Are bank mergers good or bad? A welfare analysis with financial instability and bank synergy.

Final Report

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1.Introduction

Mergers play important role in the banking industry of the United States. In the 1990s, there have been more than 500 mergers each year, and as a result, the number of banks decrease from approximately 16,000 to 6,600.

Since the model in this paper is a partial equilibrium model, the social welfare in this paper is defined as a sum of consumer surplus, equity value of banks, and deposit insurance costs. While mergers may lower competition in the banking sector and harm consumer surplus, they may improve profitability of the merged bank and decrease default probabilities. This leads to stabilizing the whole banking sector as a failure of individual bank may result in a crisis of the whole banking sector. So lower competition may increase social welfare by increasing equity value of banks and decreasing deposit insurance costs.

In this paper, we develop a framework to study the effect of a merger in the banking industry on social welfare by taking into an account the instable financial system. To do so, we use the structural model of imperfect competition in the banking sector with a bank run developed by Egan et al. (2017) and calibrate the parameters before and after the merger.

We use the calibrated model to study the merger between Wells Fargo and Wachovia in 2009. According to the result, the social welfare is higher after the merger. One of the reason that social welfare after the merger is higher could be because after the merger, the financial system is stabilized, and the deposit insurance cost is lowered.

This paper contributes to the literature of the structural models of banking sector. Corbae and D'Erasmo (2013) builds a banking industry dynamics model with imperfect competition in the banking sector. Corbae and D'Erasmo (2021) use this model to study the effect of capital requirement on the banking sector, and Corbae et al. (2018) conduct a stress test of banking industry. Egan et al. (2017) build a simple model of imperfect competition in the banking sector with possibilities of bank runs. We contribute to this literature by applying the structural model of banking sector to banking mergers.

This paper is related to the empirical analysis of banking mergers. Bergers et al (1999) summarizes the earlier literature. Several studies (Sapienza (2002), Montoriol-Garriga (2008), and Ere (2011), among others) use contract level data of bank loans to study the effect of bank merger on loans. Uchino and Uesugi (2012) studies the effect of the merger between Bank of Tokyo-Mitsubishi and UFJ Bank in 2005 on the availability of funds for firms. Our paper contributes to this literature by developing a structural model of banking mergers for a counterfactual analysis, which is difficult to conduct with observational data. Akkus et al. (2016) estimated the matching function of acquirer and target banks in the merger market. Although their model is also structural, their focus is on the relationship between acquirer and target bank, rather than the merger and its implication on the financial system.

Ino and Matsuki (2020) studied the welfare effect of bank mergers using a structural model of imperfect competition in the banking sector. Their analysis assumed that the loan profit and cost parameters are the same before and after a merger. In this paper, we analyse how a merger changes these parameters by calibrating the model to the data before and after the merger.

The paper is organized as follows. Section 2 explains the data we use in this paper. Section 3 lays out a structural model of imperfect competition in the banking sector with bank runs. Section 4 describes the calibration procedure of the model parameters. Section 5 discusses how the merger between Wells Fargo and Wachovia affect the equilibrium allocation and social welfare. Section 6 concludes.

2. Data

This study uses the following four datasets on financial institutions in the United States.

- Deposit data from the FDIC
- CDS data from Markit
- Merger data from Federal Reserve Bank of Chicago
- Interest rate data from RateWatch
- Merger Data from Federal Reserve Bank of Chicago

For FDIC, Merger data, and interest rate we have the same identifier for a bank, RSSD number assigned by the Federal Researve. We don't have such identifier in the CDS data so we tried to match the data using the bank names. We describe the data below.

2.1 FDIC Data

We use Statistics on Depository Institutions issued by The Federal Deposit Insurance Corporation (FDIC). This data holds a number of variables related to financials, including the amount of deposits at financial institutions. In this study we use, among others, total deposits and FDIC-insured deposits. Since we know the total deposit of a bank, by subtracting the amount of FDIC-insured deposits from the amount of total deposits, we can compute the amount of non-FDIC-insured deposits. Using these data, we compute the market share of a bank in FDIC-insured and non-FDIC-insured deposit markets.

