Mergers and Acquisitions of Financial Institutions in the US:

Does Experience of Collaboration Matter?

By

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Abstract

This study deals with merger and acquisitions topic in financial industry. The purpose of this study is to determine what are the factors increasing chances of a bank to become a merger target. A number of factors suggested in the existing literature have been tested in a logit model on a sample of 2,346 US banking mergers occurring from 2001 to 2015. The empirical results support the hypothesis that acquirers are mostly looking to expand growth opportunities: other things equal banks with higher loans-to-deposits ratio, lower ROA, and higher income growth ratios are more likely targets. Additionally, the factor of preceding collaboration between an acquirer and a target has been suggested as a potential mechanism to enhance target's trustworthiness and increase the likelihood of a merger. The collaboration was measured in terms of proximity in a network of US-affiliated lenders in syndicated loan market over the period 1987-1997. Based on the estimated logit coefficients on a sample of 1,890 bank pairs the hypothesis that the experience of direct collaboration is positively associated with the probability of a merger could not be rejected. However, the closeness of two banks in the network of other lenders does not seem to affect the likelihood of a future merger.

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Introduction

Mergers in any industry are very important for a number of reasons. First of all, they have a potential to influence an industry structure dramatically causing the number of operating firms to decline. As a result, industry output is being produced by a smaller amount of larger firms raising up the questions of concentration, economic performance, pricing policy and other implications of reduced competition. This is why mergers and acquisition trends have been always in particular interest among public policy makers and academic researchers. The banking industry is no exception to this rule. Furthermore, taking into consideration the industry size and the role it is playing in the global economy, understanding the trends, underlying drivers of the agents involved, and tracking the consequences is absolutely vital.

Many models have been published on *what* happens after the merger, or *why (when)* firms are entering merger market (for the summary of empirical studies see Jones and Critchfiled 2005). At the same time, the question of *whom* the acquirer chooses is most often left out of the model. This study attempts to bring some value to this scarce knowledge domain.

The ability to predict which firms are going to be targeted could be beneficial for many parties. In particular, the investors might win financial benefits by correctly predicting which firms are going to be acquired. Predicting merger events is also in the best interest of potential targets themselves, as they might alter the bids by adjusting their financial indicators in a way, which would show them as less desired targets.

So, what are the factors the acquirers are looking for, when making a bid? Are there some features, which makes another bank a particularly appealing target? Are those characteristics general, or rather acquirer-specific? Those questions are addressed further in this study.

In general, this thesis attempts to develop a model to define important factors in predicting targets. I examine a sample of 2,346 mergers in the US banking industry over fifteen-year period between 2001 and 2015. The US market was selected as the largest and most developed financial service market. Last but not least, the data availability for the US is sufficient for running empirical analysis on it at a proper scale.

I would like to contribute further to literature by studying the effect of partnership within syndicated loan market on the probability of a merger or an acquisition in the future. The hypothesis is that those institutions are more likely to merge, who have already worked together. While working together the partners are more likely to disclose some financial information, to reveal their business processes, and to facilitate strong connections between managers at a personal level. All of these could establish an incomparable level of trust, which might play a curtail part in making an M&A decision thereafter.

In order to address this question the dataset on syndicated loan market transaction was used consisting of over 90,000 deals involving more than 5,500 financial institutions. Importantly, more than a half (54.79%) of the loan transaction records are arranged in North America, which gives me an opportunity to run a proper statistical analysis on this data. The time frame for syndicated loan data was restricted to 1987-1997 to make sure the collaboration took place *before* the merger.

The results contribute to existing literature in several ways. First of all, the potential merger factors suggested in multiple research papers have been consolidated and tested on the most recent data sample. Secondly, a completely new hypothesis has been proposed on the topic together with the innovative methodology to test it. The methodology is based on employing network analysis techniques, and estimating a regression model in a two-step fashion. To the best of the author's knowledge, no research on the relationship between partnerships and mergers has been published before.

Before proceeding further, few methodological remarks have to be outlined. Since the difference between merger and acquisition is minimal, in the current work those terms are going to be used interchangeably. A target firm is defined as the one being bought by another firm, which is called an acquiring or a source firm. Finally, by bank I understand any of the following without making a difference: domestic commercial bank, a domestic thrift institution, or the US office of a foreign bank.

The rest of the paper is organized as follows. Chapter 1 is a review of recent historical trends about mergers and acquisitions in the US banking industry, followed with literature review on potential motives behind M&A decisions, as well as the existing empirical evidence on the topic. In Chapter 2 the different factors are empirically examined on the most recent data available on US banking industry. Chapter 3 deals with one of the factors specifically – namely, the experience of prior collaboration in lending syndicates. In that chapter the data on lenders of US syndicated loan market is analyzed by means of network science toolkit, post which the importance of the collaboration and trust is tested in the regression model. Finally, policy implications are discussed, followed by more general conclusion.

Chapter 1. Mergers and acquisitions of financial institutions

Historical trends: volumes, changes in regulation

The current structure of the banking industry was shaped as a result of sustained merger activity, which has been booming since 1980s. Financial services industry has been one of the most active industries involved in the global merger and acquisitions flows. According to SDC data, financial services industry accounted for more than 44% of total value in merger and acquisitions transactions over the period 1985-1995 (Smith and Walter 1996). As for the United States, this industry was top one by sellers, and the second in terms of buyers involved.

Even reading financial news can reveal that bank mergers have become more frequent in the last decades both in developed and developing world. The press mostly covers the merger activity of the largest banks, however, the mergers involving small and medium sized banks have been also on increase recently.

The amount of firms specializing in financial services has dropped steadily and significantly over the last few decades. According to the OECD report the number of commercial banks has declined from about 11,000 in 1985 to about 7,000 in 1997 (OECD 2000). Given that some of the banks were created throughout that period, Stephen A. Rhoades (2000) estimates the number of the mergers in the US banking industry between 1980 and 1997 to be 8,000 with the total of $2.4 trillion of acquired assets. The same dynamics was observed in the thrifts, savings or loans institutions, credit unions, insurance companies. Overall financial service industry accounted for more than 58,000 reported transactions between 1985 and 1995, with 47% of the value arriving solely from the United States, and another 14% from the cross-border transactions with the United States being one of the parties (Smith and Walter 1996). Although the peak of merging activity seems to pass in 1995-1998 (this period accounts for almost half of $2.4 trillion of acquired bank assets), the process of banking industry consolidation continued thereafter, showing the second wave in the aftermath of the recent financial crises. The amount of merger deals is only one side of the story. In addition to that, the typical surviving firm has become much larger and more diversified both in terms of its operational scope and geographically. Since 1990s a fair share of the mergers happened between the top banks in terms of both real value of assets involved in the deal and of the share of total US bank assets accounted for by the banks participating in mergers (Berger at al. 2004). This fact is well illustrated in the Figure 1 below by DeYoung (2009).

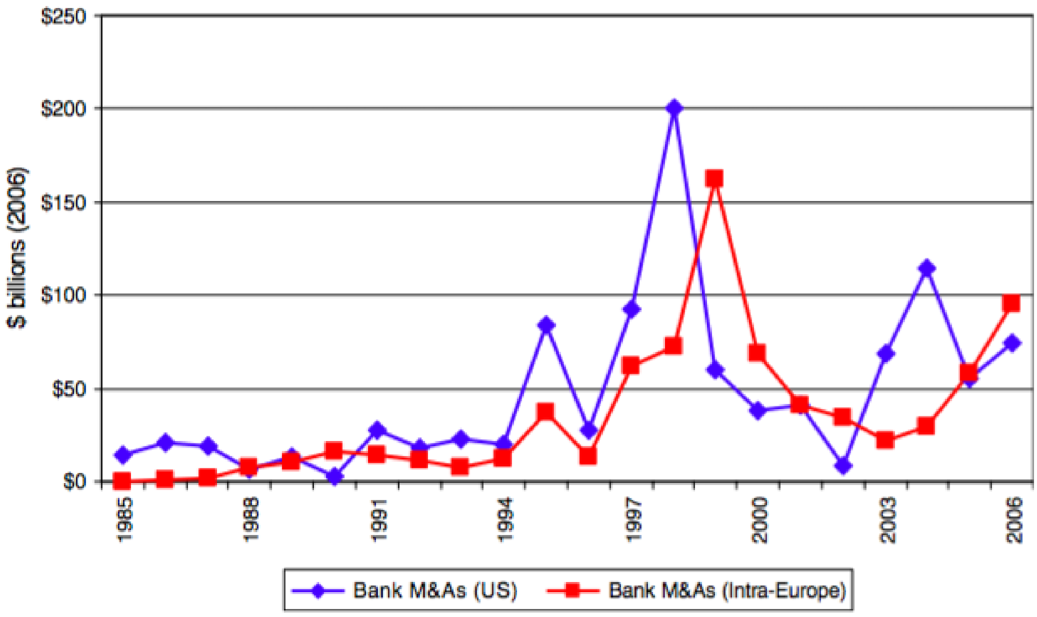

Figure 1. ***Consolidation of bank: historical trend.***
Source: DeYoung et al. 2009

The literature on mergers and acquisitions distinguishes a few main driving forces for a merger movement in the banking industry. What makes bank mergers special as compared to nonbank mergers is mostly the regulatory process involved (Cheng et al. 1989). Before a merger can occur, the approval of multiple bank authorities was required, both at state and federal levels. Rhoades (2000) underlines regulatory reforms as a main facilitator of the changes.

