ESSAYS ON BANKS' AND CONSUMERS' BEHAVIOR IN THE PRESENCE OF GOVERNMENT AS THE CREDIT INSURER OF LAST RESORT

A Dissertation

by

SHUOXUN ZHANG

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2011

Major Subject: Economics

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Approved by:

Chair of Committee,	Li Gan
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ABSTRACT

Essays on Banks' and Consumers' Behavior in the Presence of Government as the Credit Insurer of Last Resort. (August 2011)

Shuoxun Zhang, B.A., Wuhan University;
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My dissertation investigates the behavior of consumers and banks in the presence of government as the credit insurer of last resort. Consumers have an option to file for bankruptcy under law when there are unexpected adverse shocks, while banks, especially large banks, are supported by the government during financial crisis because of systemic risk. I explore the heterogeneous behavior among consumers and banks with adverse shocks.

In the first chapter of my dissertation, my inquiry focuses on the heterogeneous behavior of households in filing for bankruptcy. In the literature, there are two theories in explaining personal bankruptcy: adverse event theory and strategic timing theory. Fay, Hurst and White(FHW) 2002(AER) include both financial benefit and adverse event variables in explaining the bankruptcy decision, and they find only financial benefit from filing is significant in explaining whether to file or not. Our argument is that adverse events may not work directly on bankruptcy decisions, however, they operate by running a higher amount of debt. Thus FHW's setting may not be appropriate. Instead, adverse event consumers' debt occurs after adverse events, while strategic timing consumers' debt decision and bankruptcy decision are jointly determined, which means their debt or financial benefit is endogenous; thus we propose that the endogeneity test of financial benefit is a way to distinguish the two types of consumers. Assuming only one type exists in the sample, we find support for adverse event theory. Extending the analysis to allow for both adverse events and strategic timing consumers shows existence of both types of filers, and strategic timing filers are more sensitive to financial benefit. Additionally, lower access to debt markets and lower income significantly increase the chance of strategic behavior.

The second part of my dissertation is to study the effectiveness of the Troubled Asset Relief Program(TARP) on banks' loan to asset ratio. One of the fundamental objectives of the Troubled Asset Relief Program (TARP) is to stimulate bank loan growth. I use panel data to study the dynamic effect of TARP investments on banks' loan to asset ratio (LTA). I find that TARP stimulate recipients' LTA growth as a whole, and the effect is significant only for medium banks(asset between 1 billion and 10 billion), with an annual decrease of 14 percentage points in LTA with the LTA in treatment quarter as benchmark. In terms of a dollar amount, 7.71 dollar more loans are generated for every TARP dollar invested in medium banks, compared with the average level of the quarters before TARP. There is no significant effect on small banks or big banks. Using graphs and different regression models, I argue that the dynamic setting, rather than the cross-sectional comparison, is more appropriate.

To my parents and Jerry

ACKNOWLEDGMENTS

First, I am heartily grateful to my advisory committee. Professor Li Gan, chair of my advisory committee, recommended reference papers and suggested alternative methods whenever I met difficulties. Without his continuous encouragement and guidance I would not have finished my dissertation smoothly. I really appreciate his kindness and patience. Professor Thomas Saving Professor Qi Li, and Professor Ximing Wu gave me many constructive suggestions on my dissertation.

Thanks go to the professors in the Economics Department. I took classes and learned economics from them. I would like to express my thanks to the staff for their administrative and computer support. I would like to express my thanks to all the friends who supported me, and the financial support from the Economics Department, and the Gail Frey Monson Memorial Fund.

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CHAPTER I

PERSONAL BANKRUPTCY: RECONCILING ADVERSE EVENTS AND STRATEGIC TIMING THEORIES USING HETEROGENEITY IN FILING TYPES

1.1. Introduction

The study of consumer bankruptcy has highlighted several reasons why a consumer files for bankruptcy[1]. Two theories, adverse events theory and strategic timing theory, have received particular attention.

The adverse events theory postulates that consumers file for bankruptcy mainly because they experience adverse events, and financial stresses associated with such events. Adverse events occur, for example, in the form of a job loss, medical problems, and particular family issues such as divorce. Financial stresses associated with such events arise, for example, in the form of income interruption, income reduction, or debt increase.

The strategic timing theory postulates that a rational consumer incorporates in her decision-making, the bankruptcy option available under law, and its associated costs and benefits, and making the best use of her economic environment, chooses

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This dissertation follows the style of *Journal of Economic Theory*.

[1]The literature on consumer bankruptcy is very large. A partial list includes the following. Stanley and Girth (1971) presents early work in this area. Sullivan, Warren, and Westbrook (1989, 1994, and 2000) present a version of the adverse events theory. White (1988, 1998), Domowitz and Sartain (1999), Gross and Souleles (2002), Fay, Hurst, and White (2002), Fan and White (2003), Han and Li (2011), Livshits, MacGee, and Tertilt (2007, 2010) explore versions of adverse events and strategic timing theories and their impact on micro and macro decisions. Ausubel (1991, 1997) explores aspects of competition in the credit card industry. Theoretical models for default and bankruptcy with competitive and incomplete markets are considered in Zame (1993), Modica, Rustichini, and Tallon (1998), Araujo and Pascoa (2002), Sabarwal (2003), Dubey, Geanakoplos, and Shubik (2005), Geanakoplos and Zame (2007), and Hoelle (2009), among others.

an optimal time to file for bankruptcy. In particular, if the best choice includes a strategic, and lawful, use of debt and the bankruptcy system, then that is reflected in consumer choice.

At the heart of each theory is the role of financial benefit in the bankruptcy filing decision.

In the "strict"interpretation, strategic timing theory holds, if, *ceteris paribus*, filing benefit affects the bankruptcy decision positively, and adverse events theory holds, if, *ceteris paribus*, adverse events variables affect a consumer's decision to file. Using data from the Panel Study of Income Dynamics (PSID), Fay, Hurst, and White (2002) (henceforth, FHW), show that financial benefit is positively and significantly related to the filing decision, and after controlling for financial benefit, adverse events variables do not affect the bankruptcy decision (except for a marginally significant positive effect of divorce). Using Survey of Consumer Finances (SCF) data, we document a similar effect of financial benefit, but a strongly significant and positive effect of divorce. Thus, using the strict interpretation, the PSID dataset provides some support for the strategic hypothesis while the SCF dataset provides some support for both the strategic and the adverse events hypothesis.

The strict interpretation implicitly assumes that strategic behavior is the only behavior affecting financial benefit.

More realistically, financial benefit from filing goes up when a consumer strategically increases unsecured debt before filing, consistent with strategic behavior; and it also goes up when she uses unsecured debt (e.g. a credit card) to pay for expenses due to adverse events, consistent with adverse events behavior. Therefore, financial benefit is affected by both types of behavior, and a positive coefficient on financial benefit alone may not be sufficient to distinguish between the two theories. This point may be made more generally; we show that in the standard random utility model underlying the binary choice of filing and not filing, the coefficient on unsecured debt (and hence, on financial benefit from filing) is positive, regardless of how debt is accumulated.

In this paper, we propose that even when financial benefit may affect the filing decision in either theory, the inclusion of financial benefit as an optimizing variable is a testable difference between the two theories. In other words, strategic consumers may additionally manipulate debt before filing, but adverse events consumers do not. We formalize this distinction by inquiring whether financial benefit is exogenous or endogenous to the filing decision[2]. The discussions provide a set of natural instrumental variables, the adverse events. Using both PSID data and SCF data, we show that financial benefit is exogenous to the bankruptcy decision, consistent with adverse events theory. With both datasets, the coefficient on financial benefit from filing is strongly significantly positive. To inquire into the possibility of both types of behavior existing simultaneously, we extend the analysis by estimating a regime-switching model with two types. We find evidence of heterogeneity in types consistent with both behavior. In particular, financial benefit is shown to be endogenous for the strategic type, and exogenous for the adverse events type. The coefficient on financial benefit is significantly positive for the strategic type and insignificant for the adverse event type.

To inquire into the possibility of both types of behavior existing simultaneously, we extend the analysis by estimating a model with two unobserved types. We find evidence of heterogeneity in types consistent with both behavior. In particular, financial benefit is shown to be endogenous for the strategic type, and exogenous for the adverse events type. The coefficient on financial benefit is significantly positive for

[2]FHW do not explore potential endogeneity of financial benefit.

the strategic type and positive but insignificant for the adverse events type. These results show a role for both hypotheses.

Moreover, most of the variables for adverse events have the same effect on financial benefit for both types, but with a larger absolute effect for strategic types. Not working lowers financial benefit, increasing unemployment spell increases financial benefit, and divorce increases financial benefit. Health problems present a mixed picture, a positive (and marginally significant) effect on financial benefit for adverse types, but decreasing (and insignificant) effect for strategic types. These results document a *financial-benefits channel* for adverse events.

As the types are unobserved, a mixture-density type of model is used. The exclusion restriction includes access to debt markets (in terms of the number of credit cards), income, a measure of risk aversion, and a measure of financial savviness. Henry, Kitamura, and Salanie (2010) provide conditions for the non-parametric identification of mixture-density models. Both Henry, Kitamura and Salanie (2010) and Gan, Huang, and Mayer (2011) suggest a Hausman-type specification test. We find supporting evidence of the current two-type model when applying the test.

We find that lower access to debt markets and lower income significantly increase the chance of strategic behavior. There is little evidence, however, of the effect of risk aversion and financial savviness. On average, about 16 percent of the sample is strategic type, and 84 percent is adverse events type, providing support for the exogeneity of financial benefit in the one-type model.

For comparisons between the two types, the population is divided into two groups. A household is of strategic type, if its type probability is greater than 0.5, and is of adverse events type otherwise. We find that as compared to adverse events types, strategic types have higher probability of filing and higher (log) financial benefit from filing, consistent with the theoretical framework.

The estimated model is used to predict effects of hypothesized changes in key variables. In particular, we document the effects on filing probabilities resulting from the effect of adverse events on financial benefits; exhibiting a financial-benefits channel for adverse events effects. As bankruptcy is a form of insurance, the ideas here may be related to moral hazard in insurance markets, as follows. Moral hazard relates to increasing the benefit from insurance by taking some (additional) actions that increase insurance payoffs. In our version, strategic timing behavior is similar to moral hazard, in the sense that these consumers may additionally increase unsecured debt before filing to increase their financial benefit from filing. Adverse events consumers do not exhibit such moral hazard. Thus, another way to formulate a distinction between the two hypotheses is to inquire whether, and to what extent, moral hazard is present in the bankruptcy decision.

