis that banks without strength funding constraints and loan origination are more likely involve in the loan sale secondary market.

Figure 10.3 and 10.4 present the distribution of distressed loan sale from December 1994 to June 2019, we believe that the waves of financial crisis need time to hit the beach, therefore, the strongest spike is around 2009. The only difference between Figure 10.3 and 10.4 is that we include all the financial institutions in Figure 10.4. Moreover, Table 11.9 show us that the number of loan sale transaction across years.

Table 11.10 summarizes discount rate across the distressed loan quality and loan type. Non-surprisingly, the highest discount rate column is the Non-Performing loan sale. we also found out that some of the categories may not have sufficient observation in regression, thus we did not contain them in the analysis.

Bank needs profits and shareholder even needs more profits, thus it's asking question related to the profit, we have several options in our data such as ROA, ROE, net income, and the most important one which is the gains form the loan sale transaction. Table 11.12 is a summary of changes from purchasing loan sale. Simply, we marked the present-time of purchasing loan sale as zero, **0**, we marked before-time of purchasing loan sale as negative 1 to 12, **-1 ~ -12**, and we also marked after-time of purchasing loan sale as positive 1 to 12, **1 ~ 12**. We conjecture that ROA (roaa), ROE (roee) and HHI (hhi_loan), etc., could be changed due to the purchasing, at least, there should have something changed because of the loan purchasing. Surprisingly, we found some interesting patterns. Almost all of the variables (without capital ratio, actually I use it as the comparative group for verifying the others) reached the peak at purchasing time and bank to normal as after-time. The main investigation in this ranking is to find out the variable changes in the time-line.

Table 11.11 is a summary of discount rate in 10 (1 is the smallest quantile and 10 is the highest quantile) different quantiles of 10 different variables. There are some interesting uptrend and downtrend in this table. we ask one question here: Does the different size of asset (for example, we rank loan-sale-involved-banks into 10 equal segments) reflect any higher or lower loan sale discount? we can see that the higher the asset quantiles (the highest in 3th quintile), the lower the discount rate, thus, we pre-conclude that banks with larger asset more likely acquire a lower discount rate (many reasons here, for example, they only buy good quality product).

11. Empirical results

This section provides explanations to tables and figure. Paragraphs follow the order of tables and figures.

Table 11.5 Summary Statistics

	Mean	St.Dev	max	min	skewness	kurtosis
Discount rate	.471	.298	.99	-.025	.081	1.784
HHI loan	.532	.425	5.332	0	1.363	5.187
Sale ratio	.006	.041	3.607	0	15.298	340.955
Netcharge off ratio	.001	.009	5.778	-1.076	280.402	133000
Gain ratio	4.272	2.254	14.898	0	.335	3.162
NetIncome(in thousand $)	7494.729	178000	2.92e+07	-2.46e+07	56.624	7058.834
Nonperforming loans ratio	-7.297	1.78	-1.125	-17.455	-.415	3.02
Deposit ratio	.826	.115	5.143	0	-3.676	26.683
Hot funds	.162	.161	60.384	-2.555	104.331	37690.39
Goodwill	.003	.015	.777	0	20.171	682.154
Uncertainty Index	103.573	32.782	245.127	57.203	1.193	4.134
Asset (in thousand $)	1220000	2.45e+07	2.35e+09	1	57.895	3887.858
Num of office	10.115	95.368	6730	0	41.97	2216.129

The discount rate mean is around 50% indicating the loan price cut is pretty common in the loan sale secondary market. Moreover, the minimum is negative implying in some transactions buyers are willing to purchase loans in a premium price. The mean of HHI loan is around 0.5, skewness and kurtosis are 1.4 and 5.2, respectively. The minimum of sale ratio is zero because some buyers do not hold any loans to sale. Nonperforming loans ratio equals to a ratio of C&I loans in nonaccrual status plus C&I passed due 90+ days over the total asset. The mean of deposit ratio is 82.6% implying most of FDIC-insured financial institutions are depository orientation. The Quarterly Uncertainty Economics Index directly comes from the FRED. Banks assets is in thousands of dollars. We see that the minimum number of offices is zero indicating some of the financial institutions do not have more than one office in U.S. market.

Table 11.6 The Overview of Banks' Characteristic

Note: % means item of included divide item of included.