To investigate the size of each merger recorded in the merger data, we use RSSD ID to link this data to the FDIC data, and then Non-Survivor and Survivor deposits are merged. We use the deposit amounts immediately before the merger as representative values. In this process we eliminate irregular records.

A scatterplot of Non-Survivor and Survivor deposits for each merger is shown in the figure below. The horizontal axis represents the deposits of the Non-Survivor and the vertical axis represents the deposits of the Survivor. Both values are logarithmic. The red line in the figure represents the 45-degree line. This plot shows that Survivor is approximately larger than Non-Survivor for each merger and mergers are assortative matching.

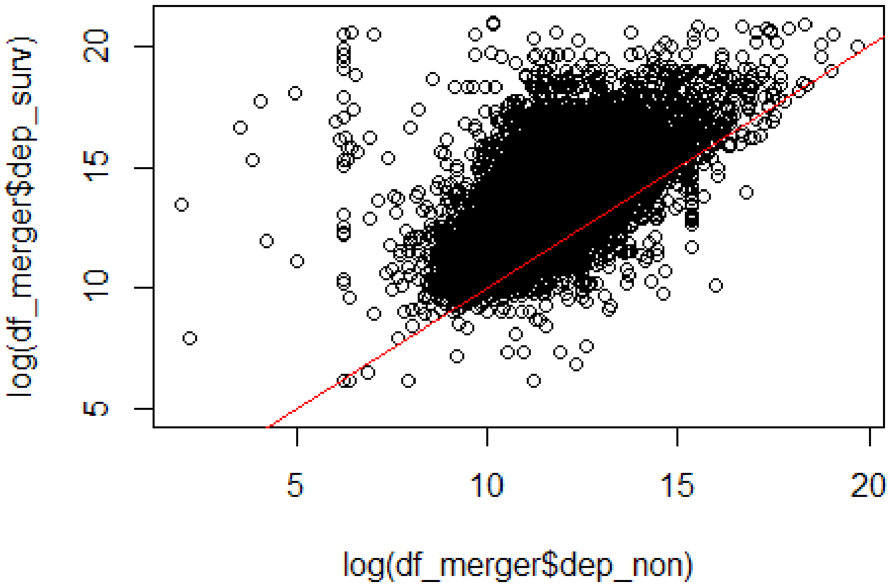

Figure 1: Relationship between survivor and target bank; deposit

We further examine the size of the mergers. Table 6 describes the top 15 mergers by Survivor deposit size. For some mergers, we see considerable asymmetry in the size of deposits. Table 7 shows the top 15 mergers by deposit size for Non-Survivor. This table gives a better indication of the size of the mergers. The top-ranked merger case is the merger between Wachovia and Wells Fargo. We will focus on this merger first.

2.2 CDS Data

We purchased the CDS data from Markit. This data records daily CDS spreads for financial institutions. We follow the EHM and use the spread of CDS with a 5-year maturity for the calculation of the probability of bankruptcy. We have already processed the data and have calculated the average monthly spread for each financial institution. We follow Hull(2012) to convert the CDS spread to default probabilities of banks.

The simple average of the spread plotted over the range we have is shown below. The numbers are roughly stable through 2007, but we see that the values have jumped since mid-2007, reflecting the financial turmoil and the Lehman Brothers collapse. This reflects the increase in the probability of bankruptcy of financial institutions.

2.3 RateWatch Data

We use the interest rate data provided by RateWatch. This dataset contains daily data of bank-level deposit rates for many deposit types, including the one-year certificate of deposit (CD) rate with a minimum deposit of \$10k and \$100k. From this data, we obtain insured and uninsured deposit rates for each bank. As EHM explains, insured and uninsured deposit rates are not directly recorded. As with EHM, the one-year certificate of deposit (CD) rate with a minimum deposit of \$10k is considered as the insured deposit rate because this deposit is subject to deposit insurance. The one-year CD rate with a minimum deposit of \$100k is considered as the uninsured deposit rate because this deposit is not subject to deposit insurance at that time. Monthly interest rates for each financial institution and deposit type were calculated by taking the median of the daily rates.