The question of adverse selection is not as relevant here; in principle, everyone under the U.S. legal jurisdiction has access to bankruptcy, without having to pay something to be selected into having a bankruptcy option.

The chapter proceeds as follows. Section 1.2. presents the theoretical models and testable predictions, and section 1.3. presents the econometric specifications, data, and results.

1.2. Theoretical Models and Predictions

First, we show a positive relationship between unsecured debt and probability of filing for bankruptcy, regardless of how debt is accumulated. Next, we formulate simple models of adverse events and strategic timing hypotheses, and highlight their different predictions.

1.2.1. A Positive Correlation between Financial Benefit and Filing Probability

FHW indicate that a positive and significant relationship between household financial benefit and probability of filing for bankruptcy signals strategic behavior by a consumer. Similarly, Adams, Einav, and Levin (2009) suggest that an increase in probability of default with loan size is consistent with either moral hazard behavior or adverse selection behavior. In the same spirit, we present a simple model showing that financial benefit may affect the probability of filing, regardless of how debt is accumulated.

In most empirical work, filing for bankruptcy is modeled as a binary choice model. According to McFadden's Random Utility Maximization model, a person would file for bankruptcy if his utility difference between filing and not filing is positive. To investigate this difference, let d be unsecured debt and w be assets minus secured debt. For simplicity, the exemptions are normalized to be zero. Financial benefit from filing, given d, is $fb(file, d) = max(d - w, 0)$, and financial benefit from not filing, given d, is $fb(Not, d) = max(w - d, 0)$. Notice that $fb(file, d) \geq fb(Not, d)$ if and only if $d \geq w$.

Let u denote utility from monetary outcomes. Assume that u is strictly increasing and continuously differentiable. We may write utility from filing, given d as: $U(file, d) = u(fb(file, d))$; utility from not filing, given d as $U(Not, d) = u(fb(Not, d))$; and the difference in these utilities is $\Delta U(d) = U(file, d) - U(Not, d)$. Therefore,

$$\Delta U'(d) = u'(fb(file, d))fb'(file, d) - u'(fb(Not, d)fb'(Not, d))$$

Consider the following cases.

$d > w$: In this case, $fb'(file, d) = 1$ and $fb'(Not, d) = 0$. Therefore, $\Delta U'(d) =$

$u'(fb(Not, d)) > 0$.

$d < w$: In this case, $fb'(file, d) = 0$ and $fb'(Not, d) = -1$. Whence, $\Delta U'(d) = u'(fb(Not, d)) > 0$.

$d = w$: In this case, $lim_{d \to w} u'(fb(file, d)) = u'(fb(file, w)) = u'(0) > 0$ and similarly, $lim_{d \to w} u'(fb(Not, d)) = u'(fb(Not, w)) = u'(0) > 0$.

In all cases, we have $\Delta U'(d) > 0$.

In terms of empirical prediction, this implies that the coefficient on unsecured debt (and consequently, on financial benefit from filing) is positive, regardless of how debt is accumulated[3]. Therefore, given unsecured debt d, a positive relationship between financial benefit from filing and filing for bankruptcy is expected.

1.2.2. Adverse Events Hypothesis

Frequent support for adverse events hypothesis has been advanced by Sullivan, Warren, and Westbrook (1989, 1994, 2000), among others. Using data from bankruptcy filings in 1981 (for Illinois, Pennsylvania, and Texas), and in 1991 (for Illinois, Pennsylvania, Texas, California, and Tennessee), these authors paint a rich portrait of consumers in bankruptcy, they present statistics that indicate similarities between bankrupt debtors and the general population, especially middle-class families, and they present a variety of cases and statistics to conclude that while some cases of abuse of bankruptcy law may exist, bankruptcy is predominantly due to adverse events. As they put it succinctly[4], “No one plans to go bankrupt”.

In terms of formulating a model for this hypothesis, it is useful to keep in mind that a pattern that emerges consistently in this hypothesis is that there are some

[3] Notice that all we used here was that u is strictly increasing and continuously differentiable. No additional restriction is imposed on utility.

[4] Sullivan, Warren, and Westbrook (2000), page 73.

events for which consumers do not plan (even if they may, in principle, be aware of the existence of such events), and if such an event occurs, then they may be compelled to file for bankruptcy. If such an event does not occur, consumers do not consider filing for bankruptcy. For a statement like this to be true in a model of this hypothesis, it is important to answer at least two questions. First, why don't consumers plan for some events? Second, even if they don't plan for some events, why do they not include a bankruptcy option in the events for which they do plan?

Consumers might not plan for some events if they assign an event a subjective probability of zero. For example, we observe that in surveys of individual mortality, some consumers list as zero their probability of next-period mortality (Gan, Hurd, and McFadden, 2005). Such an assignment can arise if the cost of making very fine probability distinctions is relatively high, or it can arise as a mistake that has a miniscule impact. For example, in the PSID data, the probability of bankruptcy is 0.003017, as reported in FHW.

It is somewhat harder to justify theoretically why, in events for which consumers otherwise plan, they do not include a bankruptcy option that is legally, and in principle, widely available. One explanation for this is that ex ante, the benefit from a bankruptcy filing is low relative to costs; for example, as reported in FHW, for families that can gain from a bankruptcy filing, the mean benefit from filing is $7,813, and the probability of filing is 0.003017, for an ex-ante filing benefit of about $25. This is less than the cost of a planning session with a bankruptcy lawyer, or the resources expended to purchase and plan with a book on how-to-file. Another explanation can be provided in terms of utility penalties arising from future reputation losses from filing; for example, see Dubey, Geanakoplos, and Shubik (2005). Such losses can arise from a combination of restricted future access to debt markets, credit score impact (for severity of credit score impact, see Musto 2004,) and loss of option to re-file for some period (six years for a Chapter 7 filing). If such losses are very high when consumers file in the absence of adverse events, and such losses outweigh benefits of filing, then in non-adverse events, consumers may optimally decide not to consider a bankruptcy option. For example, a bankruptcy flag on a consumer credit report is one of the worst derogatories on a credit report, and it stays there for ten years, but the legal system allows a Chapter 7 re-filing after six years. Consequently, the longer memory of financial institutions of a consumer bankruptcy filing increases the cost of filing by increasing future costs of accessing debt markets.

Therefore, as a first approximation, we may view adverse events consumers as taking decisions sequentially; in period 1, they plan for some events, and in such events, they do not plan to file for bankruptcy, but they do not plan for other events (termed adverse events). In period 2, if a planned-for event occurs, they consume as planned, and if an adverse event occurs, they include a bankruptcy option in their decision-making and re-optimize accordingly. In other words, in period 1, "adverse events consumers do not plan to go bankrupt".

Consider a standard, two-period decision-making framework. In the first period, there is one decision node. In the second period, one of three states of the world prevails; a good state, indexed g, a bad state, b, and a terrible state, t, thought of as an adverse events state. Each state corresponds to a decision node, and the probability of each state is π_g, π_b and π_t, respectively, with $\pi_g + \pi_b + \pi_t = 1$.

As usual, a consumer has to decide how much to consume at each node; his consumption is indexed c_0, c_g, c_b and c_t. Moreover, lending markets are available to him at a one-period, risk-adjusted, market interest rate r. As usual, a single consumer takes interest rates as given. His endowment in consumption units at each node is denoted w_0, w_g, w_b and w_t. (For convenience, suppose $w_0 = 0$, $0 < w_t < w_b < w_g$.) Moreover, he has to decide how much debt to take, subject to some exogenously specified debt limit; indexed $\bar{d} > 0$. His twice continuously differentiable von Neumann-Morgenstern utility is denoted $u(c)$ with $u' > 0, u'' < 0, \lim_{c\to 0} u'(c) = \infty, \lim_{c\to\infty} u'(c) = \infty$. His expected utility is $U = u(c_0) + \delta[\pi_g u(c_g) + \pi_b u(c_b) + \pi_t u(c_t)]$.

An adverse events consumer takes decisions sequentially. In period 1, he plans for states g, b, and he plans to remain solvent in these states, but he does not plan for state t, the adverse events state. In period 2, if g or b occurs, he consumes as planned, but if t occurs, he considers the option to file for bankruptcy. There are some costs of filing for bankruptcy; usually some loss of assets, court fees, lawyer fees, limited future participation in debt markets, and so on. Benefits of filing include, among others, discharge of debt, fresh start, and accompanying wealth insurance. Adapting a simple form of a Chapter 7 filing[5], it is assumed that a filer gives up all his assets except any exemptions from forfeiture provided by law, and his debt is discharged[6]. Exemptions specified under law are summarized by e. Consequently, an adverse events consumer solves the following problem.

$$Stage \;\; I : \max_{d, c_0, c_g, c_b, File, Not} u(c_0) + \delta[\pi_g u(c_g) + \pi_b u(c_b) + \pi_t u(c_t)$$

[5]Historically, Chapter 7 bankruptcies account for about 70 percent of all bankruptcies.

[6]The other main personal bankruptcy category, Chapter 13 bankruptcy, accounting for about 29 percent of all cases, can be viewed in this formulation as follows. In this type of filing, a repayment plan proposed by the debtor is confirmed by the Court, and a discharge of remaining debt is provided on successful completion of the plan. In this case, net assets saved and debts discharged depend on the repayment plan, and can be mapped to this model after an appropriate discounting for period of plan. Exemptions provided under law are the same in both cases.

$$\begin{aligned} subject\ \ to\quad c_0 &= d \\ c_g &= w_g - (1+r)d \\ c_b &= w_b - (1+r)d \\ d &\leq \bar{d} \end{aligned}$$

$$Stage\ \ II\ :\ \ If\ \ t\ ,\ \ then\ \ set\ :$$

$$c_t = \max(w_t - (1+r)d, min(w_t, e))]$$

In Stage I, a consumer decides optimal debt and consumption (d, c_0, c_g, c_b), and by assumption, he does not file in g, b. Given $d > 0$, and $w_t < e$, in Stage II, if t occurs, optimal choice is to file and consume $c_t = w_t$.