Gradual reduction of state and federal restrictions on the broadness of geographical presence has played crucial role in industry reshaping and restructuring. Historically, the legislation in the US was preventing financial power from concentration and geographical expansion. Relaxation of such restrictions (e.g. with the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994) allowed interstate banking, and as such opened up radically new opportunities for the banks. The role of this legislation can be easily assessed by looking on the Figure 2 from Jones and Critchfield (2005): the overall increase in number of mergers was mostly due to interstate mergers, which started booming right after 1994. The US literature tends to find empirical evidence for that hypothesis. For instance, Brewer et al. (2000) showed that regulation relaxation has boosted bid premiums in the market.

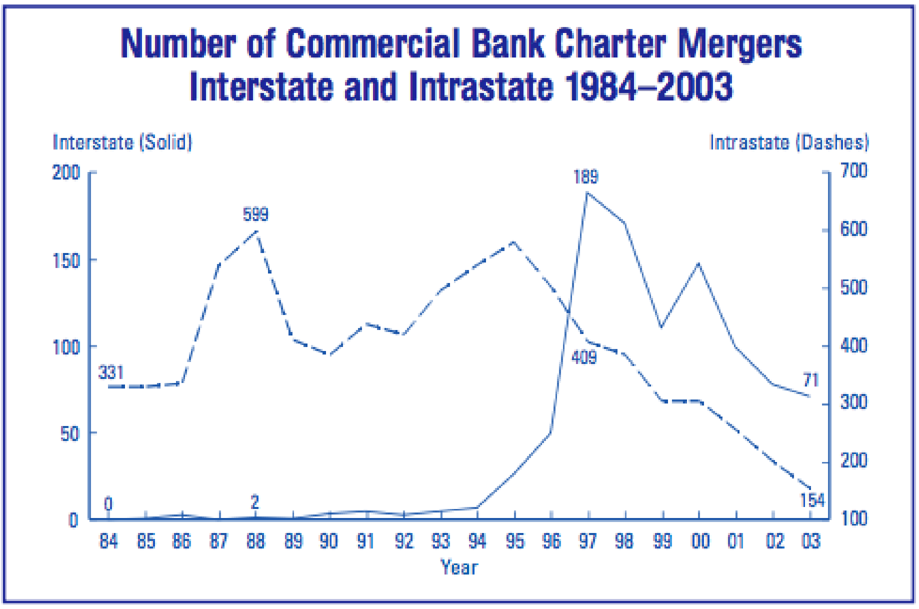

Figure 2. Number of Commercial Bank Charter Mergers 1984-2003.
Source: Jones and Critchfield 2005

Another important reason behind merger movement is the technological boom that has drastically affected the optimal production functions of firms operating in banking industry. Technological innovations had revolutionary effect on both back-office and front-office processes resulting in a completely new competitive conditions being set in the market. Those included, but were not limited to, electronic banking (on-line banking, ATMs), new risk management and data processing systems, evolving of more complex derivatives market and severe customization of already existing products, and the appearance of debt securities in private sector (DeYoung 2009). Both product and geographical expansion within banking industry could be associated with the positive shift of risk-return curve through diversification.

In addition to regulatory changes, and technological innovation, two other broad forces are often highlighted in the literature as being responsible for the big merger push. Those are globalization in both financial and non-financial markets and financial distress of the 1990s (OECD 2000). In addition to that, there are such factors as underestimation of companies' values relative to their replacement values; and existence of strong bull markets (Smith and Walter 1996).

Motivation of agents, benefits and costs

As discussed above, the consolidation trend in the US banking industry was driven by regulatory changes, technological innovation and other environmental changes. But let us now focus on microeconomic factors responsible for the general macroeconomic trend. After all, any merger is a result of individual decision-making process. What would make a bank manager desire to achieve by acquiring another bank? The general answer is that the decision should be made in an attempt of maximizing or preserving firm value in response to competitive pressure.

In fact, various motivations can be standing behind the decision to acquire another company. Those include but are not limited to:

- Increase market share and hence market power
- Get proprietary knowledge from the target company
- Economy of scale, cost-cutting (getting rid of reluctant facilities and

administrative employees), tax benefits

- Economy of scope (synergy)
- Diversification
- New growth opportunities
- Management personal goals (utility maximization at the expense of shareholders, or achieving “too-big-to-fail” status)

As Berger et al. notes, “It is difficult to determine the goals of M&A participants, but there is evidence consistent with the notion that some M&As are designed to increase market power” (Berger et al. 1999, p. 144). The market power growth is an attractive strategy for banks to achieve revenue enhancement, as it enables them to fix higher prices.

For banking industry, which is known for very high fixed costs, the potential for economy of scale should be one of the main strategic drivers for mergers. By achieving the large size, management can mitigate administrative costs, costs arising from agency problem, and others. Importantly, besides the economy of scale banks might also experience so-called diseconomies of scale meaning administrative overhead, increased complexity and consequent agency problems (Walter 2004). The efficiency of the deal would depend on which one of the two prevails.

Another group of drivers for mergers relate economies of scope, which is driven by both supply and demand sides. On the supply side, the reasoning is very similar to the economies of scale: reducing costs by merging operational practices, joint production, improving on technological solutions, expanding the production line. From the demand side, the economies of scale relates to so-called cross-selling practice, when customers are offered multiple complementary products or services, which saves them the costs of search and contracting with another supplier. Diseconomy of scope in turn might arise from inertia and lack of responsiveness (Walter 2004). In some cases, due to unreasonably large size of a merged institution and consequent heavy bureaucratization might result in slow decision-making and erosion of delivery quality.

Diversification is yet another popular motivation for a merger. Unlike economy of scope, in this case the benefits arise from dissimilarities rather than similarities between source's and target's models of operation. Diversification is a well-known strategy for risk mitigation, as it makes a portfolio more stable in face of market risks. In this case diversification can be of two kinds – either product or geographical diversification (or both at a time). Product diversification mostly relates to inter-sector transactions, e.g. between banks and insurance companies, or between banks purchasing securities firms, etc. Acquisition was the preferred approach of banks to expand into new financial areas due to its high speed and expected efficiency: it brings the required expertise and missing human capital is much faster than launching new franchise in-house (DeYoung et al. 2009).

The difference between economy of scale motive and diversification motive is essentially the difference between a preference for complementarity versus a preference for similarity. Little is known about which one dominates when, although some researches attempted to address this question empirically (e.g. Yu et al. (2015)).

Notably, such benefits as diversification and economies of scale and scope are often targeted by existing regulatory restrictions. This is why relaxing those restrictions automatically would cause a boom of M&A deals.

Finally, the M&A transactions might open for the participants new growth opportunities arising from creation of new technologies, entering new markets, or launching new product lines.

All in all, the above mention value-maximizing reasons were most often cited among bank managers as main motives to engage into a merger (G10 2001). However, the decision could be also driven by reasons other than value maximization. A merger can come out as a result of a defensive strategy, or it could be also influenced by pure self-interest of bank management. For example, as suggested by Jones and Critchfield (2005), Bliss and Rosen (2001), and Ryan (1999), mergers are often initiated in a hunt for higher managerial compensation and empire building. The idea is that managerial rewards are positively associated with the firm size, creating for them a personal interest in growing the company bigger. Another non value-maximizing motive described in the literature (Jones and Critchfield (2005), Penas and Unal (2004)) is getting a "too-big-to-fail" status with all the perks of becoming one of the largest financial organizations.

It is very likely that the motives of the agents pursuing M&A deals could vary over time, as economic and regulatory conditions change shaping different market environment. The empirical studies on that matter are hence problematic, as any of them attempt to reveal true motives behind people actions.

Factors and determinants: empirical evidence

As mentioned by Focarelli et al. (2002, p. 1049), "The operating performance and efficiency of the U.S. banks involved in M&As have been examined in many studies on different samples over different periods, but none offers a definitive explanation for the motivation and the benefits of concentrations". Similarly, Nguen at el. (2012, p. 1357) concludes that "despite extensive research, the motivation behind mergers had been largely illusive". The only fairly common point is that in general larger and more profitable banks tend to buy smaller and less efficient ones.

Historically, the first big attempt to predict merger targets by a set of firms' financial characteristics was undertaken by Simkovitz and Monroe (1971). Comparing financial indicators of target versus acquiring firms, the authors found evidence for target firms having on average smaller market capitalization, lower equity growth, lower dividends, and finally, lower price-to-book rations as compared to their acquires.

By applying similar methodology, Stevens (1973) discovered that liquidity-related indicators differ substantially between the buyers and the targets. The price-to-earnings and dividend factors, however, turned out insignificant.

Later, Palepu (1986) criticized the methodology of previously published papers, which were based on linear models and had no rational behind selecting variables to be included to the model. Instead he suggested using the logit model arguing for more robust and sustainable results. Furthermore, he formulated six hypotheses about which firms are more likely to become acquisition targets, and then selected variables based on the set of outlined hypothesis, out of which the following four received an empirical support:

1) Inefficient management hypothesis: acquisition as a mechanism to replace inefficient manager.
2) Growth-Resource mismatch hypothesis: high-growth, resource-poor firms as well as low-growth, resource-rich forms are likely targets.
3) Industry disturbance hypothesis: acquisitions cluster by industry.
4) Firm size hypothesis: the likelihood of a merger decreases with the firm size, as they have less transactional costs associated with a merger.

However, the predictive power of the model is not very impressive (i.e. using model predictions would not lead to any potential excess returns, according to the author).

Similarly, Adelja et al. (1999) tested a few hypotheses covering financial, legal, and organizational dimensions as potential factors for a merger. For instance, the authors argued that the probability of a takeover is related to the degree of control the officers have over the boards, with the number of previous bids for that firm, the absence of litigation, the absence of other ongoing acquisition plans, etc.