2.4 Merger Data

The data includes merger date, Non-Survivor RSSD ID and name, Survivor RSSD ID and name, etc. On the other hand, this data does not contain financial data such as deposit amounts. For this reason, the FDIC data will also be used. In this study we didn't use this data set directly, but we can extend our approach to more broad cases using this dataset.

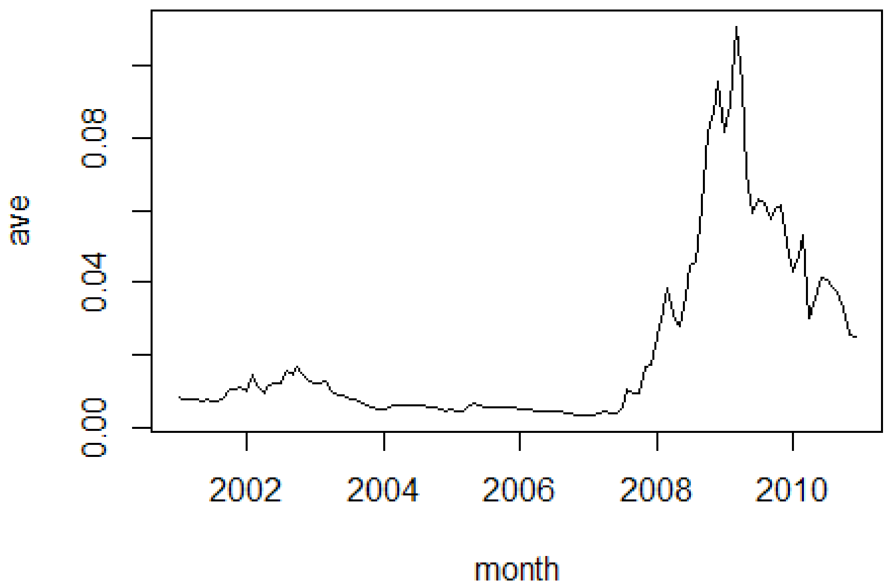

Figure 2: Average CDS spread

3. The model

The model in this paper is based on Egan et al. (2017). Time is discrete and continues forever. There are tree types of agents in this model: a mass M^I of insured depositors, a mass M^N of uninsured depositors, and K banks. Insured and uninsured depositors differ in the treatment of their deposit when a bank defaults: the deposit of uninsured deposit cannot be salvaged, while the one of the insured depositors will be fully salvaged. The timing of the model in each period is as follows.

1. Each bank k chooses interest rates for insured and uninsured deposits, $i^I_{k,t}, i^N_{l,t}$.
2. Depositors choose where to deposit.
3. Banks make loans and profit shocks realize.
4. Banks choose whether to repay deposits or default.

3.1 Depositors

An uninsured depositor j with type derive utilities from depositing to the bank k as follows:

1. Interest rate, $\alpha^N i^N_{k,t}$,
2. default probabilities, $-\gamma\rho_{k,t}$,
3. bank specific fixed effect δ^N_k, and
4. i.i.d utility shock, $\varepsilon^N_{j,k,t}$

So the utility the uninsured depositor j will obtain from depositing to the bank k is given by

$$u^N_{j,k,t} = \alpha^N i^N_{k,t} - \rho_{k,t}\gamma + \delta^N_k + \epsilon^N_{j,k,t}.$$

Insured depositors have a similar preference, but because of the deposit insurance, they do not lose utilities from default:

$$u^I_{j,k,t} = \alpha^N i^I_{k,t} + \delta^I_k + \epsilon^I_{j,k,t}.$$

We assume that the utility shock is distributed as the type-1 extreme value. Then given the interest rates, the market share can be written as

$$s_{k,t}^{I}\left(i_{k,t}^{I}, i_{-k,t}^{I}\right) = \frac{\exp\left(\alpha^{I} i_{k,t}^{I} + \delta_{k}^{I}\right)}{\sum_{l=1}^{K} \exp\left(\alpha^{I} i_{l,t}^{I} + \delta_{l}^{I}\right)} \tag{1}$$

$$s_{k,t}^{N}\left(i_{k,t}^{N}, i_{-k,t}^{N}, \rho_{k,t}, \rho_{-k,t}\right) = \frac{\exp\left(\alpha^{N} i_{k,t}^{N} - \rho_{k,t}\gamma + \delta_{k}^{N}\right)}{\sum_{l=1}^{K} \exp\left(\alpha^{N} i_{l,t}^{N} - \rho_{l,t}\gamma + \delta_{l}^{N}\right)} \tag{2}$$

In the following, market share functions omit dependency on interest rate and default probability to shorten the notation.