1.2.3. Strategic Timing Hypothesis

A strategic timing consumer is a standard fully rational consumer who includes the bankruptcy option in her maximization problem. Assumptions regarding decision nodes, endowments, utility functions, and expected utility are the same as in the previous case. Moreover, it is assumed that the bankruptcy process is the same as in the previous case. Of course, the difference is in the optimization problem. In each state in the second period, a strategic timing consumer has an option to file for bankruptcy, and solves the following problem.

$$\max_{d,c_0,c_g,c_b,File,Not} u(c_0) + \delta[\pi_g u(c_g) + \pi_b u(c_b) + \pi_t u(c_t)]$$

$$
\begin{aligned}
subject\ \ to\ \ c_0 &= d \\
c_g &= max(w_g - (1+r)d, min(w_g, e)) \\
c_b &= max(w_b - (1+r)d, min(w_b, e)) \\
c_t &= max(w_t - (1+r)d, min(w_t, e)) \\
d &\leq \bar{d}
\end{aligned}
$$

The maximum operator for decision nodes in the second period corresponds to the bankruptcy decision. For example, if a consumer decides not to file in g, her constraint is $w_g - (1+r)d$, and if she decides to file, her constraint is $min(w, e)$, where, as before, e captures exemptions permitted in bankruptcy.

1.2.4. Comparisons between the Hypotheses and Empirical Predictions

One distinction between strategic timing and adverse events hypothesis is that for strategic timing consumers, the bankruptcy decision and the debt decision (and consequently, financial benefit) are jointly determined, whereas for adverse events consumers, the debt decision (and consequently, financial benefit) is exogenous to the filing decision. This follows immediately from the construction of the two models.

For the clearest distinctions between the two hypotheses in terms of financial benefits and probabilities of filing, suppose $0 < w_t < w_b \leq e < w_g$. That is, exemptions are sufficiently high to have non-negative financial benefit from filing in bad and terrible states, but not necessarily in a good state.

In this case, strategic timing consumers file for bankruptcy in states t and b, and perhaps in g as well, whereas adverse events consumers file only in state t. Therefore, a second distinction is that adverse events consumers may file less frequently (or equivalently, with lower probability) than strategic timing consumers.

Another intuitive comparative statics result that can be seen here formally is that debt use by adverse events consumers is sometimes less, and never more than that for strategic timing consumers. Of course, when debt limits are sufficiently low, both types might decide to use maximum possible debt, and in this case, debt levels are the same. But notice that the optimal debt level for adverse events consumers can be lower than that for strategic timing consumers, because for every d,

$$\begin{aligned} MU^{AE}(d) &= u'(d) - \delta(1+r)\pi_g u'(w_g - (1+r)d) - \delta(1+r)\pi_b u'(w_b - (1+r)d) \\ &< u'(d) - \delta(1+r)\pi_g u'(w_g - (1+r)d) \qquad [= MU^{ST}(Not, d)] \\ &< u'(d) \qquad [= MU^{ST}(File, d)] \end{aligned}$$

Here, $MU^{ST}(Not, d)$ is the marginal utility to the strategic consumer from not filing in state g when debt is d, and $MU^{ST}(File, d)$ is the marginal utility to the strategic consumer from filing in state g when debt is d. Therefore, if not filing in g is optimal for the strategic consumer, then $MU^{AE}(d^{*ST}) < MU^{ST}(Not, d^{*ST}) = 0 = MU^{AE}(d^{*AE})$, whence $d^{*AE} < d^{*ST}$. (Here, d^{*AE} is the optimal debt level for the adverse events consumer, d^{*ST} for the strategic consumer, and we used the easy-to-check fact that $\partial MU^{AE}(d)/\partial d < 0$.) Similarly, if filing in g is optimal for the strategic consumer, then $MU^{AE}(d^{*ST}) < MU^{ST}(file, d^{*ST}) = 0 = MU^{AE}(d^{*AE})$, and again, $d^{*AE} < d^{*ST}$. Consequently, unsecured debt (and therefore, financial benefit from filing) is larger for strategic consumers than for adverse events consumers.

In summary, the empirical predictions from the theoretical analysis include: (a) financial benefit is endogenous to the bankruptcy decision in the strategic timing hypothesis and exogenous in the adverse events hypothesis; and (b) financial benefit and probability of filing for bankruptcy are higher in strategic timing hypothesis than in adverse events hypothesis.

1.2.5. Some Limitations

The models presented above are simple models, and by no means capture all relevant aspects of the bankruptcy decision. Issues related to choosing a particular period to file for bankruptcy, or to repeat interactions with credit markets, or to choice of bankruptcy chapter, or to role of legal advertising, or to effects on supply of credit, or to effects on work incentives, and so on are not considered here. (Some of these are the subject of other papers, listed above.) It is possible to consider some of these issues here in a reduced form by including parameters for expected gains and losses from delaying a decision, or reduced access to credit markets, or utility penalties for default, and then focusing on parameter values which make particular versions of the models more likely to occur, but it is unclear if such additions would yield tractable models, or have additional applications given the paucity of available data.

The results here can be viewed as providing an indication of alternative hypotheses being borne out in the data, rather than a definitive conclusion in favor of one hypothesis or the other. For example, in addition to research supporting different hypotheses, the reported surge in bankruptcy filings before the deadline of October 17, 2005 for the new bankruptcy law to go into effect suggests that other factors (perhaps informational spillovers emerging from declining social stigma, or lawyer advertising) are important as well. No doubt, additional work may yield additional testable predictions, and additional research would be very welcome.

1.3. Econometric Models and Results

In this section, we first provide some information on the data and construction of variables. Next, we present three specifications and estimation results for each specification. The specifications considered are: a simple Probit model, a one-type model (with joint maximum likelihood estimation), and a two-type model (with joint maximum likelihood estimation).

1.3.1. Data Description and Variables

We use two different datasets to check robustness of our results. One is the combined cross-section and time series sample of PSID households over the period 1984-1995; the same dataset is used in FHW. The other is the cross sectional dataset of SCF from 1998.

In 1996, the PSID asked respondents whether they had ever filed for bankruptcy and if so, in which year. This information, combined with other household characteristics forms the basis of our first dataset. The PSID data are generally of high quality, but they have some limitations for a study of this kind. In particular, wealth is only measured at 5-year intervals, and it contains less detail on some aspects of use in this study. Moreover, as documented in FHW, there are only 254 bankruptcy filings over the period 1984-1995, and bankruptcy filings in the PSID are only about one-half of the national filing rate. There were 55 bankruptcy filings in 1997, or about 1.28 percent of households, comparable to the 1997 national bankruptcy filing rate of 1.16 percent. The SCF is cross-sectional only, so we lose the time-series aspect in this case, but there is some information for the year prior to the survey, and on future expectations.

SCF also provides us with better wealth data, which reports 1997 wealth information and 1997 bankruptcy filings. (The survey itself was conducted between June and December of 1998 [7].) In Table I, we compare financial benefits (discussed below) and unsecured debt between filers and non-filers for both PSID and SCF.

[7] See Kennickell et. at (2000).

Table I. Summary Statistics

Variables	PSID data		SCF data	
	Mean value	Standard deviation	Mean value	Standard deviation
Number of bankruptcy filings	254		55	
Financial benefit	$1,411	$10,523	$3,991	$26,001
Log(financial benefit +1)	1.64	3.24	1.95	3.69
Those file for bankruptcy	3.65	4.26	6.78	4.38
Log(unsecured debt+1)	3.85	3.94	4.35	4.45
Those file for bankruptcy	5.74	3.96	5.88	3.96
Household labor income	$26,552	$32,672	$43,035	$37,967
Age of household head	44.19	15.96	49.84	16.52
Years of education of household head	12.43	5.1	13.74	2.9
Family size	2.9	1.55	2.65	1.44
Own home	0.59	0.49	0.7	0.46
Self employed/own business	0.11	0.31	0.25	0.44
Head is divorced	0.03	0.18	0.13	0.33
Head is unemployed	0.06	0.23	0.23	0.42
Weeks of unemployment of head	6.76	2.01	2.39	6.34
Head has health problem	0.07	0.26	0.04	0.19
ln(income)			10.89	1.98
Number of credit cards			4.44	4.36
Risk averse			0.3	0.46
Shop around			2.95	1.41
Total number of observations	64,200		4,305	

Similar patterns emerge. In PSID, the mean log(financial benefit) for filers is more than twice as much than those non-filers. In SCF, filers have more than three times as much mean log(financial benefits) than non-filers. In both SCF and PSID, the mean log(unsecured debt) for filers is greater than that of non-filers.

Financial benefit from filing is the key variable in this paper. It is calculated as follows:

$$fb = max[debt - max(wealth - exemption, 0), 0]$$

In this formula, $max(wealth - exemption, 0)$ calculates the nonexempt assets that a filer loses in bankruptcy. It measures financial cost of filing for bankruptcy[8]. The variable *debt* measures the unsecured debt that will be discharged in bankruptcy; a measure of benefit of filing. As not filing dominates filing when $debt - max(wealth - exemption, 0)$ is negative, the financial benefit from filing is truncated at 0 to yield the above formula.

To calculate financial benefit in the PSID, we use the same dataset as FHW.

For the SCF, we make the following adjustments. The SCF provides only region codes; state codes are not released in public data. To get a relative weight for each state in a region, we use Regional Economic Information System (REIS) from the Bureau of Economic Analysis. These state weights are based on the population of a state relative to the region in which it is included. These weights are used to compute the composite exemption level of a region.

Using Elias, Renauer, and Leonard (1999), we determine each state's exemption levels for 1998 for homestead equity in owner-occupied homes, equity in vehicles,

[8]A more complete measure of costs would include both out-of-pocket filing costs, and future costs resulting from more restricted access to debt markets. Reliable data on these measures is not available. Adding a constant, of course, would not change the qualitative results.

personal property, and wildcard exemptions. We adjust for state level variables to the extent we can. For example, if a state doubles exemptions for married households, we do the same. For the fifteen states allowing residents to choose between state or federal exemptions, we take the larger of the exemptions. For households in states with an unlimited homestead exemption, we take the homestead exemption to be the average of home values in the entire sample.

The variable *exemption* is assumed to be the sum of these exemptions, because we do not observe a household's state of residence. The variable *wealth* is the sum of net worth of businesses a household owns, current values of the vehicles it owns, and value of real estate it owns.