It is important to mention studies, which were focusing on banking and financial service industry, as there might be some factors driving merger decisions, which were banking-specific. Focarelli et al. (2002) in their research distinguished between mergers and acquisitions motives. They showed that diversification ("expanding revenues from financial services") was a prevailing strategy in case of a merger, whereas for acquisitions the more typical reasoning was improving the quality of a loan portfolio. Strategies based on economies of scale and other cost cutting incentives were relatively not common.

In another banking study, Nguyen et al. (2012) examined post-acquisition performance and found evidence for such motives as market timing (overvaluation of an acquirer), agency problem and managerial hubris, synergies, and response to industry shocks. Importantly, they also found that single-motive mergers made only 20% of the sample.

As shown above, the literature extensively examines the factors and determinants of mergers and acquisitions at a micro level. Researchers have been heavily arguing on which economic indicators are the most predictive of the coming mergers. One of the goals of this thesis is to develop a model that incorporates the parts of the prior studies on the more recent data. Later, I would also specifically examine the importance of the factor of preceding collaboration, which has not been studied much in the literature before.

Chapter 2. Empirical Analysis of Merger Factors

Data

For the empirical part of this study I use the Mergers and Acquisitions Data published by Federal Reserve Bank of Chicago ("Mergers and Acquisitions" 2017). The dataset contains comprehensive information on acquisitions and mergers that have occurred in the US since 1976 including data on the top holding companies of both the non-surviving and surviving institutions. In order to get the detailed financial characteristics of the entities I have linked this dataset with the dataset on bank financial reports (call reports) published by Federal Deposit Insurance Corporation ("Commercial Bank Data" 2017). It is published on a quarterly basis, and it contains information on financial indicators of more than 13,000 financial institutions in the USA. The data covers fifty states, the District of Columbia and Puerto Rico (as US affiliated area).

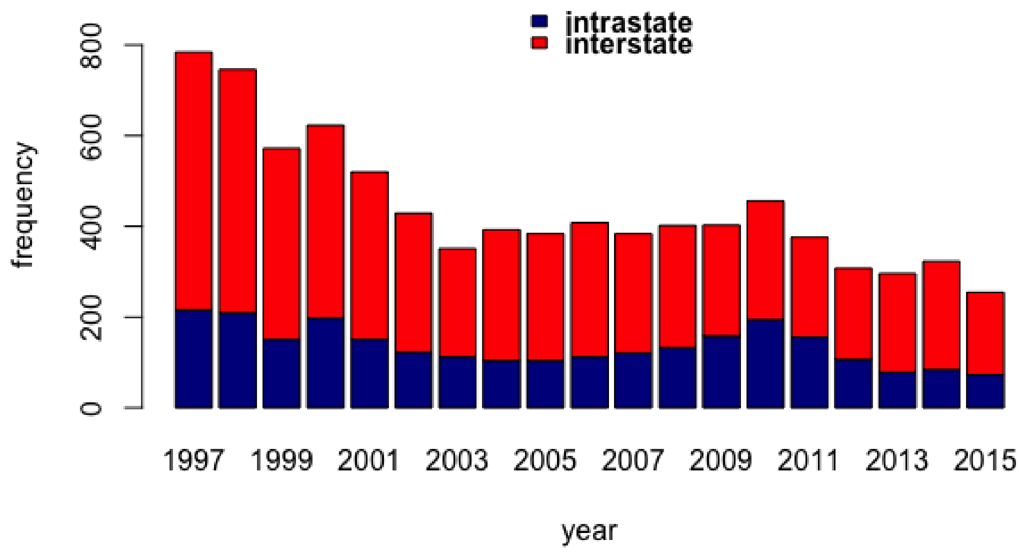

Figure 3. Number of mergers per year
Source: Federal Reserve Bank of Chicago, own calculations

Figure 3 above plots the number of mergers annually. It shows the extremely heavy merger activity in the beginning of the period studied followed by a steady decline starting from beginning of 2000s. That is the period I am going to examine empirically in more details below. One can also see that proportion of the interstate mergers remains relatively flat over time accounting for around quarter of the total number.

The current study mostly focuses on predicting the ‘target side’ of M&A deals. In other words, I would like to examine the factors and motives behind acquiring decision from the acquirer angle: which banks look catchier and more appealing as potential targets?

In order to examine empirically potential factors for mergers and acquisitions, I linked the merger dataset to bank financial indicators submitted in the Call Reports. As I am interested in the characteristics actual at the time of a merger / prior to a merger, I manually formed a consistent time series collecting all the reports for each bank into one dataset. I then merged the resulting dataset with the dataset on mergers in a way that for every bank I only kept the information on a year preceding the year when a bank was acquired. For most of the variables, the data on the four quarters was averaged in order to get more robust and consistent estimates for certain indicators. This was the case for all the balance sheet (stock) indicators. In addition to that, I performed basic data cleaning exercises, such as getting rid of outliers, cleaning out NA values, etc. The initial time frame of the study was 2001-2015. However, given that some of the variables required for the model measure the growth rates for some of the indicators declared in the calls reports, I forcedly had to sacrifice the first year when constructing the final sample, thus examining mergers starting from 2002 onwards.

Descriptive statistics

The section summarizes some patterns of the dataset related to merger activity.

The total amount of assets acquired over the period 2002-2015 is $3.6 trillion. The respective amount of total deposits exceeds $2.3 trillion. Average size of acquired banks across years is $1,230 million in terms of total assets and $796 million in terms of deposits. As for the median values, those equal to $149 and $121 respectively. The values have been fluctuating from year to year, however no clear trend could be identified throughout the period (for details and annual-level statistics please see Appendix Table 9). Such a huge gap between median and mean values reflects skewed nature of both distributions, meaning large number of relatively small deals accompanied by a small number of extremely large deals. For certain years, like 2009 and 2011 the mean-median gap was even larger. With approximately the same median assets figures, the averages for those years are much higher – $1,945 and $1,722 million respectively. Few very big-scale takeovers might be responsible for increasing the gap particularly in the after-crises period.

Looking more closely at the distribution of target size, one can notice that the majority of the deals involved targets of relatively small size: more than 62% of acquired banks had total assets of less than $250 million (first three columns in the Table 1 below). Out of those, for more than a half total assets are less than $100 million. The number of mergers, where size of a target exceeded $10 billion, was 154 out of total 2,997 throughout the course of fourteen years. Out of those, only 15 banks are larger than $50,000 million, accounting for 0.5% of all mergers.

Not surprisingly, targets tended to be smaller than acquirers (for a direct comparison of mean and median values see Appendix, Table 9). On average, the acquirer was 15.5 times larger than the target. Again, the relation was largely driven by few large-scale deals, where the acquirer's size was exceeding the target's size by many digits. For acquirers, the gap between median and mean is even larger, implying the existence of complete "outliers" – banks of extremely large size. The median for target-to-acquirer ratio is 15% in terms of total assets, and

16% in terms of deposits.

Table 1. Number of Bank Mergers by Year and by Target Size, 2002-2015.
Source: Federal Reserve Bank of Chicago, Federal Deposit Insurance Corporation; own calculations

Year	**Total**	**Asset size of target (million of dollars)**						
		<50	**51-100**	**101-250**	**251-500**	**501-1,000**	**1,001-10,000**	**>10,000**
2002	**211**	46	46	44	28	13	15	19
2003	**200**	40	42	47	21	11	21	18
2004	**207**	33	35	65	23	13	25	13
2005	**233**	27	50	81	31	20	11	13
2006	**241**	47	53	54	31	29	14	13
2007	**233**	27	48	62	37	28	16	15
2008	**226**	36	34	58	36	26	21	15
2009	**217**	37	38	64	25	20	22	11
2010	**259**	32	30	62	62	39	27	7
2011	**189**	29	33	61	24	17	17	8
2012	**221**	42	36	70	38	19	12	4
2013	**206**	41	30	59	37	18	15	6
2014	**215**	31	32	75	30	24	16	7
2015	**139**	31	24	33	19	15	12	5
All	**2997**	**499**	**531**	**835**	**442**	**292**	**244**	**154**

The substantial mean size differential supports the hypothesis that smaller firms are likely to be takeover target, commonly tested in the economic literature in banking industry and beyond. That hypothesis was confirmed in the works of Palepu (1986), Cudd and Duggal (2000), Focarelli et al. (2002), Pervan (2010), and others.

Table 2 provides some additional insights on nature of relationship between size of a target vs. size of an acquirer. First of all, it shows that the large banks (the ones with more than $1 billion total assets) have been very active in merger activity acquiring the whole spectrum of targets in terms of size. At the same time, a large number of small banks were acquired by other relatively small banks. 896 merger deals were conducted when both parties were smaller than $250 million accounting for 46.8% of all the mergers of the targets falling in that category. The findings are very much in line with those of Piloff (2004), who studied bank merger activity in the United States one decade behind the period I am focusing on in this study (1994-2003). This implies that the described results are robust to different time frames as well as different datasets, and they reveal rather general patterns in typical size of merger participants.