3.2 Banks

We assume that the number of bank, K, is exogenously given and constant over time. The objective of banks is to maximize its equity value. A return on loans is exogenously given as a stochastic shock by $R_{k,t} \sim N(\mu_k, \sigma_k)$. In addition to the deposit rate, for insured deposits banks need to pay insurance costs c_k.

Banks have issued a Consol bond in the past, so they need to repay b_k every period. This assumption ensures that banks choose to default with positive probabilities.

The profit function for Bank k at time t is then

$$\pi_{k,t} = M^{I} s_{k,t}^{I}\left(R_{k,t} - c_k - i_{k,t}^{I}\right) + M^{N} s_{k,t}^{N}\left(R_{k,t} - i_{k,t}^{N}\right).$$

Banks do not retain earnings, so they use the net cash inflow $\pi_{k,t} - b_k$ to pay dividends.

If a bank chooses to default,

1. equity holders lose their claim on future dividends,
2. the bank is liquidated to repay the depositors and bondholders,
3. exactly the same bank enters into the market so that the market structure does not change.

The last assumption is unrealistic, but it makes the computation of equilibria very simple by ensuring that the equilibrium is stationary.

3.2.1 Default choice

Let E_k denote the expected discounted value of future dividends of Bank k. Banks chooses to default if amount of capital injection needed to keep operating, $\pi_{k,t} - b_k < 0$, is larger than the future value:

$$\pi_{k,t} - b_k + \frac{1}{1+r} E_k < 0.$$

From the definition of the profit function, the left-hand side of the equation above is monotonically increasing in the loan return shock $R_{k,t}$. So there is a threshold value of the loan return shock, $\overline{R}_k$, below which banks chooses to default. It is given by

$$M^I s^I_{k,t}\left(\overline{R_k} - c_k - i^I_{k,t}\right) + M^N s^N_{k,t}\left(\overline{R_k} - i^N_{k,t}\right) - b_k + \frac{1}{1+r} E_k = 0.$$

After some manipulations, we can obtain the default threshold as a solution to the following equation:

$$-M^I s^I_{k,t}\left(\overline{R_k} - c_k - i^I_{k,t}\right) - M^N s^N_{k,t}\left(\overline{R_k} - i^N_{k,t}\right) + b_k =$$

$$\frac{1}{1+r}\left(M^I s^I_{k,t} + M^N s^N_{k,t}\right)\left[\mu_k - \overline{R_k} + \sigma_k \lambda\left(\frac{\overline{R_k} - \mu_k}{\sigma_k}\right)\right]\left[1 - F(\overline{R_k})\right]. \tag{3}$$

3.2.2 Interest rates choice

Banks choose the interest rates before they observe the loan return shock. In addition, banks will choose to default if the loan return shock is below $\overline{R_k}$. As a result, the Bellman equation for Bank k can be written as

$$E_k = \max_{i_k^I, i_k^N} \int_{\overline{R_k}}^{\infty} [M^I s_k^I(i_k^I, i_{-k}^I)(R_k - c_k - i_k^I) + M^N s_k^N(i_k^N, i_{-k}^N, \rho_k, \rho_{-k}^N)(R_k - i_k^N)$$

$$-b_k + \frac{1}{1+r} E_k] dF(R_k)$$

.