P1: The Number of Banks in 6 Quantiles of number of offices							**P2: Interstate Branches**			
	1	2	3	4	5	6		NO	YES	Total
Excluded	7,270	236	2,874	1,720	2,190	1,967	Excluded	16,114	143	16,257
Included	139	9	37	23	27	50	Included	281	4	285
%	1.91%	3.81%	1.29%	1.34%	1.23%	2.54%	Total	16,395	147	16,542

<Table 11.6 cont.>

P3: The Number of Banks in 10 Quantiles of Asset										
	1	2	3	4	5	6	7	8	9	10
Excluded	3,243	1,626	1,496	1,408	1,424	1,408	1,397	1,405	1,408	1,442
Included	90	27	16	17	16	13	29	19	26	32
%	2.78%	1.66%	1.07%	1.21%	1.12%	0.92%	2.08%	1.35%	1.85%	2.22%
P4: The Number of Banks in 10 Quantiles of ROA										
	1	2	3	4	5	6	7	8	9	10
Excluded	3,643	1,462	1,404	1,384	1,379	1,375	1,383	1,386	1,385	1,387
Included	98	17	17	23	22	21	22	13	17	34
%	2.69%	1.16%	1.21%	1.66%	1.60%	1.53%	1.59%	0.94%	1.23%	2.45%
P5: The Number of Banks in 10 Quantiles of Goodwill										
	1	2	3	4	5	6	7	8	9	10
Excluded	369	394	387	371	340	349	324	336	332	348
Included	7	7	7	6	5	4	10	4	11	7
%	1.90%	1.78%	1.81%	1.62%	1.47%	1.15%	3.09%	1.19%	3.31%	2.01%
P6: The Number of Banks in 10 Quantiles of C&I /asset ratio										
	1	2	3	4	5	6	7	8	9	10
Excluded	2,330	1,751	1,600	1,534	1,508	1,499	1,499	1,479	1,499	1,558
Included	40	47	27	21	22	26	25	22	28	27
%	1.72%	2.68%	1.69%	1.37%	1.46%	1.73%	1.67%	1.49%	1.87%	1.73%
P7: The Number of Banks in 10 Quantiles of net charge off ratio										
	1	2	3	4	5	6	7	8	9	10
Excluded	1,486	2,717	2,219	1,427	1,391	1,390	1,382	1,387	1,392	1,426
Included	23	71	51	13	21	24	25	20	20	17
%	1.55%	2.61%	2.30%	0.91%	1.51%	1.73%	1.81%	1.44%	1.44%	1.19%
P8: The Number of Banks in 10 Quantiles of nonperforming loans ratio										
	1	2	3	4	5	6	7	8	9	10
Excluded	915	922	925	926	918	919	924	927	918	921
Included	23	12	10	11	16	13	11	14	14	18
%	2.51%	1.30%	1.08%	1.19%	1.74%	1.41%	1.19%	1.51%	1.53%	1.95%
P9: The Number of Banks in 10 Quantiles of Deposit Ratio										
	1	2	3	4	5	6	7	8	9	10
Excluded	3,503	1,494	1,436	1,414	1,400	1,407	1,402	1,393	1,399	1,409
Included	110	20	21	17	17	14	25	28	18	15
%	3.14%	1.34%	1.46%	1.20%	1.21%	1.00%	1.78%	2.01%	1.29%	1.06%
P10: The Number of Banks in 10 Quantiles of 1 -4 family loan ratio										
	1	2	3	4	5	6	7	8	9	10
Excluded	2,984	1,650	1,521	1,486	1,438	1,423	1,422	1,431	1,428	1,434
Included	79	34	24	21	25	25	23	19	18	17
%	2.65%	2.06%	1.58%	1.41%	1.74%	1.76%	1.62%	1.33%	1.26%	1.19%

At the table 11.6, we can see some features from the loan buyer in the secondary market. For example, Table 11.6 presents valuable results to understand the relevant features of buyer bank. Panel 1 (P1) indicate that the second lowest quartile of number of bank owned office has the highest volume, thus, bank with limited number of office more likely involved in the market, we confirm this evidence by the panel 2 (P2) due to the fact that 281 banks or saving associations involved in the market more likely participate in the loan sale secondary market. those of having limited interstate branch, this evidence supports the diversification hypothesis that banks without extensive branches more likely step in the loan sale market. Based on the whole sample size, banks involved in the loan sale market are predictively and majorly local-based reputational financial institutions, according to the Demsetz (2000), banks may be not allowed get in the market because of the reputational barriers, in our paper, the FIs with relative high reputation are more likely purchase loans from the counterpart. We have a conclusion from the panels from 4 to 10 that these FIs present very small ratios because of the property of local-based bank. Our research evidences support the comparative hypothesis that banks with less lending and loan origination opportunities are more likely involved in the buyer group of loan sale secondary market. Panel 3 (P3) show that the group of banks with lowest asset (some high asset quantile also joins the part) more likely step in the secondary market. P7 indicate that bank with lower net charge off ratio more likely involve in the market, meanwhile, P8, the ratio of non-performing loan support our panel seven. Panel 10 provides an interesting pattern on 1 - 4 family loan, the downtrend implies that banks with smallest ratio of family over asset are more likely involved in the sale market. We also found out that most of the banks or saving associations eventually were merged by other banks or were name-changed for some reasons. The dominant component of the buyers in the distressed loan sale market is the group of local banks whose have good reputation, lower non-performing ratio, higher capital ratio (total risk-based capital ratio) and lowest net charge-off ratio.