To make the two datasets consistent with each other, we include a vector of demographic variables which may be related to households' filing decisions, such as age of household head, years of education of the head, family size, whether head owns their home. Moreover, as adverse events variables, we include spell of unemployment, its squared term, whether the head is unemployed, whether the head's marital status is divorce, whether the head's health condition is poor. For the PSID dataset, these variables are calculated using the values of corresponding variables in the year prior to their bankruptcy. For the SCF data, we also included whether the head has health insurance, and we include only the region dummies rather than macro information to capture the local fixed effects due to the lack of information regarding state of residency.

1.3.2. Simple Probit Model

Let's first consider a simple Probit regression, similar to FHW's specification.

$$file = 1(\gamma fb + X\beta + \alpha AE + u > 0)$$

This specification explores the strategic timing and adverse event hypotheses by running the Probit regression of whether households file for bankruptcy ($file$) as a function of their potential financial benefit, fb, from filing, their personal and state characteristics X, and the adverse events they encountered in the previous year, AE.

As described above, the strict interpretation focuses on the significance of the coefficients on financial benefit and on adverse events. If strategic timing theory is true, the coefficients of financial benefit should be positive and significant while the adverse event variables should not be significant. If adverse event theory is true, then adverse event variables should be positive and significant while the coefficient of financial benefit should be insignificant.

Table II and Table III illustrate this simple specification with PSID data and SCF data[9]. (For ease of comparison, we keep the other variables same as those in FHW.) As shown in Table II, using PSID data, the coefficients on the variables are comparable to those reported in FHW. In particular, financial benefit affects the filing decision positively and highly significantly, and its squared term is highly significant. Among statistically significant adverse events, divorce is positive but only marginally significant. Moreover, using SCF data, financial benefit continues to be positive and highly significant, but its squared term is not significant any more. The coefficient on divorce remains positive, but is highly significant.

Thus, using the strict interpretation, and the simple Probit model, the PSID dataset provides support for the strategic hypothesis while the SCF dataset provides support for both the strategic and the adverse events hypothesis.

[9]For all estimates, * indicates significance at 90 percent, ** at 95 percent, and *** at 99 percent.

Table II. Simple Probit Model

Variables	PSID data		SCF data	
	without adverse event variables	with adverse event variables	without adverse event variables	with adverse event variables
financial benefit	0.00006***	0.00006***	0.00002***	0.00002***
	(0.00001)	(0.00001)	(6.60E-06)	(6.85E-06)
financial benefit squared	-1.04e-9***	-1.03e-9***	-1.09E-10	-1.08E-10
	(4.04E-10)	(3.99E-10)	(6.98E-11)	(7.36E-11)
lagged bankruptcy rate	5.95905**	5.62294**		
	(2.67377)	(2.68448)		
household labor income	-4.98e-6***		-3.46e-6**	
	(1.41E-06)		(1.80E-06)	
reduction in income	-2.17e-6***		-3.06e-6***	
	(5.92E-07)		(1.02E-06)	
age of household head	0.02917**	0.01846	0.0285	-0.00296
	(0.0137)	(0.01306)	(0.0327)	(0.0319)
age squared	-0.00048***	-0.00036**	-0.00035	-0.00003
	(0.00016)	(0.00015)	(0.00036)	(0.0003)
education	-0.02981***	-0.03879***	0.0088	-0.0101
	(0.01155)	(0.01097)	(0.0218)	(0.0218)
family size	0.03736**	0.03228*	0.0687**	0.0951***
	(0.01673)	(0.01669)	(0.0332)	(0.0363)
own business	0.04037	0.09489	-0.1608	-0.1661
	(0.0918)	(0.09147)	(0.263)	(0.24)
own home	-0.1371*	-0.19982***	-0.1084	-0.1663
	(0.07437)	(0.06757)	(0.1553)	(0.1484)

Table III. Simple Probit Model, Part II

Variables	PSID data		SCF data	
	without adverse event variables	with adverse event variables	without adverse event variables	with adverse event variables
lawyers per capita	-0.7776	-0.98042		
	(0.74456)	(0.73636)		
county unemployment rate	0.09337	0.10714		
	(0.10457)	(0.11386)		
state income growth	-2.39603**	-2.23304*		
	(1.19746)	(1.18386)		
state income deviation	-0.12465	-0.12976		
	(0.08725)	(0.08821)		
divorce		0.23206*		0.6434***
		(0.13196)		(0.1578)
period of unemployment		0.0134		-0.0066
		(0.02435)		(0.011)
health problem		0.09265		-0.1097
		(0.11733)		(0.3149)
state fixed effects	yes	yes	yes	yes
year fixed effects	yes	yes	no	no
constant	-2.3797***	-2.23563***	-3.0914***	-2.6235***
	(0.71384)	(0.75997)	(0.8504)	(0.8231)

1.3.3. One-type Model

Given the limitation of the strict interpretation, we propose to test the endogeneity of financial benefit by jointly estimating financial benefit and the bankruptcy decision. The basic empirical model here is:

$$file^* = X\beta + \gamma ln(fb+1) + u \quad \begin{cases} file = 1 \;\; if \;\; file^* > 0 \\ file = 0 \;\; if \;\; file^* \leq 0 \end{cases} \tag{1.1}$$

$$ln(fb^*+1) = X\delta + \mu AE + v \quad \begin{cases} fb = fb^* \;\; if \;\; fb^* \geq 0 \\ fb = 0 \;\; if \;\; fb^* < 0 \end{cases} \tag{1.2}$$

Notice that endogeneity of $ln(fb+1)$ is equivalent to whether the error terms u and v are correlated. The key difference between this model and FHW's specification is the role of the set of adverse events, AE. Here, AE no longer directly affects a person's bankruptcy decision. Instead, it serves as the set of instrumental variables that directly affects the financial benefits, fb, in (1.2). Another minor difference between these two models is that the logarithm of financial benefit is used here while FHW use the level of financial benefits. As fb depends on the wealth level, it is most likely to exhibit a log-normal distribution, although censored at zero. With a logarithm transformation, we will assume that v is normally distributed.

Let $Var(u) = 1, Var(v) = \sigma_v^2$, and assume the relationship between u and v as follows:

$$u = \theta v + \varepsilon$$

where $Cov(v, \varepsilon) = 0$, and $Var(\varepsilon) = 1 - \theta^2\sigma_v^2$. In this version, testing if $ln(fb+1)$ is endogenous is equivalent to testing if the parameter $\theta = 0$. The probability a household files when financial benefit is zero is given by

$$Pr(file = 1, ln(fb + 1) = 0) = \int_{-\infty}^{-X\delta-\mu AE} \Phi(\frac{X\beta + \theta v}{\sqrt{1-\theta^2\sigma_v^2}})\frac{1}{\sigma_v}\phi\frac{v}{\sigma_v}dv \quad (1.3)$$

and therefore, the probability it does not file when financial benefit is zero is given by

$$Pr(file = 0, ln(fb + 1) = 0) = \int_{-\infty}^{-X\delta-\mu AE} \Phi(-\frac{X\beta + \theta v}{\sqrt{1-\theta^2\sigma_v^2}})\frac{1}{\sigma_v}\phi\frac{v}{\sigma_v}dv$$

Similarly,

$$\begin{aligned} Pr(file = 1, ln(fb + 1)) &= \Phi(\frac{X\beta + \gamma ln(fb + 1) + \theta(ln(fb + 1) - X\delta - \mu AE)}{\sqrt{1-\theta^2\sigma_v^2}}) \\ &* \frac{1}{\sigma_v}\phi(\frac{ln(fb + 1) - X\delta - \mu AE}{\sigma_v}) \end{aligned}$$

and

$$\begin{aligned} Pr(file = 0, ln(fb + 1)) &= [1 - \Phi(\frac{X\beta + \gamma ln(fb + 1) + \theta(ln(fb + 1) - X\delta - \mu AE)}{\sqrt{1-\theta^2\sigma_v^2}})] \\ &* \frac{1}{\sigma_v}\phi(\frac{ln(fb + 1) - X\delta - \mu AE}{\sigma_v}) \end{aligned}$$

The log-likelihood function over the sample is given by

$$\begin{aligned} L = &\sum_{file=0,ln(fb+1)>0} ln(Pr(bank = 0, ln(fb + 1) > 0)) \\ &+ \sum_{file=1,ln(fb+1)>0} ln(Pr(bank = 1, ln(fb + 1) > 0)) \\ &+ \sum_{file=0,ln(fb+1)=0} ln(Pr(bank = 0, ln(fb + 1) = 0)) \\ &+ \sum_{file=1,ln(fb+1)=0} ln(Pr(bank = 1, ln(fb + 1) = 0)) \end{aligned}$$

Estimation results are presented in Tables IV and V[10]. We find that using either

[10]We apply a log transformation to financial benefit, because this variable exhibits

Table IV. One Type Model(MLE;PSID data)

Variables	coefficient	standard error
Correlation between the two error terms θ	-0.1423	0.3562
Bankruptcy equation		
Log financial benefit	0.0791***	0.0321
Age	0.0146	0.0124
Age squared	-0.000264**	0.000138
Lagged bankruptcy filing rate	5.805***	2.791
Education	-0.0204***	0.0098
Family size	0.0223	0.016
Own business	0.0531	0.0837
Own home	-0.05835	0.0565
Lawyer per capita	-0.0389	0.7598
Growth rate of income	-1.915	1.344
State income deviation	-0.1424*	0.0774
State and time dummies	yes	
constant	-2.1573***	0.5716
Financial benefit equation		
Excluded adverse event variables		
Health	1.924***	0.2295
Divorce	0.3603	0.3356
No work	-1.358***	0.2552
Period of unemployment	0.7635***	0.1968
Period of unemployment squared	-0.0475***	0.0123
Other control variables		
Age	-0.1338***	0.0261
Age squared	-0.00067***	0.00027
Lagged bankruptcy filing rate	-3.523	8.545
Education	-0.0305***	0.0147
Family size	0.4157***	0.0398
Own business	-3.204***	0.2238
Own home	-3.215***	0.1332
Lawyer per capita	-2.942*	1.618
Growth rate of income	-2.302***	3.439
State income deviation	-0.2989***	0.1997
State and time dummies	yes	
Constant	-0.8642**	1.6281
Standard deviation of error term	3.2073***	0.0127
Log-likelihood	-61773	

PSID data (Table IV), or SCF data (Table V), the estimated parameter θ is not statistically different from zero, consistent with the adverse events hypothesis. At the same time, log financial benefit has a positive and highly significant effect on the decision to file for bankruptcy in both datasets.