Table 2. Number of Bank Mergers by Target Size and Acquirers, 2002-2015.
Source: Federal Reserve Bank Of Chicago, Federal Deposit Insurance Corporation; own calculations

			Total Assets Acquirer							
			<50	51-100	101-250	251-500	501-1,000	1,001-10,000	10,001-50,000	>50000
		Total	**43**	**109**	**353**	**423**	**507**	**1059**	**276**	**178**
Total Assets Target	<50	**573**	37	89	188	106	69	66	8	10
	51-100	**530**	3	16	114	151	117	112	12	5
	101-250	**813**	3	4	47	138	214	341	46	20
	251-500	**434**			4	23	84	245	62	16
	501-1,000	**282**				3	21	177	61	20
	1,001-10,000	**257**				2	2	117	76	60
	10,001-50,000	**44**						1	11	32
	>50000	**15**								15

It is worth noting, that the sample is quite heterogeneous in terms of geography. Especially after the interstate merger restrictions have been relaxed, even banks from distant locations have commonly become targets for the banks located in more centered states in terms of banking industry. The most ‘popular’ target states are Illinois, Texas, and California (251, 233 and 184 deals respectively), whereas the states hosting the least number of mergers are Hawaii, Maine, and Vermont, each accounting for less the 5 deals over the 14-years time frame. For details please turn to Table 8 in Appendix.

Variable Selection

Following the approach of Focarelli et al (2002), Nguyen et al. (2012) and taking into account data availability of Calls Report database, the following variable have been used for a regression model (for the methodological notes please see Table 3).

The size of a bank is proxied by Total Assets variable. As shown in many existing research papers typically larger banks tend to acquire smaller ones. Small banks are presumably more likely to become targets given that they would have less of transactional costs in case a merger takes place. Additionally, in face of a hostile takeover they also have less power to ‘defend’ themselves against larger, more influential bidders.

I use loans-to-deposits ratio as a rough estimate for liquidity. The high ratio means that in case of unforeseen fund requirements, a bank might not have enough requirements to cover for it. If the other way around the ratio is too low, a bank is earning less than it could have been earning in the optimal scenario.

This variable was constructed in order to check for the growth-resource mismatch hypothesis raised by Palepu (1986). According to this hypothesis those firms are more appealing targets, which experience a mismatch between the growth and the financial resources at hand. As Palepu suggested, “two types of firms are more likely targets: low-growth, resource-rich firms and high-growth, resource-poor firms”. (Palepu 1986, p.17). The hypothesis was empirically tested in a number of papers using sales growth, leverage, liquidity and other indicators to capture the mismatch. Following Palepu (1986), Cudd and Duggal (2000), Baixauli (2009), Pervan (2010) and others supported the growth-resource mismatch hypothesis after conducting empirical investigation.

Table 3. Variables description

Variable Name	**Calls Report Variable**	**Comments**
Target		1 if is the bank was targeted; 0 otherwise
Total Assets	RCON2170	The sum of all assets items
Loans To Deposits	RCON3360 / RCON2200	
Loans to Assets	RCON3360 / RCON 2170	The quarterly average of Total Loans divided by Total Assets
Bad Loans	RCON2123/ RCON3360	Proxy for riskiness of the portfolio: unearned income on loans over total lending
ROA	RIAD4340 * 4 / RCON2170	Proxy variable: Net Income divided by Total Assets
Inc Growth	(RIAD4340(i) - RIAD4340(i-1))/ RIAD4340(i-1)	Year-to-Year Income growth

The loans-to-asset ratio was included to the model following Focarelli et el. (2002), who suggested to use this banking-specific indicator to check if mergers are motivated by the transfer of managerial skills to handle credit risk. In this sense, the target might be interesting to an acquirer, if it got large exposure to the lending business. Furthermore, banks with high ratio of loans are likely to have large number of debtors, who could be potential customers for other financial institutions (synergy & economy of scope).

The riskiness of a bank portfolio was proxied via Bad Loans variable, which was calculated as a ratio of bad loans to total lending. The bad loans are defined in terms of unearned income from the lending business. The relatively high levels of this variable might indicate that a bank is following high risk – high return strategy, or just experiencing poor risk management quality. Thus, I expect targeted banks to have higher values of this ratio.

Profitability indicator, usually measured as return on assets (ROA), is also a commonly used control variable in M&A literature. Basically, ROA defines how effectively bank uses its assets to generate profits. Some scholars expect that less efficient banks are generally more likely to get acquired. For example, that was empirically proved by Focarelli et al. (2002) on a sample of Italian banks. However, Hadlock et al. (1998) have concluded insignificance of ROA is a potential indicator of acquisition in the US. I build the ROA variable up by dividing net income in the year prior to year of a merger to average of quarterly total assets book value numbers.

I also include income growth variable to see whether in fact acquirers are more interested not just in relatively poor target, but rather poor *and* fast growing companies. In other words, I am intending to check if mergers attempt to buy growth, so I expect to get a positive coefficient in a regression model.

Methodology

I am going to test a number of hypotheses described above by running a regression model on the collected dataset.

Having full set of data on 2,346 mergers occurring between 2002 and 2015, I then proceeded to building up a comparison group for my model. As I am aiming to empirically assess the effect of a number of factors on the likelihood of being acquired, I need to compare the profiles of the actual targets (the dataset I have collected) to the pool of profiles of the banks, which have not been targeted. Taking all the banks listed in calls report database other than the targeted ones would have been resulted in unreasonably unbalanced data most likely causing serious issues with model overfitting and instability of estimators. Some authors take source banks as oppose to target banks as a comparison group (e.g. Foracelli 2002, Nguyen et al. 2012, etc.). The disadvantage of the method is that banks in the target and control group could be of completely different profile, and therefore the comparison of those via the regression model might be not very insightful with regard to the purpose of this study. Instead, I have randomly selected some share of non-target bank for every year. Creating comparison group for every year separately is crucial as some of the banks being acquirers in one period could become targets themselves thereafter, and vice versa. Furthermore, to exercise the importance of various factors on a likelihood of becoming a target, one needs to make sure the comparison group is balanced along the time dimension.

It is important to note that despite the fact that I have collected massive financial data prolonged in time, the final dataset is a simple cross section, since for every bank I would consider its indicators for one time period only (i.e. the year before it got acquired). I have all the years between 2002 and 2015 pooled together into one dataset.

Alternatively, one might consider working with this data as a wide panel one, i.e. include multiple observations for the same bank and track when its status has changed from non-target to target. If such patterns could be detected, like e.g. the huge drop in assets in period t followed by a takeover happening in period $(t+1)$, that might be indicating that total assets affect the likelihood of a takeover in a negative way. Technically, those hypotheses could be tested via pooled OLS / fixed effects / random effects models. This way one would not need to construct a comparison group artificially, as it would naturally come as a part of the sample.

However, I deliberately preferred not to go this way in this study. First of all, having multiple observations for the same variable might cause substantial troubles with serial correlation (autocorrelation). Secondly, the cross section type of sample better serves the purpose of this thesis, i.e. to check *which* banks are more likely to be acquired, as opposed to *under what circumstances* this is happening to them.

Treating the share of non-target banks used for sample creation as a parameter, I created three different samples based on the values of the parameter – 5% (small sample), 10% (medium sample), and 20% (large sample) and estimated regression model coefficients on each of them separately. After adding randomly selected non-targets observations to my sample, I ended up having all together 8,213, 13,427, and 22,824 observations in the corresponding final samples. Thus, actual targets accounted for 28.56% (2,346/8,213), 17.47% and 10.27% of the sample respectively.

In order to get more robust results, I performed certain data cleaning technics prior to running a regression model. In particular, along every variable I had cut first and last 1% of the distribution. I have also manually gotten rid of observations with 0 or negative values for total assets.

Descriptive statistics for the resulted distribution in three samples is presented in Table 4. As a result of data cleaning exercises, the distribution of Total assets became less skewed, with the mean value being around $400 billion. The mean value for loan-to-deposits ratio is around 75%, meaning that average bank in the sample lends out 75 cents per every dollar, which was brought it as deposit.

Median level of ROA in the sample is around 2%, meaning that for every $100 million assets, median bank made $2 million profits annually on average in the given period. Interestingly, the income growth of a median bank has been slightly negative in all three samples on average over the period.

Table 4. Descriptive statistics for variables used in the regression model

	Mean	St.dev.	Median
(1) Small sample (8,213 obs.)			
Total_Assets	436,825	1,175,688	138,469
Loans_to_Deposits	2.2036	127.9299	0.7650
Loans_to_Assets	0.622	0.159	0.639
ROA	0.013	0.067	0.017
Bad_Loans	89	297	0
IncGrowth	0.2008	2.2	-0.0078
(2) Medium Sample (13,437 obs.)			
Total_Assets	410,603	1,095,332	135,566
Loans_to_Deposits	3.1645	188.2062	0.7574
Loans_to_Assets	0.614	0.152	0.631
ROA	0.017	0.065	0.019
Bad_Loans	85	294	0
IncGrowth	0.043	1.612	-0.051
(3) Large Sample (23,884 obs.)			
Total_Assets	391,076	1,027,001	134,574
Loans_to_Deposits	2.310	109.471	0.755
Loans_to_Assets	0.608	0.149	0.622
ROA	0.019	0.090	0.021
Bad_Loans	78	267	0
IncGrowth	-0.021	1.415	-0.066

Given that in most of the cases the explanatory variables' distribution is heavily shifted to the left (mean value being much higher as compared to the median), I am applying logarithmic transformation before plugging them into regression model.

I use logit regression on order to model the probability of bank becoming a merger target in the US between 2002 and 2015. Since the left-hand side variable can only take values of 0 and 1, I will be using a binary logistic model to test the above-described effects.