Table 11.7 The Empirical Result of Loan Quality

The Target Variable is Loan-Quality and The Dependent Variable is Discount rate
t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

	(1)	(2)	(3)	(4)
	Non-Perfor~g	Perform/No~f	Performing	Sub-Perfor~g
hhi loan	-0.130	-0.0990	-0.184	-0.119
	(-1.41)	(-0.93)	(-1.73)	(-1.08)
sale ratio	2.889	1.841	3.184	2.045
	(1.41)	(0.87)	(1.46)	(1.00)
netcharge ~f	-4.073	-2.003	-3.563	-2.012
	(-1.51)	(-0.66)	(-1.35)	(-0.67)
Gain	0.0250	0.036*	0.026*	0.036*
	(2.02)	(2.52)	(2.28)	(2.69)
log netinc~e	0.0110	0.0270	0.022*	0.0290
	(1.09)	(1.50)	(2.57)	(1.78)

<Table 11.7 cont.>

nonperform~s	0.0160	0.0180	0.0140	0.0180
	(0.98)	(1.02)	(0.66)	(0.94)
deposit ra~m	0.922***	0.824***	0.932***	0.843***
	(6.54)	(4.75)	(6.36)	(4.84)
Hot funds	-0.168	-0.0850	-0.130	-0.0800
	(-1.87)	(-0.77)	(-1.19)	(-0.64)
Goodwill	-0.743	0.534	1.613	1.279
	(-0.24)	(0.19)	(0.47)	(0.40)
log uncert~y	0.114	0.185*	0.0880	0.169*
	(1.68)	(2.45)	(1.44)	(2.44)
log asset	0.00800	0.0390	-0.00500	0.0340
	(0.20)	(1.08)	(-0.13)	(1.01)
1.year	0.227***	0.219***	0.222**	0.218***
	(5.26)	(7.83)	(4.30)	(6.63)
1.stmult	-0.188	-0.188	-0.140	-0.164
	(-1.95)	(-1.75)	(-1.08)	(-1.40)
num office	-0.0420	-0.060**	-0.0380	-0.057*
	(-1.99)	(-3.13)	(-1.64)	(-2.94)
1.stmult#c~e	0.045*	0.055**	0.0390	0.052*
	(2.43)	(3.10)	(1.80)	(2.84)
NonPerf	0.236***			
	(8.69)			
Perf Nonperf		-0.0810		
		(-1.01)		
Perf			-0.200***	
			(-8.19)	
Sub Perf				0.084*
				(2.45)
cons	-0.813	-1.471**	-0.431	-1.369**
	(-1.45)	(-3.67)	(-0.76)	(-3.72)
r2 within	0.479	0.302	0.447	0.300

In the table 11.7, the best quality is performing loan (column #3), the second-best quality is sub-performing loan (column #4), the third one is the performing/nonperforming loan (column #2) and the worst quality is the non-performing loan (column #1). The dummy variables are YEAR (1 is year from January 2008 to December 2009, 0 otherwise) and STMULT (1 represent banks with interstate branches, 0 otherwise). We apply various fixed effect (FE), the individual fixed effect, the geopolitical state and city fixed effect, and loan classification fixed effect. The positive gain and deposit ratio support that banks with observable profits and high deposit ratio more likely undertake significant loan discounts. Unsurprisingly, at the high economic risk, the discount rate could be higher. Moreover, we prove our hypothesis 3 that, at the crisis time, discount rate is significantly higher than its' non-crisis time. In table 11.7, the approval of loan quality (hypothesis 1) is the significant positive non-performing loan and negative performing loan respectively, the good quality loan desires higher price instead of lower price and the no-good quality loan ask higher discount instead of lower discount. It is widespread fact because of better quality and high price. We conclude that the loan quality does affect the discount rate in the market. The interestingly evidence is that the sub-performing loan sells at a small discount rate. In addition, because of the negative and significant sign on dummy interstate and number of offices, our evidences support that banks with more than one branches are more likely purchase less discounted loans, because they have multiple sources to originate funds and relatively less concern about the diversification issues. Thus, they may more likely buy small discounted product (good quality and higher price). The positive interaction term because buyers with interstate offices have better abilities to manage the risk fund and better risk tolerance.