Both datasets confirm the view that adverse events may affect financial benefit. In the PSID data (Table IV), health shocks and period of unemployment increase financial benefit highly significantly, whereas a switch from working to not working (no work dummy) decreases financial benefit. In the SCF data (Table V), divorce increases financial benefit highly significantly, whereas no work decreases financial benefit. In both datasets, period of unemployment increases financial benefit (highly significantly in the PSID data, but insignificantly in the SCF data), and its square term is negative.

1.3.4. Two-type Model(MLE)

To inquire into the possibility of both types of behavior existing simultaneously, we extend the analysis to allow for heterogeneity in types by proposing a two-type model.

Let a random variable $T = 1$ if a person is a strategic type, and $T = 2$ if a person is a non-strategic (or adverse events) type. For simplicity, we let

$$Pr(T = 1) = \Phi(W\alpha)$$

and

$$Pr(T = 2) = 1 - \Phi(W\alpha)$$

W is a set of type-determinant variables.The filing decision may be impacted

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a distribution that is similar to log-normal but is left-censored at zero. In particular, we use $log(financialbenefit + \$1)$. This is to capture the characteristics of censored data at zero. The transformed variable is also left-censored at zero.

Table V. One Type Model(MLE;SCF data)

Variables	coefficient	standard error
Correlation between the two errors θ	-0.2845	0.2032
Bank equation		
Log financial benefit	0.1377***	0.036
Age	0.0447*	0.024
Age squared	-0.0004*	0.0002
Family size	0.0551	0.0394
Own home	0.019	0.1285
Own business	-0.2	0.1981
Years of education	0.225	0.1643
Years of education squared	-0.0092	0.0064
Region dummies	Yes	
constant	-5.5722***	1.2724
Financial benefit equation		
Excluded adverse variables		
Health	1.041	1.1136
No work	-4.6296***	0.8369
Period of unemployment	0.1472	0.1248
Period of unemployment squared	-0.0027	0.0033
Divorce	2.6813***	0.595
Other control variables		
Age	-0.0628	0.0845
Age squared	-0.0014	0.0009
Family size	0.2121	0.1516
Own home	-5.1205***	0.49
Own business	-7.5376***	0.6801
Years of education	0.5068	0.3661
Years of education squared	-0.0483***	0.0152
Region dummies	yes	
Constant	7.8295**	3.1007
Standard deviation of error term	9.3535***	0.1262
Log-likelihood	-4812.66	

differently for each type, as follows.

When T = 1, the filing equation is

$$file = 1[X\beta_1 + \gamma_1 ln(fb + 1) + u_1 > 0] \tag{1.4}$$

When T = 2, the filing equation is

$$file = 1[X\beta_2 + \gamma_2 ln(fb + 1) + u_2 > 0] \tag{1.5}$$

We normalize the variances of the error terms for both types to be 1, i.e. $Var(u_1) = Var(u_2) = 1$.

Similarly, we allow behavior in accumulating debt or financial benefit to be different for each type. For the strategic type, financial benefit is assumed to be endogenous, and for the adverse events type, it is assumed to be exogenous. Thus, for the strategic type,

$$ln(fb^* + 1) = X\delta_1 + \mu_1 AE + v_1 \quad \left\{ \begin{array}{l} fb = fb^* \;\; if \;\; fb^* \geq 0 \\ fb = 0 \;\; if \;\; fb^* < 0 \end{array} \right. \quad and \quad u_1 = \theta_1 v_1 + \varepsilon_1$$

where the variance for the error term ε_1 is $Var(\varepsilon_1) = 1 - \theta^2\sigma^2_{v_1}$, if we assume that $Var(v_1) = \sigma^2_{v_1}$.

For the adverse events type,

$$ln(fb^* + 1) = X\delta_2 + \mu_2 AE + v_2 \quad \left\{ \begin{array}{l} fb = fb^* \;\; if \;\; fb^* \geq 0 \\ fb = 0 \;\; if \;\; fb^* < 0 \end{array} \right.$$

where $Cov(u_2, v_2) = 0$. In empirical estimation, we will allow the possibility that $Cov(u_2, v_2) \neq 0$, and estimate their correlation.

Notice that the joint density of $(bank, ln(fb+1))$ consists of four parts, $(bank = 0, ln(fb + 1) = 0), (bank = 1, ln(fb + 1) = 0), (bank = 0, ln(fb + 1)),\ and\ (bank =$

$1, ln(fb+1))$. In the last two cases $ln(fb+1)$ is positive and continuous. The density function for each of the four cases is given in Appendix A.

The model suggested here belongs to the class of the mixture density models. A well-known necessary identification condition of the model requires the exclusion restriction, i.e., the set W is different from X and AE. Henry, Kitamura, and Salani (2010) show that a correlation between W and T and the independence between W and the error terms (u_1 and u_2) in equations (1.4) and (1.5) are sufficient to identify the model up to a linear transformation non-parametrically. When the set W has more than one variable, Henry, Kitamura, and Salani (2010) and Gan, Huang, and Mayer (2011) show that a using the full set of W and a subset of W would both produce consistent estimates of parameters of the model except the coefficients to determine the type. A Hausman-type specification test can be implemented by comparing estimates using the full set of W with those using a subset of W [11]. This test is similar to an overidentification test in the instrumental variable models.

Here we suggest a set of variables that includes number of credit cards, logarithm of income, whether the person is risk averse[12], and whether the person shops around for the best term[13]. These variables are not in the set of X that directly explains the bankruptcy decision.

Our prior is that a person's credit worthiness may be an important factor in

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[11]Gan, Huang, and Mayer (2011) provide an economic interpretation of this type of mixture density model.

[12]SCF asks its respondents: "Which of the statements on this page comes closest to the amount of financial risk that you are willing to take when you save or make investments?" and we define the variable "risk averse" to be one if the respondent chooses "not willing to take any financial risks".

[13]SCF asks its respondents: "When making major saving and investment decisions, some people shop around for the very best terms while others don't. What number would you be on the scale?" And this variable is a number between 1 and 5, the larger the number, the greater the shopping.

determining her type. A better credit-scored person may be less likely to be the strategic type. Since credit scores are not available in the data set, several variables that are related to credit scores are used. Therefore, the person with fewer numbers of cards is more likely to belong to the strategic type. Moreover, it is reasonable to postulate that a person who shops around is more frugal, and hence less likely to take on debt, and therefore, less focused on planning for bankruptcy. Thus, a person who shops around more may be less likely to be a strategic type. The effect of risk aversion on determining the type is unclear. It is not necessarily the case that a more risk-averse person is more likely to file for bankruptcy[14]. The summary statistics of these four variables can be found in Table I. All variables have substantial variations.

Table VI shows estimation results for this model, using SCF data[15]. This framework provides the clearest distinctions between the two models, as described in section 1.2. above.

One important distinction between the two models is endogeneity or exogeneity of financial benefit. Although we allow for the possibility of non-zero correlation between the error terms in the bankruptcy model and the financial benefit model for both types, only the strategic type exhibits a statistically significant (at the 90 percent level) correlation, at -0.5846 (0.3285), while the correlation for the adverse events type is statistically insignificant, at 0.2581 (0.4163). Thus, financial benefit is endogenous to the bankruptcy decision for strategic types, and exogenous for adverse events types, as predicted by the hypothesis.

The coefficient on log of financial benefit is positive and highly significant for

[14]Gan and Mosquera (2008) (Appendix) show that a more risk averse person may or may not have a higher probability of default, depending on relative current income and future income.

[15]The two-type model could only be estimated using SCF data, partly because PSID does not have the type-determination variables similar to those in SCF.

Table VI. Two Type Model(MLE;SCF data)

Variables	coefficient	standard error	coefficient	standard error
	Strategic type		Adverse event type	
Correlation b/w two errors θ	-0.5846*	0.3285	0.2581	0.4163
Bankruptcy equation				
Log(fb+1)	0.2770***	0.057	0.011	0.0858
Age	0.0222	0.0369	0.1172*	0.0653
Age squared	-0.0002	0.0004	-0.0015**	0.0007
Family size	-0.1045	0.0876	0.1053*	0.0588
Own home	0.239	0.3136	-0.2482	0.3033
Own business	0.7114*	0.4029	-5.5096	7.44
Years of education	1.3436*	0.724	-0.0134	0.1644
Years of education sqaured	-0.0443*	0.0266	-0.002	0.0071
Region effect	Yes		Yes	
Constant	-12.3733**	5.0088	-7.2476	13.5505
IV equation (dependent variable=log(financial benefit+1))				
Health problem	-0.7917	2.3225	2.4583*	1.3444
No work	-6.4100***	2.3011	-3.5781***	0.9846
Period of unemployment	3.2717**	1.5428	0.3178**	0.1384
Period of unemployment squared	-0.5806**	0.2441	-0.005	0.0036
Divorce	5.1524***	1.3938	1.8007***	0.6611
Age	0.1664	0.2156	-0.1673*	0.0973
Age squared	-0.0023	0.0024	-0.001	0.001
Family size	1.1862***	0.3552	0.048	0.1715
Own home	3.7440**	1.4665	-7.0255***	0.5391
Own business	-5.4919*	2.8768	-6.9133***	0.6964
Years of education	-0.6585	0.7818	0.6253	0.4773
Years of education squared	0.0206	0.0393	-0.0618***	0.0188
Region effect	Yes		Yes	
Constant	-4.4446	7.9765	15.1605***	3.8812
Standard deviation of error term	8.4186***	0.2958	8.5855***	0.1337
Type equation (strategic type = 1)				
ln(income)	-0.5552***		0.1115	
Number of credit cards	-2.3736***		0.4912	
Risk averse	0.2923		0.2453	
Shop around	-0.0519		0.0804	
Constant	5.9368***		1.1521	
Log-likelihood	-4650.25			

the strategic type, at 0.2770 (0.0570), but for adverse events type, this coefficient is positive and insignificant, at 0.0110 (0.0858). The coefficient for the strategic type is larger than the coefficient for the adverse events type, as predicted by the hypothesis.

Similarly, variables for adverse events (other than health problems) have the same effect on both types, but with a larger absolute effect for strategic types. Not working lowers financial benefit, increasing unemployment spell increases financial benefit, and divorce increases financial benefit. Health problems present a mixed picture, a positive (and marginally significant) effect on financial benefit for adverse types, but decreasing (and insignificant) effect for strategic types. These results document a financial-benefits channel for adverse events.