We can compute the conditional expectation analytically as

$$E_k = \max_{i_k^I, i_k^N} [M^I s_k^I(i_k^I, i_{-k}^I)\left(\mu_k + \sigma_k \lambda \left(\frac{\overline{R_k} - \mu_k}{\sigma_k}\right) - c_k - i_k^I\right)$$

$$+M^N s_k^N(i_k^N, i_{-k}^N, \rho_k, \rho_{-k}^N)\left(\mu_k + \sigma_k \lambda \left(\frac{\overline{R_k} - \mu_k}{\sigma_k}\right) - i_k^N\right) - b_k + \frac{1}{1+r} E_k]\left[1 - \Phi\left(\frac{\overline{R_k} - \mu}{\sigma_k}\right)\right]$$

The first order condition with respect to the interest rates are given by

$$i_k^I: \quad 0 = M^I \frac{\partial s_k^I(i_k^I, i_{-k}^I)}{\partial i_k^I}\left(\mu_k + \sigma_k \lambda \left(\frac{\overline{R_k} - \mu_k}{\sigma_k}\right) - c_k - i_k^I\right) - M^I s_k^I(i_k^I, i_{-k}^I),$$

$$i_k^N: \quad 0 = M^N \frac{\partial s_k^N(i_k^N, i_{-k}^N, \rho_k^N, \rho_{-k}^N)}{\partial i_k^N}\left(\mu_k + \sigma_k \lambda \left(\frac{\overline{R_k} - \mu_k}{\sigma_k}\right) - i_k^N\right) - M^N s_k^N(i_k^N, i_{-k}^N, \rho_k^N, \rho_{-k}^N).$$

We can simplify the equation above to obtain the following equations:

$$\mu_k + \sigma_k \lambda \left(\frac{\overline{R_k} - \mu_k}{\sigma_k}\right) - c_k - i_k^I - = \frac{1}{\alpha^I\left(1 - s_k^I(i_k^I, i_{-k}^I)\right)}, \tag{4}$$

$$\mu_k + \sigma_k \lambda \left(\frac{\overline{R_k} - \mu_k}{\sigma_k}\right) - i_k^N = \frac{1}{\alpha^N\left(1 - s_k^N(i_k^N, i_{-k}^N, \rho_k^N, \rho_{-k}^N)\right)}. \tag{5}$$

These equations can be interpreted as follow. The left-hand side is the expected return on loans minus the cost of loans, which is called the loan markup. These equations tell us that the loan markup is determined by the market share of the bank, s_k^I, s_k^N, as well as the sensitivity of depositors to the interest rate. α^I, α^N.

3.3 Equilibrium

An equilibrium in this model is (1) default probabilities ρ_k, (2) default threshold $\overline{R}_k$, (3) interest rates for insured and uninsured deposits i_k^I, i_k^N, and (4) market shares of insured and uninsured deposit markets s_k^I, s_k^N , $k = 1, \ldots, K$, such that

1. Depositors choose where to deposit to maximize their utility: (1) and (2)
2. Banks choose default threshold to maximize its equity value: (3)
3. Banks choose interest rates to maximize its equity value: (4) and (5)
4. Depositors' belief on the default probability is consistent with the default threshold chosen by banks:

$$\rho_k = P(R_k \leq \overline{R_k}) = \Phi\left(\frac{\overline{R_k} - \mu_k}{\sigma_k}\right) \tag{6}$$

There are 6 equations for each bank k, so we have $6K$ equilibrium conditions in total. The number of variables we have is also $6K$, so we can solve this system of equation to compute equilibria.

3.4 Financial instability due to self-fulfilling property

This model exhibits financial instability due to self-fulfilling property in the following way. Suppose that uninsured depositors suddenly believe that Bank k is going to default. Then they will incur higher deposit rate, or they will withdraw their deposits. To attract deposits, Bank k should increase deposit rate for uninsured deposits, which leads to lower profit and higher default probability. As a result, the initial belief that Bank k is going to default can be correct. Because of this nature, this model is suitable to study the effect of mergers on the competition and financial stability.

4. Calibrations

In this section, we use the merger between Wells Fargo and Wachovia to study the effect of a banking merger on the social welfare. We set $K = 5$ (Bank of America, Citibank, JP Morgan, Wells Fargo, Wachovia) before the merger and $K = 4$ (Bank of America, Citibank, JP Morgan, Wells Fargo) after the merger.