Table 11.8 The Empirical Result of Loan Classification

The Target Variable is Loan-Type and The Dependent Variable is Discount rate
t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	BankCharge~f	Commer	Installment	Mixed	Other	RECommer	REResi
rfamily loan	-0.414	-0.423*	-0.467	-0.429*	-0.394	-0.477*	-0.456
	(-2.12)	(-2.26)	(-2.08)	(-2.23)	(-2.10)	(-2.57)	(-1.96)
rindivi loan	1.081*	1.135*	0.956*	1.124*	1.091*	1.210*	1.064*
	(2.31)	(2.42)	(2.50)	(2.43)	(2.34)	(2.64)	(2.60)
rreal ratio	0.0560	0.0870	0.0960	0.0860	0.0670	0.119	0.0940
	(0.24)	(0.38)	(0.40)	(0.38)	(0.30)	(0.52)	(0.39)
rcredit laon	-2.204	-1.771	-2.064	-2.318	-3.105	-1.976	-3.386
	(-0.56)	(-0.47)	(-0.52)	(-0.60)	(-0.80)	(-0.56)	(-1.10)
sale ratio	4.930*	4.259	4.574*	4.727*	4.561*	4.602*	4.550*
	(2.61)	(1.73)	(2.58)	(2.27)	(2.30)	(2.30)	(2.30)
netcharge ~f	-1.679	-0.702	-2.183	-1.794	-1.540	-0.544	-1.599
	(-0.49)	(-0.24)	(-0.61)	(-0.53)	(-0.45)	(-0.18)	(-0.45)
Gain	0.0160	0.0180	0.0170	0.0140	0.0140	0.0170	0.0140
	(1.05)	(1.07)	(1.21)	(0.97)	(0.86)	(1.03)	(0.86)
log netinc~e	0.0130	0.00500	0.0130	0.0110	0.0130	0.00400	0.0120
	(1.61)	(0.72)	(1.14)	(1.44)	(1.63)	(0.47)	(1.41)
nonperform~s	0.0110	0.0100	0.0100	0.00900	0.00900	0.00900	0.00700
	(0.50)	(0.45)	(0.49)	(0.37)	(0.38)	(0.36)	(0.33)
deposit ra~m	0.894**	0.943**	0.865**	0.885**	0.905**	0.910**	0.864**
	(3.87)	(4.07)	(4.07)	(3.86)	(4.00)	(3.92)	(3.61)
Hot funds	-0.222	-0.278	-0.195	-0.225	-0.235	-0.258	-0.209
	(-1.47)	(-2.14)	(-1.43)	(-1.47)	(-1.49)	(-2.01)	(-1.56)

<Table 11.8 cont.>

Goodwill	2.444	1.960	2.508	2.638	2.755	2.554	3.057
	(0.75)	(0.68)	(0.99)	(0.83)	(0.86)	(0.75)	(1.05)
log uncert~y	0.0600	0.108	0.0510	0.0620	0.0600	0.0880	0.0440
	(0.72)	(1.21)	(0.63)	(0.74)	(0.72)	(0.99)	(0.54)
log asset	0.0170	0.0350	0.0110	0.0200	0.0160	0.0370	0.0100
	(0.21)	(0.47)	(0.15)	(0.24)	(0.20)	(0.49)	(0.14)
1.year	0.242***	0.247***	0.242***	0.241***	0.242***	0.239***	0.236***
	(7.28)	(8.00)	(7.01)	(7.18)	(7.22)	(7.44)	(6.52)
1.stmult	-0.199*	-0.220*	-0.213**	-0.214*	-0.214*	-0.212*	-0.203*
	(-2.46)	(-2.64)	(-3.16)	(-2.63)	(-2.61)	(-2.46)	(-2.42)
num office	-0.051*	-0.058*	-0.054**	-0.054*	-0.055*	-0.058*	-0.054*
	(-2.39)	(-2.63)	(-3.35)	(-2.49)	(-2.48)	(-2.36)	(-2.37)
1.stmult#c~e	0.055*	0.062**	0.058**	0.059**	0.059**	0.061*	0.057*
	(3.03)	(3.25)	(4.31)	(3.14)	(3.14)	(2.93)	(2.99)
Bank Charg~f	0.201*						
	(2.25)						
Commercial		-0.0540					
		(-0.90)					
Installment			0.173				
			(1.83)				
Mixed				-0.286***			
				(-8.92)			
Other					0.0370		
					(0.77)		
RECommercial						0.0520	
						(1.22)	
REResident~l							-0.0460
							(-1.51)
cons	-0.628	-1.017	-0.504	-0.654	-0.609	-0.965	-0.438
	(-0.47)	(-0.81)	(-0.41)	(-0.49)	(-0.46)	(-0.75)	(-0.36)
r2 within	0.370	0.373	0.382	0.375	0.367	0.372	0.370