The last panel in Table VI shows that fewer numbers of credit cards increases the chance of strategic behavior, as does an increase in risk aversion. Consumers who shop around more are less likely to be strategic type. A lower income also increases the chance of strategic behavior.

As shown in Table VII, the average probability of being a strategic type is 0.1566. This provides additional confirmation for the exogeneity of financial benefit in the one-type model.

For additional analysis of the two types, we divide the population into two groups. A household is of strategic type, if its type probability is greater than 0.5, and is of adverse events type otherwise. According to this criterion, 802 households are strategic type and 3,503 households are adverse events type, as shown in Table VII.

Notably, on average, a strategic type has a 3.37% chance to file for bankruptcy, more than 4 times higher than the 0.8% chance of the adverse type. This greater filing probability is consistent with the empirical prediction of the model in section 1.2.. Similarly, in terms of the predicted probabilities, a strategic type is expected to have 9.84% chance to file for bankruptcy while the adverse events type would have

Table VII. Comparing Strategic Type and Adverse Events Type

	mean	standard error	min	max
Probability of being strategic type	0.1566	0.3069	0	1
Strategic type if predicted prob (type = 1) > 0.5				
	Strategic type		Adverse event type	
Observed probability of filing for bankruptcy	0.0337		0.008	
Predicted probability of filing for bankruptcy	0.0984		0.0061	
Log(financial benefit)	2.4523		1.8287	
% financial benefits > 0	30.80%		20.81%	
Number of households	802		3503	

0.61% chance to file for bankruptcy.

Moreover, the two types exhibit different levels of financial benefits. The average level of log of financial benefit is 2.4523 for the strategic type, about 34 percent larger than 1.8287 for the adverse events type. The larger financial benefit for strategic type is again consistent with the prediction of the model. Similarly, on average, about 30.8% of strategic type consumers have strictly positive financial benefit, as compared to 20.81% of adverse events type.

As shown in Table VII, the predicted probability of filing for bankruptcy is higher than actual for both types. One possible explanation is that financial benefit from filing for bankruptcy is heavily censored at zero (about 80 percent of the financial benefit calculations take the value of zero), and the predicted value is close to the true data of the percentage of those zeroes. This may also provide a reason why the bias of mean of log financial benefit is so large.

Table VIII shows the effects of hypothesized changes in particular variables on

Table VIII. SCF Predictions(Two Type Model)

Hypothesized variable change	Mean effect on log financial benefit(std)		Percentage point marginal effect(std)			Percentage change in the filing rate		
	Strategic type	Adverse type	Strategic type	Adverse type	Total	Strategic type	Adverse type	Total
Financial benefit +$1000	—	—	0.0221	1.95E-05	0.0035	65.58	0.24	27.4
from mean $3990.772			(0.0045)	(0.0001)	(0.0007)			
Financial benefit +$1000	—	—	0.0047	1.00E-05	0.0007	13.95	0.13	5.48
from positive mean $ 17602.74			(0.0009)	(8.00E-05)	(0.0002)			
Age of household head +1	0.1646	-0.1651	0.0129	0.0097	0.0102	38.28	121.25	78.94
years from mean 49.84	(0.2148)	(0.096)	(0.0146)	(0.0215)	(0.0183)			
Family size +0.5	0.5928	0.0239	0.0135	1.30E-06	0.0021	40.06	0.02	16.44
from mean 2.65	(0.1794)	(0.0857)	(0.0102)	(2.10E-06)	(0.0016)			
Own home +5%	0.1869	-0.3514	0.007	-2.60E-08	0.0011	20.77	-3.30E-04	8.61
from mean 70%	(0.0733)	(0.0269)	(0.0043)	(5.40E-07)	(0.0007)			
Education +1 year	-0.6839	0.624	0.0515	0.0076	0.0145	152.82	95	113.5
from mean 13.74	(0.7922)	(0.4777)	(0.1221)	(0.0234)	(0.0277)			

We compute each household's estimated probability of bankruptcy under the hypothesized change, holding all other household characteristics at their mean. The marginal effect is the change in the probability of bankruptcy for that household. The column labeled "Total" gives the weighted average of the changes, using probability of strategic type as 0.1566 and that of adverse events type as 0.8434. The last three columns translate the marginal effects into the corresponding percentage change in the filing rate, as follows: divide the marginal effect of the strategic type by the filing probability of strategic type, which is 0.0337 in the sample, that of adverse type by their filing probability, which is 0.008, and the total by the total filing probability, which is 0.01278. Figures in parentheses are bootstrapped standard errors, computed using 5,000 repetitions of the sample.

the probability of filing[16]. For example, if financial benefit goes up by $1,000, and all other characteristics are held constant at sample means, the average strategic type's filing probability goes up 0.0221 percentage points (equivalently, the filing probability increases by 0.0221), that of an adverse events type goes up negligibly, and the total filing probability goes up about 0.0035 percentage points. In terms of a percentage change in the filing rate, filing rates for strategic types go up by 65.58 percent, those for adverse types go up by 0.24 percent, and total filings go up by 27.4 percent[17]. Similarly, if home-ownership increases by 5 percentage points, the filing rates of strategic types go up about 21 percent, those of adverse types go down negligibly, and the overall filing rate goes up about 9 percent.

Our framework allows estimates of the effects of adverse events on filing probabilities through the channel of financial benefit. Table IX presents some of these effects. If the average spell of unemployment goes down by 1 week, the filing rate of strategic types goes down 93 percent, that of adverse events goes down negligibly, and the overall filing rate goes down 38 percent. A 5 percentage point decrease in the proportion of people not working leads to an increase in filing rate of strategic types by 27 percent, a negligible increase for adverse types, and an 11 percent increase in the overall filing rate. Similarly, a decrease of 5 percentage points in divorce, lowers the overall filing rate by about 8 percent. Notice that the comparatively smaller effects for adverse type (as compared to strategic type) are in part due to their much

[16]The columns for percentage point marginal effect show the change in filing probability. The column labeled "Total" gives the weighted average of the changes, using probability of strategic type as 0.1566 and that of adverse events type as 0.8434.

[17]The last three columns in Table VIII translate the marginal effects into the corresponding percentage change in the filing rate, as follows: divide the marginal effect of the strategic type by the filing probability of strategic type, which is 0.0337 in the sample, that of adverse type by their filing probability, which is 0.008, and the total by the total filing probability, which is 0.01278.

Table IX. SCF Predictions(Two Type Model):Adverse Events

Hypothesized variable change	Mean effect on log financial benefit(std)		Percentage point marginal effect(std)			Percentage change in the filing rate		
	Strategic type	Adverse type	Strategic type	Adverse type	Total	Strategic type	Adverse type	Total
Percentage of no work -5 percentage points (from mean 23%)	0.3185	0.1796	0.0091	2.20E-07	0.0014	27	0.003	10.96
	(0.113)	(0.0487)	(0.0037)	(6.00E-07)	(0.0006)			
Period of unemployment -1 week from mean 2.39	-3.2235	-0.3191	-0.0315	-3.30E-07	-0.0049	-93.47	-0.004	-38.35
	(1.5438)	(0.1385)	(0.0104)	(8.50E-07)	(0.0016)			
Percentage with health problems -1 percentage point (from mean 4%)	0.0079	-0.0246	0.0002	-2.80E-08	3.30E-05	0.59	-3.50E-04	0.26
	(0.0235)	(0.0136)	(8.00E-05)	(7.40E-08)	(1.30E-05)			
Percentage of divorce -5 percentage points (from mean 13%)	-0.2589	-0.0897	-0.0064	-1.00E-07	-0.001	-18.99	-0.001	-7.83
	(0.0698)	(0.0335)	(0.0025)	(2.60E-07)	(0.0004)			

lower responsiveness to financial benefit in the bankruptcy equation.

Finally, Table X lists the Hausman specification test suggested in Henry, Kitamura, and Salanie (2010), and Gan, Huang, and Mayer (2011). As described in Table VI, the full set of type determination variables includes ln(income), number of credit cards, an indicator for risk aversion, and an index variable for financial savviness (shopping around). The first column in Table X presents estimates of several key variables of the model using the full set of W. The second column has the estimation results without the indicator for risk aversion and the "shopping around" variable. The test shows that coefficients for all parameters (except type-determination variables in W) from the full set of W and from a subset of W are not statistically different[18]. This result provides supporting evidence on the specification of the current model. Column 3, however, tells a different story. This column is estimated

[18] The critical value of χ^2 at significance level of 99% is 112.

Table X. Hausman Test

	Benchmark model	Without risk averse and shop around	Without ln income and number of cards
ln(income)	-0.5552***	-0.5730***	—
Number of credit cards	-2.3736***	-2.4796***	—
Risk averse	0.2923	—	2.0280***
Shop around	-0.0519	—	-0.2146***
Log financial benefit	0.277	0.2739	0.2478
(strategic type)	(0.057)	(0.0547)	(0.047)
log financial benefit	0.011	0.0101	0.0847
(adverse type)	(0.0858)	(0.086)	(0.065)
Correlation coefficient	-0.5846	-0.5913	-0.6192
(strategic type)	(0.3285)	(0.3196)	(0.2428)
Correlation coefficient	0.2581	0.2627	-0.1823
(adverse type)	(0.4163)	(0.4236)	(0.2988)
Hausman test statistics	—	3.3	9738.35
p-value	—	1	0

without the "ln(income)" and "number of credit card" variables. The difference of coefficient estimates with the estimates from the full set of W is statistically significant. This contradictory testing result is likely due to the rather weak relationship between the unobserved type and the risk aversion variable and the shopping around variable (both of these two variables are statistically insignificant in Table VI).

1.4. Conclusion

The adverse events and strategic timing hypotheses have received particular attention in the debate on bankruptcy. Existing work proposes to distinguish between these hypotheses in a "strict" manner, which does not allow adverse events to affect probability of filing through the channel of financial benefits.

We propose testing for endogeneity of financial benefit as a distinguishing feature between the hypotheses. Financial benefit is endogenous to the filing decision for strategic types, and exogenous for adverse events types. This test allows adverse events to affect probability of filing in both hypotheses through the channel of financial benefit.

Using a single-type model, we show that both the PSID and the SCF data support the adverse events hypothesis.