The functional form of my model looks as follows:

$$Prob(Target = 1) = F(\propto_1 * ln(TotalAssets) + \propto_2 * ln(LoansToDeposits) + \propto_3 * ln(LoansToAssets) + \propto_4 * ln(ROA) \propto_5 * ln(BadLoans) + \propto_6 * IncGrowth + YearFE)$$

In addition to all the variables described above, I also include dummy variables for the year of a merger. Studying fourteen years of merger history, I included thirteen dummy variables in my model for all the years from 2003 up until 2015. Even though in the descriptive analysis section above I show that there is a sense of relative homogeneity across years, i.e. no particular spikes/sharp declines in the main indicators, including those dummies is a safe bet. Given large sample size, with loosing 13 degrees of freedom, I am making sure to control for changes in macroeconomic conditions, regulations, etc., which might be affecting the likelihood of a merger.

Results

Table 5 summarizes the values of estimated coefficients together with their significance levels for three subsamples as described above.

As the outcome, coefficients on three of the variables turned out to be significant at any level of significance across all three samples. Firstly, loans-to-deposits ratio seems to be positively associated with the likelihood of being acquired. The result is in line with Palepu (1986), Cudd and Duggal (2000), Baixauli (2009) and Pervan (2010) supporting the growth-mismatch hypothesis.

Secondly, ROA is negatively associated with the LHS variable with extremely high significance. This means that less profitable bank is more likely to get acquired, other things equal. One can interpret this finding as yet another supporting argument for the hypothesis that acquirers are looking for banks with some growth potential to acquire.

Table 5. Regression results for models with multiple merger factors

	(1) Small sample	(2) Medium sample	(3) Large Sample
(Intercept)	-6.414***	-6.862***	-7.265***
	(0.388)	(0.36)	(0.334)
ln_Total_Assets	0.116	0.252	0.182
	(0.158)	(0.141)	(0.126)
ln_Loans_to_Deposits	0.500***	0.576***	0.526***
	(0.117)	(0.101)	(0.083)
ln_Loans_to_Assets	-0.303*	-0.256	-0.308
	(0.176)	(0.162)	(0.196)
ln_ROA	-1.212***	-1.127***	-1.023***
	(0.047)	(0.041)	(0.036)
ln_Bad_Loans	0.017	0.028*	0.025*
	(0.013)	(0.012)	(0.011)
IncGrowth	0.189***	0.298***	0.248***
	(0.022)	(0.023)	(0.019)
Year FE	Yes	Yes	Yes
N	8,213	13,437	23,884
Pseudo R2	0.14	0.16	0.17

Dependent variable: target bank
Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Thirdly, the coefficient on income growth is positively associated with the probability of acquisition at any level of significance, meaning that acquirers are looking not just for poor targets, but the ones, which are showing positive dynamics in terms of profits.

Finally, the coefficients on two variables related to credit risk quality – namely, Bad loans variable and Loan-to-assets ratios are borderline-significant in only some of the models. The sign of bad loans coefficient is as expected, showing that poor risk management quality might actually make a merger event more likely. As for the negative loans-to-assets coefficient, it does not support the hypothesis that large exposure to credit business is something acquirers are particularly looking for to invest.

Other variables included in the regression model turned out to be non-significant at 5% level. Most surprisingly, size of a target does not seem to substantially influence the probability of a merger.

Table 6. Regression results vs. expectations

Variable Name	**Hypothesis**	**Expected effect**	**Actual sign**
Total Assets	-Small banks have less transactional costs -They are less likely to defend themselves	-	0
Loans To Deposits	Growth-resource mismatch hypothesis: acquirers buying growth potential	+	+++
Loans to Assets	Transfer of managerial skills (economy of scope, synergy)	+	0/-
Bad Loans	Poor credit risk management; acquirers buying growth potential	+	0/+
ROA	Poor general management; acquirers buying growth potential	-	---
Inc Growth	Acquirers buying growth potential	+	+++

All in all, the findings are supportive of the consolidated hypothesis that acquirers are interested in buying a target with high potential to grow. Empirical evidence suggests that other things equal banks with higher loans-to-deposit ratio, lower ROA, higher income growth ratios are more likely targets in merger deals. At the same time, there is somewhat supportive evidence for credit risk portfolio being an important factor in target choice. Finally, there is no evidence in favor of size hypothesis. There seems to be an approximately equal chance to become acquired for banks of different size.

Chapter 3: Is an experience of collaboration a factor?

As long as each acquirer maximizes its' own utility function, it seems to be quite natural that the uniform patterns are difficult to be identified. The economic decision about merger shall not be considered aside of the context in which each particular bank operates. This is how e.g. economy of scope and diversification come into picture.

While some banks are willing for a target to operate on the same market in order to play on the possible synergies, others might hunt to expand into radically new geographies and/or product lines. As a consequence, the same target with exact same scope, ranking, history, financial indicators, etc. could be a dream choice for one acquirer, while for another one it would be the least desired company to acquire.

It is also very intuitive to suggest that each acquirer makes a deliberate choice between a number of potential target alternatives. What makes an acquirer to bid for one bank over the other?

The core question of this study is whether experience of previous collaboration is actually a valid factor for a merger. My hypothesis is that having an experience of working together makes a merger between two institutions more likely in the future. The way this hypothesis is addressed is through looking at the syndicated loan market in the US, and tracking whether those institutions who were often involved in the same syndicates tend to end up merging relatively more frequently. During collaboration within the same syndicate some financial information, business processes, etc. are likely to be disclosed. Moreover, managers might establish strong connections at the personal level. All of these establishes higher level of trust, which might play an important role in making the M&A decision going forward.

Further in this Chapter I introduce the concept of syndicated loan market and the role it plays in the international financial system. Then I introduce the dataset I have been using and the methodology to test the outlined hypothesis. Finally, the results are discussed.

Syndicated loan market: description

Syndicated loan is loan provided by a group of lenders (a syndicate) to a single borrower. This form is usually chosen when a project requires too large amount of a loan for a single lender. By syndicating a loan, the participants share the risks of non-payment. As such, syndicated loans market allows financial institutions to take part in the deals they would otherwise not be able to finance given the limitations of their individual capital base. In most of the cases one of the banks takes the lead in arranging the project, negotiating the conditions with the borrower and other lenders, dispersing the case flows, and performing other administrative tasks. This bank is known as a lead bank, arranger bank, or underwriter of the loan. It typically also takes proportionally larger share of the total loan. Other banks are called participant lenders, and they usually do not have direct contact/relationship with the borrower.

Syndicated loans market is increasingly large and important source of lending. Similar to other credit risk sharing mechanisms, syndicated loan market have been experiencing booming in the pre-crisis years. For instance, the loans issued to the US borrowers skyrocketed from $130 billion in 1987 to almost $2 trillion in 2006 (Mora 2013). The volumes went back to the pre-crisis levels in 2013 and then shown slightly decreasing trend (Thomson Reuters 2015). Overall, the market covers around one third of total external financing for companies, which makes it extremely important component in global banking world (Thomson Financial 2009).

The fact that arrangement of a syndicated loan involves multiples parties and shared responsibility makes agency problem particularly important and sensitive issue here. The main domain for agency problem is the asymmetric nature of information between the borrower and the arranger lender and it has been studied e.g. in the work of Sufi (2007). However, it is also true that the information about lenders is by far not full as well. At the stage when an arranger has to determine the initial pool of participants to appoint, it considers all the information available to assess their trustworthiness and reliability as potential partners.

The process in general is very much dependent on the lead bank, since it is the one responsible for structuring the syndicate, and organizing the deal at all levels, including ex-post monitoring. However, the success of the whole transaction is dependent on all the parities involved. Eventually the decision on entering in loan transaction with other lenders comes to mutual trust and reciprocity. Loan market participants are motivated in building the reputation of a reliable lender increasing their potential exposure to the broader spectrum of deals in the future. Lenders experience and reputation basically serve as a mitigation mechanism for the problem of not full and asymmetric information. Some empirical evidence has been shown in support of this argument. For example, Champagne and Kryzanowski (2007) show that previous experience of participating in the same syndicate significantly increase the probability of getting into the same one again thereafter. Similarly, Cai (2010) discovered reciprocity as an important mechanism to cope with agency problem for a lead bank meaning that lead banks tend to pick the same lenders in different deals. All in all, it is clear that trust plays a crucial in role in information flows between the actors of syndicated loan market. This brings me to the point where I consider lenders in syndicated loan market as a social network structure. Serving as an information network, syndicated lending market allows participants to catch some private non-public insights on the lenders' reliability and trustworthiness.

Network of lenders: data and descriptive statistics

The interactions between financial institutions could be imagined using network representation. In order to define a network, one basically needs to define two object: what a node of the network is, and how links between the nodes are defined. The link represents a certain relationship between the nodes. Although the network analysis techniques are becoming more and more popular, the financial data is still rarely analyzed from that angle (Allen and Babus 2008).

In most of the cases, the inter-bank relationships are not really observed to the outsiders, making it difficult for the researchers to construct the network behind. On the contrary, syndicated lending represent visible manifestations of bank interactions, which can be easily modeled by outsiders (Champagne and Kryzanowski 2006). Baum et al. (2004) apply network analysis to study the motives of banks participating in syndicated lending in Canada. Later, Goldewski et al. (2010) used networks to examine the banks' position in the network affects loan spreads in the context of French syndicated loan market.

To study syndicated loan structures I am using the DealScan database collected by Thomson Reuters. The dataset contains comprehensive information on lending institutions participating in loan syndicates between 1987 and 1997, where USA was reported as the country of syndication. This sample consists of almost 20,000 deals involving 3,739 financial institutions. For the purpose of this study I consider the data on lenders, leaving the borrowers aside.