In the table 11.8, we divide seven industry classification in order to approve the impaction on discount rate. The bank charge off model is the first column, the second column is commercial loan, the third one is installment, the fourth column is mixed loan type, other is in the fifth column, the real estate backup commercial and residential loan present in six and seven columns, respectively. Table 11.8 explains almost same result; however, we exclude the HHI of loan type in each regression for reducing the collinearity and contain four major loan types in each column. We control the loan quality fixed effect. Interestingly, we find out that banks with high weight on family loan more likely undertake the low discount loan because of the significant negative sign on type of family, also, because of the positive significant sign on sale ratio, banks with relatively high loan-hold-for-sale are more likely undertake higher discount rate. More importantly, same as the evidence showed on table 11.7, we confirm hypothesis 3 that, at the crisis time, discount rate is significantly higher than its normal time. Interactional variable of office number and hold/not-hold interstate branches indicates that banks with multi- and interstate- branches more likely undertake higher discount rate. Both negative sign in front of number of office and hold interstate branches showing on table 11.7 and 11.8 imply that banks with interstate branches and more offices intend to take low discount loan. The most important approval is that the industry classification provides a little different loan discount across all columns. There is a significant evidence, the loading of bank charge-off and mixed type loan indicates that the bank charge-off loan provides more discount and mixed type loan actually declines discount rate. Because the mix-big is better off, We reclaim that the insignificant of other industrial classifications is because we do not have specific confidential combination and contract convent on those loans, therefore, there is no enough information to analyze these classifications. We believe that the loan quality clearly guides buyers' decision because of the predetermined rank, and that the industrial classification may relatively has limit power on buyers' decision unless they intentionally focus on a certain type.

The commercial loan may include different nature; hence it is hard to define the coefficient H1. If borrowers make the payment one time, we also cannot get a clear sign on I1. We are actually surprised by the negative J1, the confidential agreement makes researchers so hard to predict the composition of mixed loan. Eventually, we arbitrary say that this type contains some outperformance loans. We also cannot have the properties of "other loan", it is an undefined K1, again this type may include good/bad loans. Normally, we should have negative sign both on L1 and M1, however, the loan type of real estate backup commercial shows us nothing important, the M1 almost present significant impaction on discount rate. There are some limitations in our research, first, because of the confidential agreement (Loan Maturity, the status of bank holding companies, the composition of purchasing loan, etc.), it's very hard to predict the nature of underlying loan portfolios, second, we find out that buyer FIs was acquired, merged or renamed after the purchase, thus, the M&A data could be the crucial role in our research.

Figure 1 clear indicate that the highest amount of loan sale is around August 2009 and the uptrend of the loan sale emerges around 2008. It takes one year to reach the peak of loan sale; we can see a steep climbing around 2008 and 2009. in addition, this climbing shows us the strength of financial crisis. Figure 2, the discount rate of loan sale reach to the highest around 2009, thus, we confirm the regression result in table 11.7 and 11.8. The overlap of total size of loan sale book value (thick red line) and the total size of loan sale trade price/selling price (thin green line) clearly present the mechanism which the remarkable discounted behavior also presents on around August 2009. For better understanding the numeric pattern, table 11.9 numerically translates the evidence of figure 10.3 into numeric table. Both figure 10.3 and 10.4 confirm the hypothesis 3 that the financial crisis impressively pushes up the discount rate.