We can solve the equilibrium condition to obtain the parameters as a function of data variables:

$$\sigma_k = \frac{\frac{1+r}{M^I s_k^I + M^N s_k^N}\left(b_k - M^I s_k^I \mathcal{M}_k^I - M^I s_k^N \mathcal{M}_k^N\right)}{(\rho_k + r)\left[\widetilde{R_k} - \lambda\left(\widetilde{R_k}\right)\right]}$$

$$\mu_k = i_k^N - \sigma_k \lambda\left(\widetilde{R_k}\right) + \mathcal{M}_k^N$$

$$c_k = \left(i_k^N + \mathcal{M}_k^N\right) - \left(i_k^I + \mathcal{M}_k^I\right)$$

Where $\mathcal{M}_k^j = 1.0/\left(\alpha_j * \left(1.0 - s_k^j\right)\right)$ is the loan markup and $\widetilde{R_k} = \Phi^{-1}(\rho_k)$ is the normalized default thresholds. Using these equations, once we know the value of interest rates and default probabilities, we can calibrate the loan return and insurance cost parameters. For the demand side, we use values estimated by Egan et al. (2017). Since their estimates is based on the data from 2002-2013, we use the same estimates before and after the merger.

Table 1 summarizes the parameters before the merger. For the equilibrium after the merger, we re-calibrate the bank specific parameters, (μ_k, c_k, σ_k).

Parameter	value	description
α_I	58.79	Depositor sensitivity to interest rate (Insured)
α_N	16.64	Depositor sensitivity to interest rate (Uninsured)
γ	-12.60	Depositor sensitivity of bank default
r	0.05	Discount rate
M^I	4440000000	Insured deposit market size
M^N	4140000000	Uninsured deposit market size
ω	0.439	Weighting parameter for merged lending
b_k	[6547896, 23100000]	Consol bond
μ_k	[0.074, 0.081]	Mean return on loans
c_k	[0.046, 0.055]	Non-interest cost of loans
σ_k	[0.11, 0.29]	Standard error of loan return

Table 1: Parameter values before the merger

We will use the data after merger to estimate the parameter values after the merger and use it to compute equilibria and social welfare after the merger. The social welfare of this model can be computed as follows. Following chapter 3 of Train(2009), under the assumption that the error term follows i.i.d extreme distributions, we can write the consumer surplus of depositors as

$$CS = \frac{M^I}{\alpha^I} \ln\left[\sum_{l=1}^{K} \exp(\alpha^I i_l^I + \delta_l^I)\right] + \frac{M^N}{\alpha^N} \ln\left[\sum_{l=1}^{K} \exp(\alpha^N i_l^N + \delta_l^N + \gamma\rho_l)\right]$$

The annualized equity value of banks is given by

$$AEV = \sum_{l=1}^{K} r\, E_l.$$

Assuming a 40¥% recovery rate, the expected FDIC insurance cost is

$$EC = 0.6 \sum_{l=1}^{K} \rho_l M^I s_l^I.$$

Then the change in welfare can be computed as

$$\Delta W = \Delta CS + \Delta AEV - \Delta EC.$$

Since our model is a partial equilibrium model, we will use it as a social welfare.

5. Numerical results

Using parameter values in the table 1, we can compute equilibria before the merger. Table 2 summarizes the result. In addition to the observed data, we computed some equilibria where bank run takes place at each bank as well as the best equilibrium in terms of social welfare. Note that this is not an exhaustive list of equilibria: there can be other equilibria in this model. This result shows that in March 2008 there are multiple equilibria, and bank runs was possible, although we didn't observe it in the reality. In addition, this result shows a contagion of bank run through competition: when bank run occurs at a bank, it will increase its deposit rate, and through competition, other banks must increase their deposit rate. As a result, not only the bank which suffers from the bank run, but also all bank experience an increase in the default probability.