The initial dataset contained information on every deal, including date and full list of financial institutions participating in that deal. This type of data is classified as so-called bipartite network, meaning that we do not have the explicit data on how the information flows between the participants (unlike, e.g. transactional data, or data on social interactions stored in telecom companies/social media applications). Instead, the bipartite network contains objects of two types, and we only observe the connections between the nodes of two different types. The typical examples for bipartite networks are network on scientific collaboration (authors and papers) and ingredient-flavor network. In case of syndicated loan lenders the two types of the objects are the Deals, and the Banks (see Figure 4 below). The arrows here do not mean information flow like in the classical network representations, but rather ‘affiliation’ of banks to deals.

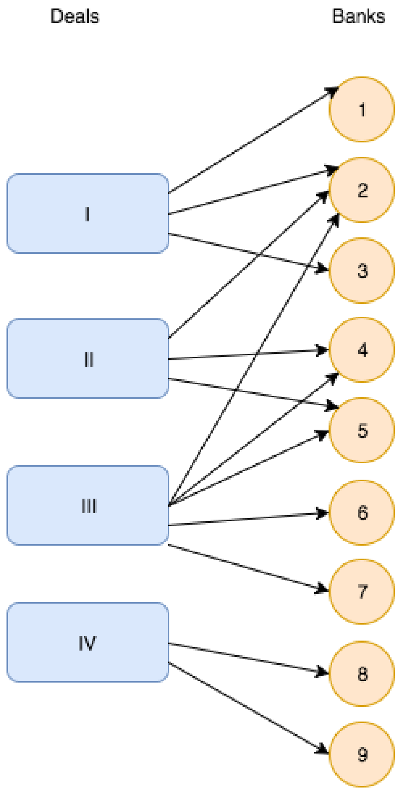

Figure 4. Constructing a network of lenders: initial dataset

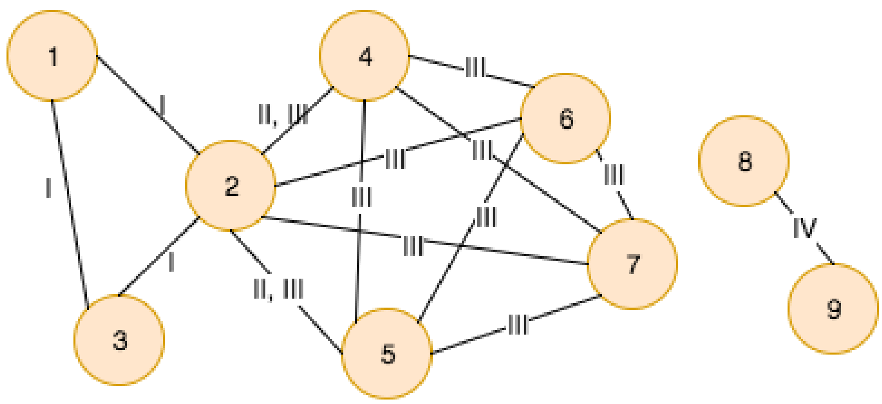

Figure 5. Constructing a network of lenders: bipartite projection

In order to compress information contained in this network, I have performed the bipartite transformation to the sub-network of class 'banks' (one-mode projection). The network was projected in a w ay, that two nodes representing banks would become connected, if and only if they have ever participated in the same deal (see Figure 5 above). The label on the link depicts the deals, where those banks have been both present. The edges in the projected network have a weight property, which basically show the number of deals where the two banks were participating together. In the example below, the majority of the bank pairs happened to participate in only of the deals together with the exceptions of banks 2 and 4, and banks 2 and 5, who have 'shared' two deals. However, in the full-scale sample, the number of deals would be way larger as compared to this dummy example, making the chances of any two banks to 'meet' multiple times much higher.

After projecting the bipartite Dealscan data to the network of banks as described above as a result I got network with 3,739 nodes (number of unique lenders in the given time frame) linked by more than 264,000 links among each other (self-links excluded).

The resulting network is extremely dense. On average a bank is directly connected to 141 other banks in the network. In network science terms, this characteristic is called the average node degree.

Given that the degree distribution illustrated in Figure 6 below clearly follows the power law, the network could be classified as a so-called small-world network. There are few huge hubs, i.e. very interconnected nodes (financial institutions, most likely the lead banks, who have come across almost all other banks). At the same time few hundreds of banks in that network have been working together with less than ten other banks. The "small-world" structure is a typical feature for many social networks (Barabasi 2016), which means that they are characterized by relatively small average path value and high clustering coefficient. The network of US lending institutions operating in syndicated loan market has a small-world property, as already was pointed out in the work of Godlewski et al. (2010).

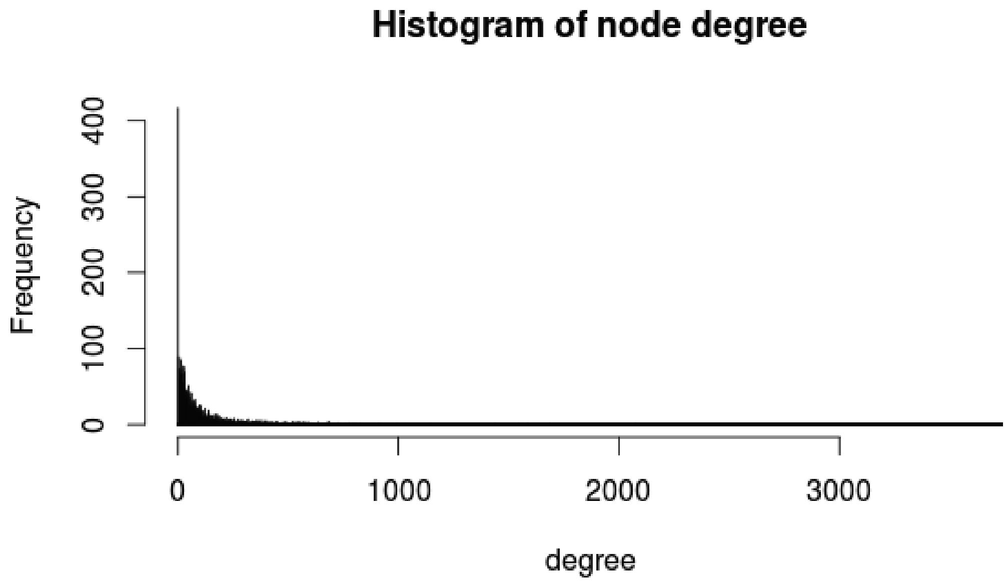

Figure 6. Degree distribution for the network of lenders

As a part of network descriptive analysis, I have attempted to detect communities, that are roughly defined as the set of nodes, which are densely connected between each other. In other words, a pair of nodes is more likely to be connected, if both of them are members of the same community. Community structure is an important property of network, as it often provides insights on network topology and helps understanding the ways information disperses over the network. To get the community structure, I have run an algorithm based on greedy optimization of modularity. As an output, the algorithm detected a huge number of communities – 342 for the sample of 3,739 nodes. In fact, there is one very large community (a clique) which accounts for more then 60% of the sample. Top-4 largest communities jointly cover around 80% of the sample, the rest being distributed equally between communities of fairly small size. This kind of topology suggests that most of the banks are highly interconnected in the network, which would only be possible if banks would be participating in multiple deals, ‘meeting’ different partners in different deals. At the same time, there are some banks, which only participated in one single deal. In this case a small community would be distinguished containing those banks only. In the fictional example in Figure 5 this would be the case of banks 8 and 9, who are basically not connected to the rest of the network.

Methodology

The central research question of the study is to examine whether the experience of collaboration affects this decision. To put it in more practical terms, I would like to test if the banks, which have been partners in syndicated loan market are more likely to sign a merger deal.

In order to address this question I am using the compiled dataset on merges and acquisition discussed in Chapter 2, as well as the DealScan database introduced in the beginning of this chapter.

It is important to keep the time frame consistent. As I attempt to study how the dealscan collaboration might potentially affect the merger events, I had to make sure, that the later occurred earlier in time. This is achieved by simply separating the time frames of the two data sources: I studied the syndicated loans activity for the period from 1987-1997, whereas the merger activity in scope started from 2001 onwards.

The sample construction process looked as follows:

1. Selecting 400 largest American banks in terms of total assets as of 1997Q4
2. Looking up the banks selected in 1 in the Mergers dataset appearing as targets starting from 2001; storing deal date, target and source name, target and source state affiliation.
3. Damping the DealScan lenders names with respect to the time frame (1987-1997).

4. Mapping the bank names from 2 (both target and sources) to those from DealScan database (applying similarity-based algorithms + hand-matching)
5. Constructing a counterfactual group based on similarity matrix

The most time consuming exercise of this thesis was step four from the above list, i.e. merging the DealScan database with the Call Reports database. To the best my knowledge, only few authors have done this before, with Guner (2007) being one of the rare exceptions. He used the merged dataset in order to study fluctuations of the cost of corporate capital in the lending market.

Only 28 bank names had exact match across the two data sources. As the naming conventions are completely different in the two datasets, the automated fuzzy string matching algorithms have given only suboptimal results. The combination of Levenshtein distance, Jaro-Winker distance and Longest common subsequence algorithms gave around 25% of the matches (100 matches out of 400 potentially possible). The rest was compiled manually. At the end, 263 acquired banks have been linked to the Dealscan database. Out of those, for 189 the name of the sourced bank was also available in the Dealscan notation. Thus, the sample consisted of 189 merged bank pairs, where for both the source and the target there was information on call reports indicators, as well as the information on history of syndicated loan business. 14 out of 189 mapped bank pairs happened to participate in at least on syndicate together. Given that both dataset cover state-level banks, no consolidation to the country level have been applied and banking subsidiaries have been treated as separate entities.