__Table 11.9 Number Transaction of Loan Sale__

	Number Transaction of Loan Sale																	
	1	2	3	4	5	6	7	8	9	10	13	14	15	16	21	34	51	83
Year																		
1994	5			8														
1995	2	14	25	5														
1996	5	5	8	10	11			11										
1997	17	3	8	13		26												
1998	1	5	25	11														
1999	1		3	8														
2000	9	6	16															
2001	6	11																
2002	4	27	6															
2003	1	6																
2004	3	2	3															
2005	2																	
2007	1																	
2008	2	2	14	5	8													
2009				4			53	30	14			27		62		77	128	239
2010			3	5	11		22	25	22	14	28		24		67			
2011	4			9				16	22	21								
2012	2	4	8	7			15	14										
2013		2	3	8			22											
2014	1	5	3	17		9												
2015	6																	
2016	2		4															
2017	7																	
2018	2																	

For better understanding and visualizing the interaction between the loan quality and classification on discount rate, in the table 11.10, the most price-cut loan quality in all aspect is the non-performing column because no matter in which row the highest discount rate always locate in nonperforming column. Table 11.12 is a summary of quarterly changes from purchasing loan sale. Simply, we marked the present-time of purchasing loan sale as zero, 0, we marked before-time of purchasing loan sale as negative 1 to 12, -1 ~ -12, and we also marked after-time of purchasing loan sale as positive 1 to 12, 1 ~ 12. We conjecture that ROA (roaa), ROE (roee) and HHI (hhi_loan), etc., could be changed due to the purchasing, at least, there should have something changed because of the loan purchasing. Surprisingly, we found some interest patterns. Almost all of the variables (without capital ratio, actually we use it as the comparative group for verifying the others) reached the peak at purchasing time and back to normal after-purchasing. The main investigation in this ranking is to find out the variable change in the time-line. Bank needs profits and shareholder even needs more profits, thus it's logically to ask question related to the profit, we have several options in our data such as ROA, ROE, net income, and the most important one which is the gains form the loan sale transaction.

Table 11.10 Discounted Rate Across Loan-Quality and Loan-Type

Discounted Rate Across Loan-Quality and Loan-Type					
All in %	Quality				
Loan Type	Mixed	Non-Performing	Perform/Nonperf	Performing	Sub-Performing
Bank Charge Off		88			
Commercial		73	59	4	35
Consumer		3			
Deficiency Bal		47			
Installment		63	5	23	39
Judgment		79			
Mixed		74	55	6	0
ORE Participation		68			
Other		55	2	16	3
RE\Commercial		64	49	26	22
RE\Residential	57	45	35	21	16
Student				18	

Table 11.11 Before, After and Present of Distressed Loan Sale (DLS)

	Before, After and Present of Distressed Loan Sale (DLS)																								
	-12	**-11**	**-10**	**-9**	**-8**	**-7**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Log asset	12.59	12.6	12.61	12.62	12.64	12.65	12.65	12.67	12.68	12.69	12.7	12.72	12.89	12.77	12.78	12.77	12.76	12.79	12.78	12.78	12.8	12.8	12.8	12.82	12.82
△ROE	0.23	0.38	0.29	0.15	0.04	0.05	-0.41	-0.58	-0.5	-0.05	0.01	0.05	0.09	0.13	0.21	0.21	-0.22	-0.18	-0.4	0.22	0.13	0.36	0.16	0.07	-0.4
ROE	6.04	5.58	5.08	4	3.65	3.78	3.87	3.21	2.7	1.56	1	1.15	12.74	8	7.18	6.23	7.5	7.35	7.33	5.69	5.45	4.21	4.62	4.85	4.1
△ROA	0.21	0.36	0.27	0.12	0.02	0.03	-0.57	-0.74	-0.65	-0.05	0	0.03	0.11	0.17	0.26	0.23	-0.31	-0.28	-0.56	0.2	0.12	0.36	0.15	0.08	-0.38
ROA	0.44	0.4	0.36	0.19	0.19	0.24	0.26	0.22	0.18	0.11	0.08	0.1	1.59	0.95	0.86	0.79	0.92	0.87	0.91	0.79	0.72	0.73	0.74	0.76	0.71
HHI of LoanType	0.74	0.74	0.74	0.73	0.73	0.72	0.73	0.73	0.73	0.72	0.71	0.71	0.8	0.75	0.75	0.74	0.72	0.72	0.71	0.7	0.7	0.69	0.69	0.68	0.68
total Gain of LS	5.03	5.08	5.11	4.99	4.9	4.86	4.89	5.01	5.06	5.16	5.2	5.17	6.18	5.73	5.74	5.67	5.51	5.47	5.31	5.3	5.3	5.36	5.39	5.44	5.5
Capital Ratio	0.11	0.12	0.11	0.1	0.11	0.11	0.1	0.11	0.11	0.1	0.1	0.11	0.11	0.1	0.11	0.11	0.11	0.1	0.1	0.11	0.1	0.1	0.11	0.1	0.09