Extending the analysis to allow for the more realistic case of both types existing simultaneously, we propose and estimate a mixture-density type model with two types. We find evidence of both types of behavior in the data. In particular, financial benefit is endogenous for the strategic type and exogenous for the adverse events type. On average, about 16 percent of the sample is strategic type, and 84 percent is adverse events type, providing support for the exogeneity of financial benefit in the one-type model. These results show a role for both hypotheses. A specification test provides some supporting evidence of this two-type model.

The estimates here are broadly consistent with theoretical predictions: the probability of filing and the financial benefit from filing are both larger for strategic type than for adverse events type. There is some evidence of a "financial-benefits" channel of the effect of adverse events on filing probability. We also find that marginal effect of financial benefit on filing probability is larger for the strategic type than for the adverse events type.

Notably, the models here are simple, and do not capture all relevant aspects of the bankruptcy decision. Similarly, data limitations prevent more thorough investigation of these ideas. Additional research on both aspects would help understand the bankruptcy decision in more detail.

CHAPTER II

DYNAMIC EFFECT OF TARP ON BANKS' LOAN TO ASSET RATIO

2.1. Introduction

The Troubled Asset Relief Program (TARP) is the largest government rescue program in US history in terms of funds appropriated. Established by the US Treasury in October 2008 to shore up the financial system after Lehman Brothers' bankruptcy, the ultimate goal of TARP is to stimulate loan supply and restore credit flowing in the economy. In this chapter, I examine the effect of a key part of the TARP, the Capital Purchase Program (CPP) on banks' loan to asset ratio (LTA). I find that TARP investment significantly boosted banks' LTA for medium banks, but had no effect on small or big banks' LTA.

Although CPP officially closed its investment program not long ago on December 31, 2009, and a substantial amount of money has not yet been returned back to the government, different evaluations of its true effect on stimulating banks' LTA have already emerged. On the one hand, a number of reports showed that TARP recipients reduced lending after receiving government help, and that consumers and small business complained about TARP banks withholding capital rather than lending it out . On the other hand, a few working papers argued positive and strong positive effect for larger and earlier-recipient banks (Bayazitova and Shivdasani 2009) or for banks with below median Tier 1 ratios (Li 2011).

In this chapter, I provide a comprehensive study of the effect of the CPP (from now on, TARP). My main result is that, there is no significant effect of TARP on small banks' and big banks' LTA. Taking the period that a bank first got TARP injection as benchmark, there is a 14 percentage point decrease in medium TARP banks' LTA.

Moreover, one dollar of TARP investment leads to 7.71 dollar more loans for them.

When I use credit as an alternative measure, I still find no effect on small banks. For medium banks, the TARP banks' credit to asset ratio (CTA) decreases by 5.49% during the treatment quarter. In terms of a dollar amount, a dollar TARP investment can be translated into 7.8 dollar more of credit for medium banks. And for large banks, there is an annual increase of 7.28 percentage point in CTA. One dollar of TARP investment can be translated into 1.25 dollar more in big banks' credit.

Previous study uses cross sectional data (Li 2011) or matching non TARP banks with TARP banks to show the effect of TARP. However, for three reasons, I cannot draw a simple conclusion from the cross section data or by matching methodology.

First, TARP investments were not randomly assigned to qualifying financial institutions (QFIs). TARP recipients are systematically different from non-recipients. For example, TARP recipients had higher level of assets, thus TARP recipients could have even lower LTA without TARP. Second, to measure the impact of TARP on bank loan supply, I also need to take into account the economic conditions in TARP recipients' service areas, since banks' LTA would be naturally low in areas with weak loan demand. Third, loans heavily rely on the historical level, and it takes time to adjust or make any response.

Further, the evolution of crisis is dynamic, and its influence on banks should be dynamic, too. Current studies are mostly using cross-sectional data to estimate the effect of TARP. Instead, this chapter employs panel data to study the dynamic effect of TARP investments on banks' LTA. Using panel data enables me to study not only the size of average treatment effect, but also the time of response in LTA.

I first graphically show the trend of all banks' LTA through the 11 quarters in my sample, and see TARP banks' LTA is higher than non TARP banks' LTA. Then, in order to find out the treatment effect of TARP, I focus on the TARP banks and adjust the time line according to the treatment date. By comparing the LTA level before and after TARP, I find some evidence of TARP's effect for different sizes of banks.

To establish a statistical inference, I try a set of regression models to uncover the real effect of TARP on banks' LTA. First, I use a difference-in-difference model to estimate the treatment effect in each period by controlling the trend; however, this model is valid with a strong assumption, that is, to be selected into TARP is a random experiment. Second, I use a fixed effect model to take care of the individual bank effect that is included in the error term. And at last, with a dynamic panel model, I am able to take care of the "dynamic panel bias".

To the best of my knowledge, this is the first empirical analysis quantifying TARP's effect on banks' LTA with panel data. It is related and complementary to several recent works. Bayazitova and Shivdasani (2009) study the allocation of TARP capital to public banks, which account for less than 10% of all commercial banks in the US. Taliaferro (2009) studies banks' self-selection into TARP based on bank characteristics only, and examines capital structure decisions of TARP banks by comparing TARP banks with matched non-TARP banks. Duchin and Sosyura (2011) study the political and regulatory influences on TARP funds distribution. There are two major differences between this chapter and the paper mentioned above. First, the panel data allow us to check the dynamic effect of LTA adjustment over time. Second, my models and specifications are more complete by controlling for not only bank characteristics, local economic conditions and time trend, but also the history influence and endogeneity of TARP decision.

This chapter contributes to the literature of financial and banking crisis. Banking crisis have significant negative effects on real economy, especially on sectors dependent on bank financing (Kronzner, Laeven, and Klingebiel, 2007; Dell'Ariccia, Detragiache, and Rajan, 2008). This effect can be largely attributed to the reduction in banks' credit supply in the economy, which could be a result of "capital crunch" of banks (Bernanke and Lown 1991). In this chapter, I test if the injection of capital can boost banks' LTA during crisis.

The rest of chapter is organized as follows. Section 2.2. introduces the TARP program and CPP in particular. In section 2.3., I introduce the data and the important variables that are used in the regressions. Section 2.4. presents with graphs and find positive evidence of TARP funds. In section 2.5., I show with a set of regression models and argue that the dynamic panel model is the most appropriate one to identify the effect of TARP investments on banks' LTA. Section 2.6. does robustness check. Section 2.7. provides concluding remarks.

2.2. A Brief Introduction of the Troubled Asset Relief Program

The Emergency Economic Stabilization Act (EESA) was enacted on October 3, 2008, in response to the severe financial crisis. TARP includes the following programs: Capital Purchase Program (CPP), Targeted Investment Program (TIP), Asset Guarantee Program (AGP), AIG Investment Program (AIG), Term Asset-Backed Securities Loan Facility (TALF), Public-Private Investment Program (PPIP), Automotive Industry Financing Program (AIFP) and Home Affordable Modification Program (HAMP). I introduce the programs related to banks below.

2.2.1. Bank-Related Programs in TARP

2.2.1.1. Capital Purchase Program (CPP)

Under the CPP, US Treasury invested in banks and other financial institutions to increase their capital. With the additional capital, CPP participants were better equipped to undertake new lending, even while absorbing write downs and charge-offs on loans that were not performing. Although many banks were fundamentally sound, because of the capital restraints caused by the troubled market conditions, they were hesitant to lend. The level of confidence between banks and other financial institutions was also low, so they were unwilling to lend to each other. Restoring capital and confidence is essential to allowing the financial system to work effectively and efficiently[1].

The CPP remained open through 2009 for investments in small banks, with terms aimed at encouraging participation by small community banks that are qualified financial institutions (QFIs) under CPP terms. The last application deadline under the CPP was in November 2009 and final closings occurred in December 2009.

Of $204.89 billion invested, as of Oct 31st, 2010, approximately $139.44 billion has already been repaid and Treasury expects it will result in a positive return for taxpayers.

2.2.1.2. Targeted Investment Program (TIP)

Treasury established TIP to provide additional assistance on a case-by-case basis in order to stabilize financial institutions that were critical to the functioning of the financial system. Through TIP, Treasury purchased $20 billion of preferred stock in each of Bank of America and Citigroup to prevent a loss of confidence that could have resulted in significant financial market disruptions, threatened the financial strength of similar financial institutions, impaired broader financial markets, and undermined the overall economy. Both institutions fully repaid their TIP funding in the fourth quarter of calendar year 2009.

[1] Troubled Assets Relief Program (TARP) Monthly 105(a) Report– August 2010.

2.2.1.3. Asset Guarantee Program (AGP)

AGP, like the TIP, was a targeted program aimed at maintaining the stability of financial institutions whose failure would have harmed the financial system. More specifically, the AGP provided protection against the risk of significant loss on pools of assets held by systemically significant financial institutions. By committing to limit an institution's exposure to losses on illiquid or distressed assets through AGP, Treasury helped the institution maintain the confidence of its depositors and other funding sources, and continue to meet the credit needs of households and businesses. Treasury used this program to assist Citigroup and also announced a commitment to assist Bank of America (BOA).

2.2.1.4. Term Asset-Backed Securities Loan Facility (TALF)

As part of the Consumer and Business Lending Initiative, the Federal Reserve and Treasury announced the creation of the Term Asset-Backed Securities Loan Facility (TALF) and launched TALF under the Financial Stability Plan on February 10, 2009. The TALF's objective is to stimulate investor demand for certain types of eligible asset-backed securities (ABS), specifically those backed by loans to consumers and small businesses. TALF has reduced the cost and increased the availability of new credit to consumers and businesses. Under the TALF, the Federal Reserve can extend up to $200 billion in three- and five-year non-recourse loans to investors that agree to purchase eligible consumer or small business ABS. Treasury provides up to $20 billion of TARP funds in credit protection to the Federal Reserve for losses that may arise under TALF loans.

2.2.1.5. Public-Private Investment Program (PPIP)

Treasury, in conjunction with the Federal Reserve and the FDIC, announced PPIP on March 23, 2009, as a part of the Financial Stability Plan. Under the PPIP, Treasury provides equity and debt financing to newly-formed public-private investment funds (PPIFs) established by fund managers with investors for the purpose of purchasing legacy securities from financial institutions. These securities are commercial mortgage-backed securities and non-agency residential mortgage-backed securities.