As I am attempting to catch the potential effect of the partnership among financial institutions on the likelihood of a merger, as a left-hand side variable I use the probability of a merger event. Since merger is a two-sided action, the dummy variable for a merger equals to one in case the merger occurs between two financial institutions, and zero otherwise. Following approach of Akkus (2014) I understand merger event as a result of matching game, meaning that each realized target-acquirer pair observed in the market have a number of counterfactual pairs in the background.

Most of the authors use non-successful mergers as a counterfactual group. It is common for an acquirer to make multiple bids, however after considering the cases carefully, only one of those would turn into an actual deal. Similarly, at a preliminary stage, a target might participate in negotiations with multiple acquirers. Thus, typically the datasets used in the merger literature contain both successful as well as a great deal of non-successful deals, providing researchers with the natural comparison group (e.g. Foracelli et al. 2002). However, in the dataset I am using in the current work, only successful mergers are listed with no reference to the bidding stage. In this case there is no way to clearly define factors distinguishing banks ended up being actual targets in merger deals. In such situations, the counterfactual group must be created artificially. Taking all the potential bank pairs is not an option given the size of the sample and the amount of hand-matching involved. Instead I proposed detecting factors inducing the probability of a merger in a two-step manner. As a first step, the comparison group is to be constructed based on the similarity matrix. The idea is that for every actual target bank I would find another nine banks, the most similar to the acquired one as of year prior to the year of merger. After that, I would check if the experience of collaboration in syndicated loan market is relatively more frequent for the banks which were actually chosen as targets as compared to the ones which were similar to them, but were not acquired at that year.

In the first step, I select the similar banks to each of the 189 pre-selected targets along the following dimensions:

- Total assets
- Total loans & deposits
- Total liabilities
- Total equity
- Total deposits

Those variables were selected from Call report database as the most basic and fundamental characteristics of bank activity. The closest neighbors were found by constructing a simple similarity matrix based on the Pearson's correlation coefficient using the five variables listed above. Ten banks with the highest similarity value (the targeted bank itself plus nine neighbors) were taken to the final sample. All the ten were 'paired' with the actual source bank. Eventually, the dataset consisted of 1890 observations, 189 were actual mergers, whereas there rest were artificially constructed pseudo-mergers. All together in 102 cases the two banks had some common history in terms of collaboration in syndicated lending.

In the second stage I ran a logistic regression on the dataset obtained in the first step. As a left-hand side variable I use the dummy variable, which is equal to 1 in case the two banks have merged, and 0 in case they have not. By construction the share of ones in the data is 10%, which makes the sample relatively balanced. The right-hand side variable of interest is related to the preceding collaboration between the two banks. I test this relationship in different specifications, varying the way the collaboration is defined and measured (the DealScan variable).

In the first specification the collaboration is measured as number of common deals the two banks had in the syndicated loan market. In 102 observations out of 1890 the two banks had at least one deal together earlier. In 48% of those cases the number of shared deals were less than five. The maximum number of common deals between the source and the target banks was 57.

Because the distribution of the number of common deals is skewed, in the second specification the logarithmic transformation was applied to the same variable (preliminary adding 1 in order to process the observations with no common deals). In the third specification the binary version of the same variable is used, which is equal to one, in case the two banks had at least one common deal together.

In the last two specifications the network science related measures were used for coding the experience of the two banks from syndicated loan market. The shortest path metric was used as the first one. Running a short path algorithm between every bank pair combination gives a minimal number of steps needed in order to get from the first node to the second, moving along network edges. It would be equal to one in case two banks share a link; equal to two in case two banks share a common neighbor, etc. By taking the shortest path between the two banks, I attempt to catch non-direct relationship between the two banks. Using this metric allows to better differentiate degrees of proximity. Even if the two banks are not directly connected in the network, i.e. they have not been part of the same syndicate in the past, the fact that they are located closely in the network might still make a difference. For instance, being connected to the same third party might actually enhance the trust level and positively affect the chances for the merger in the future. Thus the coefficient on shortest path variable is expected to be negatively associated with the probability of a merger.

Finally, based on the community split described above, the binary variable was created, which was equal to one in case both source and target did belong to the same community, and zero otherwise. The idea behind is that the pair of nodes is more likely to be connected if both of them are members of the same community. Here again, unlike in the first three specifications, I do not require the two banks to be directly connected, allowing for them not to have a direct link (a common deal), but rather belong to the same community, sharing some common links. In case trust considerations actually do have some weight on manager decisions, then one might expect that it would also spread through the 'third parties' – members of the same community – even if not connected directly.

Source and target banks, which were part of the final sample, are spread across twelve different communities. However, as noted before, one community essentially dominates in numbers. Due to this fact, in 62% of the cases the community of the target is same the community of a source bank.

Additionally, I control for the geographic proximity, by including the dummy for the same state. Clearly, if the two banks are located in the same state, their chances to participate in the same merger deal are expected to be higher than if they are located in the opposite parts of the country.

Furthermore, the size of the acquirer is controlled for, measured in total assets. As the banks participating in syndicate lending are likely to be larger on average, I would like to separate the size factor from the 'experience of working together' factor. For the sake of simplicity, no other control variables are used.

Thus I estimate the following functional model with binary logit regression:

$$Prob(Pair\_merger = 1) = F(\propto_1 * DealScan + \propto_2 * Common\ State + \propto_3 * TotalAssets(acquirer)),$$

where DealScan variable is measured according to one of the five different approaches described above. Positive significant value of $\propto_1$ would mean that experience of collaboration is associated with higher probability of a merger for any bank pair.

Results

The results for all five specifications are summarized in Table 7. Few observations were loosed in (4) and (5) specifications due to missing observations in network mapping.

In two out of five models the coefficient of interest turned out to be significant. In the baseline model (the one with simple number of common deals as an independent variable) In terms of magnitude, the effect is pretty sizable: one more deal is associated on average with ~e^(0.001) ≈1.001 change in the odds ratio of a merger event, which is equal to probability of a merger over probability of a non-merger. If considering the logarithmic version of the same variable, the significance is also there: 1% higher number of deals is associated with ~1.01^(0.019) ≈ 1% change in the odds, other things being equal.

Table 7. Regression results for models with collaboration factor

	(1)	(2)	(3)	(4)	(5)
Intercept	0.08*** (0.006)	0.079* (0.006)	0.079*** (0.006)	0.901*** (0.015)	0.904*** (0.024)
Number of Deals	**0.001*** (0.000)**				
Number of Deals (binary)		0.0372 (0.0203)			
Number of Deals (log)			**0.019* (0.009)**		
Shortest Path				-0.001 (0.003)	
Same community					0.006 (0.234)
CommonState	0.121*** (0.029)	0.16*** (0.041)	0.082*** (0.012)	0.114*** (0.031)	0.123*** (0.022)
Total assets (acquirer, log)	0.222 (0.158)	0.252 (0.157)	0.196 (0.144)	0.2 (0.161)	0.26* (0.133)
N	1,890	1,890	1,890	1,674	1,674
Pseudo R2	0.05	0.03	0.02	0.02	0.03

Dependent variable: merger event (for a bank pair)
Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

In other specifications the coefficient on that variable was insignificant at 5% level. The results suggest that only the experience of direct contact is associated with higher merger probability. The indirect relationship through the network of common ‘friends’ and communities does not seem to affect the probability of a merger event in any way. It might happen, that the trust matters are not really transferable through the network, and could only be affected by the fact of personal direct communication and collaboration. Furthermore, what seems to matter at the end is the magnitude of the direct collaborative experience (measured in terms of the number of joint deals), as opposed to the simple fact of such experience.

The coefficient on the variable Common state is very significant across all the specifications, suggesting that other things equal if the two banks are located in the same state they have higher odds of merging.

Please note that fairly low levels of R-squared imply that the model described above shall not be used for predicting purposes. Even though there is some evidence for positive association between variable of interest and the relative merger probability in some of the specifications, it is also true that many other variables predictive of merger event are missing from the model. The purpose of this thesis was to check potential importance of the collaboration factor. Building a prediction model for the future mergers was not in scope of this study.

Policy implications

Mergers and acquisition topic has always been a hot topic for policy makers. In general there are not so many areas where public policy measures have created so much public debate, but policy addressing anti-competitive mergers is definitely on of those. The potential consequences of increased market concentration on competition environment, firms' efficiency indicators, and pricing have been extensively addressed both among academic scholars and regulators.

All of the above is probably important for financial service industry more than for any other, given the central role of banking in international economic stability. Clearly, larger degree of interdependencies between large banks and other financial institutions implies also larger systematic risk. It is reasonable to assume that the level of interdependencies goes hand in hand with higher degree of consolidation. A number of issues shall be specifically addressed by policy makers in this regard. First of all, they have to decide on mechanisms assuring protection of depositors in case of financial difficulties. If a major financial distress occurs, the central banks would have to make cautious decisions about allocation of emergency liquidity across large complex consolidated institutions, as well as adjust the monetary policy stances. This is one of the main reasons justifying the existence of legal approval procedure by multiple bank authorities as a must step before any merger can take place.

This is why predicting merger activity in banking is crucially important for public authorities in order to assure overall financial stability. The current work adds to the existing literature an important factor to consider when predicting potential merger targets. As shown, the degree of previous collaboration is somewhat associated with the likelihood of a merger in the future. Provided that the experience of collaboration actually enhances the trust level and helps bank managers more informed and balanced decisions on whom they want to acquire.

The market efficiency of such acquisition would depend, however, on whether it was driven by value-maximizing motives or managerial personal goals. Be that the former or the latter, the managers would perhaps be more informed and thus more enabled to achieve whichever goal they had.