Table 11.12 Discounted Rate in 10 Quantiles of 10 variables

	Discounted Rate in 10 Quantiles of 10 variables									
	asset	Net Income	Sale Ratio	Net charge off ratio	Goodwill	Loan Gain	Non-Perf	Deposit Ratio	Hot fund	HHI loan
1	0.539	0.6550603	0.546	0.4851038	0.4960091	0.396	0.516	0.459	0.45	0.319601
2	0.467	0.6299848	0.492	0.3486843	0.4143535	0.489	0.556	0.414	0.419	0.323618
3	0.806	0.6575934	0.203	0.4734872	0.1655648	0.372	0.463	0.425	0.538	0.298848
4	0.358	0.4342033	0.268	0.4008117	0.2350735	0.41	0.411	0.415	0.555	0.444115
5	0.576	0.4721234	0.402	0.3048369	0.1194448	0.431	0.439	0.479	0.468	0.385791
6	0.617	0.5277582	0.441	0.3879582	0.6368072	0.403	0.518	0.532	0.464	0.634734
7	0.627	0.7013051	0.619	0.4257476	0.3491466	0.413	0.416	0.551	0.451	0.575077
8	0.422	0.4932221	0.7	0.5269912	0.175	0.506	0.524	0.548	0.541	0.560562
9	0.554	0.478721	0.54	0.5539311	0.6395181	0.463	0.468	0.407	0.382	0.467267
10	0.399	0.4393333	0.543	0.4859575	0.478445	0.428	0.432	0.474	0.432	0.38624

Table 11.11, we separately describe the relevant variables in 10 equal-size quantiles for capturing detailed common features. For example, there is a downtrend in the net income column, indicating the less profitable bank has the better interest to hold lower discount rate. There is an uptrend in the net charge off ratio, indicating banks or saving institutions with higher net charge-off ratio undertake higher discount rate. Unfortunately, most of volume does not provide any clear increasing or decreasing pattern.

Table 11.13 The Benefit of Loan Sale

Dependent variable is ROA
t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

	(1)	(2)	(3)
	before	mark	after
log asset	-0.0970	-0.102	-0.0990
	(-1.28)	(-1.29)	(-1.30)
hhi loan	0.766***	0.809**	0.725**
	(3.35)	(3.26)	(3.07)
Gain	0.077*	0.0640	0.083*
	(2.06)	(1.64)	(2.25)
capital ra~o	6.331	6.141	6.303
	(1.55)	(1.52)	(1.55)
1.buybe	-0.731***		
	(-5.34)		
1.Buy Mark		0.103	
		(0.15)	
1.buyaf			-0.383***
			(-4.05)
cons	0.697	0.815	0.709
	(0.69)	(0.78)	(0.69)
r2 within	0.0540	0.0320	0.0440

Table 11.13, we experimentally explore the pattern of bank's ROA (dependent variable) in ex-ante, present and ex-post of loan purchasing. The basic idea here is asking a question: Does the loan buyers get any benefit at the loan purchasing period? we arbitrarily involved several explicators in regression, such as logarithmic asset, the created HHI loan, loan sale gains, FDIC provided capital ratio and dummy time variable in ex-ante, present and ex-post of loan purchasing. In all columns, our HHI loan provides significant positive contribution on return on asset, indicating the more specific loan type concentration positively affect the bank's return on asset. Moreover, the Gain provides significant positive contribution on ROA due to the more benefits from the loan sale gain the higher ROA. The most interesting result is the significant negative on buy before and after, implying buyers actually have less profitability comparing to the buying period and explaining the potential reason of loan sale market participation is banks' goals of advance profitability. Banks may not harvest

significant profits at the buying moment but without involvement of loan sale they may have even less profitability.

12. Conclusion

We use FDIC disclosed bank loan sales dataset which comprises of a total of 4273 loan sales transactions beginning from 1994 to 2019 and explore four key questions. The dataset includes two major financial crises of the recent times, the dot.com bubble of 2001, and the global financial crisis of 2008 and 2009. Loan sales discounts, asset quality, industry classifications, compositions and buyers interest vary significantly during financial recessions and non-recessionary periods. For example, average discount is higher in recession sample 54.68% compared to 47.82% in non-recession period. 52.24% loan sales are performing during recessionary period compared to 31.86% during non-recessionary sample. In our analysis, we include a set of characteristics variables: Bank's Characteristics, the loans' relevant ratios, banks' loan type, economic conditions, and control variables.