Bank name	Obs. eqm	Best	Bank run at Wells Fargo	Bank of America	JP Morgan	Citi
Insured interest rate						
JP Morgan	1.73	0.98	2.46	2.65	10.48	3.17
Bank of America	1.98	1.53	2.13	7.34	2.44	2.46
Wells Fargo	2.13	2.05	10.05	3.06	3.57	3.68
Citi	2.23	2.11	3.01	3.21	3.72	12.26
Wachovia	2.08	2.04	2.59	2.62	2.93	2.98
Uninsured interest rate						
JP Morgan	1.73	0.94	2.41	2.56	20.35	3.02
Bank of America	1.97	1.4	1.94	11.43	2.23	2.24
Wells Fargo	2.32	2.25	17.41	3.21	3.71	3.81
Citi	2.23	2.13	2.94	3.09	3.52	24.35
Wachovia	2.23	2.19	2.67	2.71	3.00	3.04
Default probability						
JP Morgan	1.5	0.19	2.86	3.29	48.35	4.36
Bank of America	1.82	0.03	1.85	53.33	3.27	3.40
Wells Fargo	1.5	1.34	46.61	3.56	4.81	5.06
Citi	2.11	1.92	3.36	3.74	4.62	48.19
Wachovia	3.28	3.14	4.75	4.92	5.96	6.13

Table 2: Equilibria before the merger

Next, we calibrate the model using the data from March 2010. The calibrated parameters are summarized in the table 3. Since interest rates were lower after the merger, the mean of loan return becomes lower as well. The standard deviation of loan returns tends to increase except for the Wells Fargo, which experienced the merger.

	JP Morgan	BoA	Wells Fargo	Citi
μ_k (mean Loan return) : before the merger	7.95	8.09	7.78	7.38
μ_k (mean Loan return) : after the merger	6.94	6.36	5.94	6.75
σ_k (s.d. of Loan return) : before the merger	23.94	10.98	21.00	29.35
σ_k (s.d. of Loan return) : after the merger	28.33	15.74	17.81	30.08
c_k (insurace cost): before the merger	5.38	4.74	4.69	5.48
c_k (insurace cost) : after the merger	5.60	4.92	4.66	5.49

Table 3: calibrated parameters.

Bank name	Obs. eqm	Bank run at Wells Fargo	Bank of America	JP Morgan	Citi
Insured interest rate					
JP Morgan	0.20	1.70	1.88	8.35	2.43
Bank of America	0.40	0.98	6.39	1.35	1.35
Wells Fargo	0.40	6.64	1.30	1.61	1.65
Citi	0.80	1.93	2.15	2.58	10.85
Uninsured interest rate					
JP Morgan	0.20	1.57	1.70	19.57	2.18
Bank of America	0.40	0.84	12.39	1.16	1.16
Wells Fargo	0.40	12.77	1.18	1.47	1.50
Citi	0.80	1.81	1.98	2.34	23.15
Default probability					
JP Morgan	0.84	3.22	3.56	41.44	4.52
Bank of America	2.22	3.64	48.00	4.82	4.79
Wells Fargo	2.29	45.13	4.55	5.45	5.51
Citi	1.70	3.48	3.86	4.61	47.03

Table 4: Equlibria after the merger

Using the newly calibrated parameters, we compute equilibria after the merger. The result is summarized in the table 4. Here, we use the equilibrium in the table 3 as an initial guess and solve for an equilibrium after the merger. As a result of this procedure, we didn't compute the best equilibrium, as it requires comprehensive search of the space (i_k^I, i_k^N, ρ_k). From this result, we can see that even after the merger in 2010, we can still see that there are multiple equilibria with bank runs.

Then we compare the welfare before and after the merger. We normalize the social welfare so that the observed equilibrium before the merger is equal to 0. The result is summarized in the table 5. Since this model has multiple equilibria and we don't know the likelihood that each equilibrium will occur, we simply compare the social welfare in equilibria with similar properties. We can see that the social welfare is higher after the merger in equilibria we computed. One of the reasons is that because of the merger, the financial system is stabilized, and the insurance cost is lowered.

Bank name	Obs. eqm	Bank run at Wells Fargo	Bank of America	JP Morgan	Citi
Without mergers					
Insurance Cost	13.7	1080.8	979.3	1085.5	1117.3
Social Welfare	0.0	-1143.11	-1205.73	-1333.02	-1365.18
With mergers					
Insurance Cost	14.00	935.94	981.17	952.76	1096.69
Social Welfare	81.73	-1029.35	-1122.08	-1088.26	-1257.94

Table 5: Social welfare before and after the merger.