Conclusion

This paper analysis the factors and motives behind mergers and acquisitions both from theoretical perspective (Chapter 1) and empirically (Chapter 2) on a manually collected dataset of US banking institutions starting from 2001.

Among a number of factors that have been tested, some turned out to be significant in the regression model. Those are the factors related to the motive of expanding growth opportunities for a source bank: higher loans-to-deposit ratio, lower ROA, and higher income growth ratios are associated with on average higher probability of becoming a target, other things equal. Surprisingly, the size of a target does not seem to do anything with the probability of a merger in general, despite the fact that targets are on average smaller than source banks.

Further, the importance of the factor of collaboration was tested in a separate model presented in Chapter 3. The idea is that experience of working together mitigates the issue of non-full information, which often serves as an essential hindrance in the process of target selection. By working in a same syndicate the banks might get insights on strategy and operations of another party, its financial situation as well as corporate culture. All of these might establish high level of trust and alter the chances of selecting an ex-partner for a target role.

For testing this hypothesis the data on syndicated loan market has been linked to data on M&A. Some insights on the structure of network of syndicated lending participants were discovered. For example, the network of lenders is a very dense small-world network, meaning that participants are highly interconnected with each other through few ‘hub’ banks.

The two-step methodology was suggested for estimating regression model coefficients, where the unit of observation is a bank pair, as opposed to just a bank. Constructing a model in such way allows answering a question of why some targets were chosen *over the others*, as both actually merged and factious bank pairs were part of the sample.

The estimated logit coefficients on a sample of 1,890 bank pairs imply that the experience of direct collaboration is positively associated with the probability of a merger. At the same time the indirect relationship through the network of common ‘friends’ does not seem to affect the probability of a merger event. This could be the case if trust matters are not really transferable through the network, and could only be affected by the fact of direct personal communication of the two banks, without intermediaries. Furthermore, a simple fact of such experience does not affect the probability of a merger significantly, too. What seems to matter at the end is the magnitude of such experience, measured as the (log) number of the joint deals.

In the conclusion, let me discuss the limitations of this study. First of all, this work is based on a sample of mergers and acquisitions that took place in the US only. The generalization to of the results to the non-US markets should be done with caution given a number of cultural and institutional factors specific for this country.

Secondly, due to the fact that sample construction process involved the hand-matching of the two large datasets, the sample size was limited to few hundreds of observations. One of the important directions for further extending this research is applying the suggested methodology over a larger sample of banks and possibly longer and more fragmented time horizon.

Appendix

Table 8. Number of Bank Mergers by State by Year, 2002-2015

			Year													
State		**Total**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
AK	Alaska	**5**		1				1			1				2	
AL	Alabama	**39**	4	1	2	2	2	5	5	3	7	4	1	1	2	
AR	Arkansas	**55**	4	4	1	9	2	3	5	7	4			6	9	1
AZ	Arizona	**45**	2	3	1	1	4	4	3	11	2	5	2	4	1	2
CA	California	**184**	19	14	13	11	19	12	7	16	16	12	13	14	10	8
CO	Colorado	**93**	7	3	5	5	8	8	6	3	28	4	5	7	1	3
CT	Connecticut	**29**	2	2	6	2	1	2		2	2	1	3	4	1	1
DC	District of Columbia	**4**				1	1					1		1		
DE	Delaware	**23**	2	2	2	1	2	2	1	1	1	5	2		2	
FL	Florida	**168**	2	6	18	8	11	9	21	13	25	11	13	9	13	9
GA	Georgia	**170**	14	7	10	6	10	9	25	19	29	17	9	3	7	5
HI	Hawaii	**1**														1
IA	Iowa	**81**	6	8	5	3	4	5	7	6	7	8	5	7	7	3
ID	Idaho	**9**		1	1		1		1				2		3	
IL	Illinois	**251**	17	14	14	44	22	14	11	22	18	17	12	12	16	18
IN	Indiana	**62**	3	2	5	5	11	7	2	7	2	1	4	4	6	3
KS	Kansas	**100**	8	2	6	4	8	5	8	5	12	7	17	8	6	4
KY	Kentucky	**68**	8	6	7	5	6	13	7		1	1	2	4	3	5
LA	Louisiana	**30**	2	2	1	2		2	3	1		9	1	2	3	2
MA	Massachusetts	**50**	5	4	4	5		9	5	2		2	5	3	4	2
MD	Maryland	**48**	1	5	6	3	1	10	3	3	1	1	4	4	4	2
ME	Maine	**3**					1	1					1			
MI	Michigan	**49**	3	1	4	2	3	6	3	6	5	3	1	2	7	3
MN	Minnesota	**156**	16	6	6	18	16	8	7	15	6	11	8	12	18	9
MO	Missouri	**85**	4	3	6	4	10	6	7	6	9	2	14	7	3	4
MS	Mississippi	**19**	2	2			3		3	1	1	2		2	1	2
MT	Montana	**24**	1	2		1		1	2	3			7	1	3	3
NC	North Carolina	**56**	5	6	3		3	2	4	5	1	3	6	10	7	1
ND	North Dakota	**19**		3	2	3	2			1		2		2	3	1
NE	Nebraska	**63**	7	8	5	3	5	4	3	5	7	5	4	4	1	2
NH	New Hampshire	**11**			1	2	1	3	1				2		1	
NJ	New	**36**	2	3	4	5	1	2	2	2	1	3	1	7	1	2

	Jersey															
NM	New Mexico	**11**			1						1	1	1	2	2	1
NV	Nevada	**23**	2			1	5	1	2	1	4	2	1	4		
NY	New York	**54**	6	2	1	8	6	7	2	1	4	3	5	2	3	4
OH	Ohio	**73**	3	3	10	4	3	10	12	6			3	5	10	4
OK	Oklahoma	**56**	10	2	2	1	7	3	5	2	3	4	5	4	4	4
OR	Oregon	**13**	2				1	2	1		1		2	3		1
PA	Pennsylvania	**80**	4	9	7	7	6	11	9	4	4	6	3	2	5	3
PR	Puerto Rico	**6**	1		1						3		1			
RI	Rhode Island	**7**	1			1		1	1					2		1
SC	South Carolina	**45**	1	8		4	6	3	2		5	6	5	2	2	1
SD	South Dakota	**31**	4	2	1		3	1	2	4	2	3	3	1	3	2
TN	Tennessee	**57**	1	5	6	8	7	3	4	3	3	2	2	3	4	6
TX	Texas	**233**	16	22	18	21	14	7	12	13	14	11	31	24	19	11
UT	Utah	**13**		1	2	2	1	1	2	2		1				1
VA	Virginia	**69**	3	9	5	3	19	9	5		2	3	5	1	4	1
VT	Vermont	**4**		1				1						1	1	
WA	Washington	**42**	1		4	4	3	4		2	8	7		6	2	1
WI	Wisconsin	**60**	6	4	2	6	1	7	9	2	4	1	6	4	7	1
WV	West Virginia	**17**	1	3	1	3		2	1	1		2	2		1	
WY	Wyoming	**18**		4		1	1	2	4	2			2	1	1	
Total		**2948**	**210**	**196**	**199**	**229**	**241**	**228**	**225**	**208**	**244**	**189**	**221**	**207**	**213**	**138**

Table 9. Total Assets – descriptive statistics by year, 2002-2015

	Total Assets					
	Mean			Median		
Year	Target (mln USD)	Acquirer (mln USD)	Ratio (target to acquirer, %)	Target (mln USD)	Acquirer (mln USD)	Ratio (target to acquirer, %)
Total	**1 230**	**19 108**	**25,63**	**149**	**1 070**	**15,24**
2002	1 198	12 681	26,84	103	882	13,48
2003	982	17 260	26,35	109	1 061	13,27
2004	2 088	13 729	28,89	135	940	16,67
2005	1 599	14 927	37,12	139	1 168	12,74
2006	1 242	26 006	20,82	125	1 133	15,74
2007	1 254	14 188	25,19	152	951	17,29
2008	1 420	51 931	23,74	177	893	16,41
2009	1 945	26 964	28,94	149	845	19,94
2010	621	21 680	23,76	251	2 050	11,48
2011	1 722	15 334	27,90	156	859	20,31
2012	760	5 265	20,85	158	1 260	13,46
2013	570	17 316	26,15	161	967	19,70
2014	1 081	9 963	22,47	165	1 252	14,38
2015	703	16 514	18,25	133	1 147	13,74

Table 10. Total Deposits – descriptive statistics by year, 2002-2015

	Deposits					
	Mean			Median		
	Target (mln USD)	Acquirer (mln USD)	Ratio (target to acquirer, %)	Target (mln USD)	Acquirer (mln USD)	Ratio (target to acquirer, %)
Total	**796**	**12 192**	**26,07**	**121**	**855**	**15,77**
2002	633	7 620	23,02	90	622	14,45
2003	711	10 039	27,83	83	812	14,17
2004	1 054	8 526	29,58	108	694	16,69
2005	1 067	9 720	33,74	113	898	13,22
2006	612	14 703	21,47	98	922	15,69
2007	839	8 688	25,19	122	712	17,79
2008	975	30 053	24,57	143	658	16,98
2009	1 506	16 803	32,76	127	676	21,19
2010	509	15 776	25,89	210	1 574	12,20
2011	777	9 895	29,25	129	693	21,22
2012	649	3 959	22,23	137	989	14,22
2013	431	13 138	26,52	132	837	19,87
2014	836	7 763	22,96	144	1 051	14,47
2015	489	12 349	18,67	112	945	14,35

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