First, we investigate asset quality definitions disclosed by FDIC database affect the loan sales discounts. Our results suggest that loan sales discount rates are inversely related with asset quality. Performing and sub-performing loans on average are sold at less discount compared to average loan sale contracts, compared to Performing-non-performing and non-performing loan that are at higher discount compared to average loan sales.

Second, we analyze whether the industry classification determines loan sales discount rates. Bank charge off loan are sold at significant higher discount compared to average loan contract sales. Surprisingly, R.E. commercial and R.E. residential loans are not sold at lower discount. However, the mixed type loans are sold at lower discount. For consumer loans and other types of loans, their discount rates are not significantly different from average loan sales discounts.

Third, we analyze the impact of financial crisis on loan sales discounts. In our decades sample, we create a year dummy between December 2008 and December 2009 and find out that the loan sale discount rates in the financial crisis time are significantly higher than its normal period. We prove the hypothesis in our two regressions, the evidences are consistent in our research.

13. Appendix

Variable Explanation

Summary of Variable					
Bank Characteristics Variables					
Num.	Variable	Variable Name	Description of Variable	Unit	Source
1.	Asset	log_asset	Logarithmic asset	$ In thousands	Demsetz (1993, 2000) Gorton and Pennacchi (1995)
2.	Reputation	Goodwill	Intangible asset		Demsetz(2000)
3.	Gains	Gain	Logarithmic net gains (losses) on sales of loan		Irani and Meisenzahl (2017)
4.	Deposit ratio	deposit_ra~m	a ratio of total deposited to total asset		Demsetz(2000)
5.	Dummy of Interstate branches Yes/No	stmult	A 'yes' or '1' indicates that an institution has branches that can accept FDIC-insured deposits in more than one state	1 or 0	Demsetz(2000)
6.	Number of offices	num_office	Total number of offices owned by the bank		
FDIC Bank Bailout Variables					
Sl.	Variable	Variable Name	Description of Variable	Unit	Source
1.	Sale ratio	sale_ratio	A ratio loans held for sale over the total asset		
2.	Net charge-off ratio	netcharge_~f	charge-offs minus recoveries, divided by assets		Demsetz(2000)
3.	Nonperforming loan ratio	nonperform~s	a ratio of C&I loans in nonaccrual status plus C&I passed due 90+ days over the total asset		Demsetz(2000)
4.	Hot funds	Hot_funds	the sum of brokered deposits, uninsured deposits		Demsetz(2000)
5.	Net income	log_netinc~e	Logarithmic Net Income		Drucker and Puri (2008)
6.	family loan ratio	rfamily_loan	The ratio of 1 – 4 family loan to total asset		

<Appendix cont.>

7.	real estate loan ratio	rreal_ratio	The ratio of real estate loan to total asset		
8.	credit card loan ratio	rcredit_laon	The ratio of credit card loan to total asset		
9.	farmland loan ratio	rfarm_loan	The ratio of farmland loan to total asset		
10.	individual loan ratio	rindivial_loan	The ratio of individual loan to total asset		
Variables in our research					
Sl.	Variable	Variable Name	Description of Variable	Unit	Source
1.	Interaction term of dummy of interstate and number of offices	stmult#c~e	This is an interaction term of dummy interstate and number of offices		
2.	index of economic policy uncertainty (EPU)	log_uncert~y	The Economic Policy Uncertainty Index is based on newspapers in the United States.		FRED economic data (Quarterly)
3.	Herfindahl-Hirschman Index of Loan	hhi_loan	The measurement of a bank's loan portfolio concentration.		
4.	Dummy of year	year	1 represents period between 2008 and 2009, zero otherwise.	1 or 0	
Note: Most of variables are based on FIDC quarterly financial report database. In addition, we only point out the most typical paper in the sources, please go over the literature review section for more information.					

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15. Vita

Xi’an is the place where he was born. his elementary, middle, high and college school time were spent in Xi’an, Shaanxi, China, the most famous attraction in Xi’an is Terra Cotta Warrior Museum. his first degree in the United States is MBA in finance and supply chain management at the University of La Verne, Los Angeles.

Four years of studies in Financial Economics Department have positively and permanently changed his life in several ways, the improvement of communication skills, the development of practical learning processes, the enhancement of research expertise, the enrichment of personal vision. Knowledge/Education is the most important part of his whole life and he will persist in effort and enthusiasm in future studies and researches because financial data analysis is part of his life.