6. Conclusion

In this paper, we develop a flamework to evaluate a merger in the banking sector, considering the reduced competition effect as well as the increased financial stability effects. Then we use the flamework to evaluate the merger between Wells Fargo and Wachovia. We found that in equilibria we computed social welfare after the merger is higher than that of before the merger.

In this paper we studied the merger between Wells Fargo and Wachovia. One caveat of this paper is that because we only study one merger, we cannot conclude that the merger improved social welfare. The social welfare before the merger may be lower because it was in the middle of the financial crisis. For the future research, we will study how mergers change the structural parameters of the model using the histories of banking mergers in the United States.

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Table 6: the top 15 mergers by deposit size for Survivor

merge_dt	non_surv	surv_nm	dep_non	dep_surv	dep_total
2015-09-01	JPMORGAN B&TC NA	JPMORGAN CHASE BK NA	25	1330275	1330300
2014-10-01	FIA CARD SVC NA	BANK OF AMER NA	92262	1202846	1295108
2011-10-14	CUSTODIAL TC	JPMORGAN CHASE BK NA	25	1171148	1171173
2013-04-01	BANK OF AMERICA RI NA	BANK OF AMER NA	17511	1110443	1127954
2013-04-01	BANK OF AMER OR NA	BANK OF AMER NA	5282	1110443	1115725
2009-07-01	MERRILL LYNCH BK USA	BANK OF AMER NA	57791	1008386	1066177
2009-11-02	MERRILL LYNCH BK&TC FSB	BANK OF AMER NA	32528	1002709	1035237
2008-09-26	WASHINGTON MUT BK	JPMORGAN CHASE BK NA	188261	797676	985937
2009-04-27	COUNTRYWIDE BK FSB	BANK OF AMER NA	36092	946997	983089
2012-01-01	CITICORP TR BK FSB	CITIBANK NA	132	882541	882673
2008-10-17	LASALLE BK NA	BANK OF AMER NA	36153	846231	882384
2008-10-17	LASALLE BK MIDWEST NA	BANK OF AMER NA	25158	846231	871388
2011-07-01	CITIBANK SD NA	CITIBANK NA	921	861055	861976
2011-03-31	WELLS FARGO CENT BK	WELLS FARGO BK NA	1	843237	843238

merge_dt	non_surv	surv_nm	dep_non	dep_surv	dep_total
2010-03-20	WACHOVIA BK NA	WELLS FARGO BK NA	355574	471876	827450

Table 7: the top 15 mergers by deposit size for Non-Survivor

merge_dt	non_surv	surv_nm	dep_non	dep_surv	dep_total
2010-03-20	WACHOVIA BK NA	WELLS FARGO BK NA	355574	471876	827450
2008-09-26	WASHINGTON MUT BK	JPMORGAN CHASE BK NA	188261	797676	985937
1999-07-23	BANK OF AMER NT&SA	BANK OF AMER NA	182103	170053	352156
2004-11-13	BANK ONE NA	JPMORGAN CHASE BK NA	141088	330127	471215
2005-06-13	FLEET NA BK	BANK OF AMER NA	137670	544300	681970
2009-11-07	NATIONAL CITY BK	PNC BK NA	93858	95901	189759
2014-10-01	FIA CARD SVC NA	BANK OF AMER NA	92262	1202846	1295108
2012-11-01	ING BK FSB	CAPITAL ONE NA	86785	106321	193105
1996-07-14	CHASE MANHATTAN BK NA	CHASE MANHATTAN BK	78884	78494	157378
2009-07-01	MERRILL LYNCH BK USA	BANK OF AMER NA	57791	1008386	1066177
2001-08-10	U S BK NA	U S BK NA	52892	52247	105140
1998-05-07	NATIONSBANK OF TX NA	NATIONSBANK NA	47058	100970	148027
2001-11-10	MORGAN GUARANTY TC	JPMORGAN CHASE BK	47027	261142	308169
2002-04-01	WACHOVIA BK NA	WACHOVIA BK NA	46954	140786	187740

merge_dt	non_surv	surv_nm	dep_non	dep_surv	dep_total
2000-03-01	FLEET NB	FLEET NA BK	44385	55659	100044