The Legacy Securities Public-Private Investment Program is designed, in part, to support market functioning and facilitate price discovery in the commercial and non-agency residential mortgage-backed securities (MBS) markets, helping banks and other financial institutions re-deploy capital and extend new credit to households and businesses. Both residential and commercial MBS are pools of mortgages bundled together by financial institutions. Rights to receive a portion of the cash generated by the pools are sold as securities in the financial markets, in the same way a stock or bond would be sold in financial markets. The term “legacy assets” generally refers to loans, asset-backed securities, and other types of assets that were originated or issued before the financial markets for these types of assets deteriorated significantly in 2008.

In the latter months of 2009, financial market conditions improved, the prices of legacy securities appreciated, and the results of the Supervisory Capital Assessment Program enabled banks to raise substantial amounts of capital as a buffer against weaker than expected economic conditions, all of which enabled Treasury to proceed with the program at a scale smaller than initially envisioned.

2.2.1.6. Home Affordable Modification Program (HAMP)

Treasury announced a comprehensive $75 billion program, the Home Affordable Modification Program (HAMP), in February 2009 to help distressed homeowners remain in their homes and thereby prevent avoidable foreclosures. Treasury is providing up to $50 billion in funding through the TARP, while Fannie Mae and Freddie Mac agreed to provide up to $25 billion of additional funding. The program's objective is to offer affordable mortgages to three to four million qualifying homeowners by December 31st, 2012.

2.2.1.7. Temporary Liquidity Guarantee Program (TLGP)

The TLG Program includes a guarantee of newly issued senior unsecured debt of banks, thrifts, and certain holding companies (the Debt Guarantee Program). Entities that participate in the Debt Guarantee Program are required to notify the FDIC of any guaranteed debt issuance and to pay the associated assessment premiums. Additionally, entities that have issued FDIC guaranteed debt at any time since the inception of the program are required to report the total amount of all outstanding FDIC-guaranteed debt each month. These instructions provide guidance on how to report the issuance of FDIC-guaranteed debt and the outstanding amount of all FDIC-guaranteed debt.

2.2.2. How does the CPP work?

Treasury purchased senior preferred shares and other interests from qualifying U.S.-controlled banks, savings associations, and other financial institutions. Treasury also receives warrants to purchase common shares or other securities from the banks.

Banks participating in the CPP pay Treasury dividends on the preferred shares at a rate of five percent per year for the first five years following Treasury's investment and at a rate of nine percent per year thereafter. S-corporation banks pay an interest rate of 7.7 percent per year for the first five years and 13.8 percent thereafter. Preferred shares (or stock) are a form of ownership in a company.

Banks may repay Treasury under the conditions established in the purchase agreements as amended by the American Recovery and Reinvestment Act. Treasury also has the right to sell the securities. The repayment price is equal to what Treasury paid for the shares, plus any unpaid dividends or interest.

When a publicly-traded bank repays Treasury for the preferred stock investment, the bank has the right to repurchase its warrants. The warrants do not trade on any market and do not have observable market prices. If the bank wishes to repurchase warrants, an independent valuation process is used to establish fair market value. If an institution chooses not to repurchase the warrants, Treasury is entitled to sell the warrants. In November and December 2009, Treasury began public offerings registered with the Securities and Exchange Commission for the sale of warrants using a modified Dutch auction methodology.

Qualifying Financial Institution (QFI) under CPP terms includes (i) any U.S. bank or U.S savings association not controlled by a Bank Holding Company ("BHC") or Savings and Loan Company ("SLHC"); (ii) any top-tier U.S. BHC; (iii)any top-tier U.S. SLHC which engages solely or predominately in activities that are permitted for financial holding companies under relevant law; and (iv) any U.S. bank or U.S. savings association controlled by a U.S. SLHC that does not engage solely or predominately in activities that are permitted for financial holding companies under relevant law.

QFIs may sell preferred to the UST subject to the limits and terms described as following: Each QFI may issue an amount of Senior Preferred equal to not less than 1% of its risk-weighted assets and not more than the lesser of (i) $25 billion and (ii)

3% of its risk-weighted assets.

As of today, there are 707 banks or institutions getting in total of $204.9 billion from CPP. Of these banks, 82 banks have fully repaid the money to the Treasury while 8 institutions partially repaid, which makes the total amount of repayment 139.44 billion. In this chapter, I am looking into the effect CPP on QFIs' loan to asset ratio, and from now on, I consider that TARP and CPP are equivalent.

2.3. Data and Variables

There are two categories of variables: bank characteristics, local economic environment. I model banks' loan to asset ratio using bank characteristics, local economic conditions and a dummy variable called Ever TARP, which indicates if a bank has ever received the TARP funds. The health of banks determines banks' ability to make loans, and the status of local economic environment affects loan demand for banks.

2.3.1. Bank Characteristics

Bank data are extracted from the quarterly bank balance sheets published in FDIC website. The balance sheets contain basic financial information and geographic information for banks operating in US. And I include a total of 11 quarters, i.e. one year before the crisis (2007Q4) to the most recent quarter Jun 2010 (2010Q2). Since the TARP investment is made to the headquarter of bank holding companies and banks, I assume that if a bank holding company was approved for TARP funding, all of its subsidiary banks received some fraction of the TARP funds. Thus, I sum up the assets, loans, deposits and etc. of each institution if a bank holding company has more than one institution, and replace the corresponding variables of the bank holding company with the sum. In other words, in my sample I only consider the information of the bank holding company for the case of multiple institutions and leave as it is for single institution case. I append all the 11 quarters by their bank holding companies' name or bank name(sometimes, it is necessary to use the state and city to identify). And I keep only the banks that exist in all 11 quarters. My final sample consists of 6726 observations each quarter.

The TARP recipient list is from Troubled Assets Relief Program (TARP) Monthly 105(a) Report–October 2010, United States Department of the Treasury. There are 707 QFIs that received TARP funds by the end of December 2009. I match a TARP recipient by its bank holding company's name or institution name to the balance sheet. In my sample, the recipients include 109 banks and 535 bank holding companies.

The CAMELS ratings are being used by the government in response to the financial crisis of 2008 to help decide which banks to provide special help for and which not as part of CPP. The acronym CAMELS refers to the six components of a bank's condition: Capital adequacy, Asset quality, Management, Earnings, Liquidity and Sensitivity to market risk.

Since each bank's CAMELS rating is confidential information, I use several proxies for the elements in CAMELS rating to measure a bank's condition. Tier 1 ratio, defined to be Tier 1 (core) capital divided by risk-weighted total assets, is widely used by regulators to measure a bank's ability to absorb potential losses on assets of different risk classes. I use Tier 1 ratio to proxy for a bank's capital adequacy (C). I use the troubled assets ratio to approximate a bank's asset quality (A), which is computed by adding the amounts of loans past due 90 days or more, non-accrual loans and other real estate owned (primarily foreclosed property) and dividing that amount by the bank's capital and loan loss reserves. Management quality is difficult to measure. The literature has suggested proxies like the age of a bank, percentage of insider loans, and the number of corrective actions taken by regulators. Since it is a dynamic model that I am using, I choose to use the percentage of insider loans as my proxy for management quality (M) because of its time-variant property. Earning (E) is measured by the annualized ROA. Following Hirtle and Lopez (1999), I use the cash to assets ratio to proxy for liquidity (L). Finally, I approximate the sensitivity to market risk(S) by the loans to deposits ratio. The loans to deposits ratio measures the stability of a bank's funding mix. After Lehman Brothers' bankruptcy, banks' funding costs rose substantially with the shutdown of commercial paper markets and shrinkage of wholesale funding markets. Many banks found it difficult to roll over their public debt. During this period, deposits became a particularly valuable funding source for banks (Cornett, McNutt, Strahan, and Tehranian, 2011; and Ivashina and Scharfstein, 2010). The loans to deposits ratio captures a bank's sensitivity to market risk in the crisis.

There are two additional variables that I expect to be related to both the Treasury's TARP decision and bank loan growth, that is, size of a bank and its exposure to the real estate market. A bigger bank poses a greater systemic risk to the economy. With the goal of stabilizing the financial system, the last thing the government wants to see is the failure of big banks. Thus bank size would be an important factor for the TARP decision. On the other hand, the current financial crisis is initiated from the meltdown of the housing markets. A bank's exposure to the real estate market, measured as the percentage of real estate loans in a bank's loan portfolio, could be a critical factor of its financial conditions during the crisis.

The summary statistics is presented in Table XI. I can see that TARP banks have a higher level of assets and insider loans but a lower level of tier 1 ratio, which indicates that size, management and capital quality are the concerns of Treasury's TARP decision. Besides, for small and medium banks, TARP banks have a higher loan to deposit ratio, percentage of estate loans and troubled asset ratio. These

Table XI. Summary Statistics

	All banks		Small banks		Medium banks		Large banks	
	TARP	No TARP	TARP	No TARP	TARP	No TARP	TARP	No TARP
Loan to asset	1.405	0.79	1.59	0.789	1.02	0.818	0.65	0.705
Log asset	13.16	11.92	12.36	11.73	14.53	14.23	17.47	16.84
Log insider loan	7.97	6.388	7.36	6.281	9.199	7.851	10.59	8.757
ROA	0.003	0.004	0.004	0.004	0.003	0.006	0.0003	0.004
Cash to asset	0.004	0.004	0.004	0.004	0.003	0.005	0.002	0.005
Loan to deposit	1.733	1.015	1.941	0.972	1.286	1.175	0.946	5.691
Tier 1 ratio	0.092	0.112	0.096	0.112	0.085	0.098	0.077	0.095
Troubled asset ratio	0.202	0.173	0.191	0.171	0.231	0.201	0.232	0.15
Unemployment rate	7.635	7.08	7.577	7.069	7.745	7.226	7.911	7.284
Foreclosure rate	0.198	0.159	0.195	0.157	0.2	0.168	0.226	0.252
# banks	613	6158	439	5758	143	360	38	40

imply that TARP banks are the ones in trouble, or at least more affected by the crisis. The story is slightly different for big banks: the TARP banks are less sensitive to the market risk, in which sense they are “healthy banks”, but they are also with less liquidity and more troubled assets, which means that they are affected by the depression. Plus, the percentage of big banks and medium banks that receive TARP funds is much more than that of small banks. This is probably due to the concern of systemic risk.

2.3.2. Local Economic Environment

The status of local economy correlates with loan demand and could be a determinant in approving TARP application. Generally, funds should be given to the areas with large gap between credit demand and supply. I define a state to be a local market. And I relate a bank to the state where its head quarter locates. For large banks with

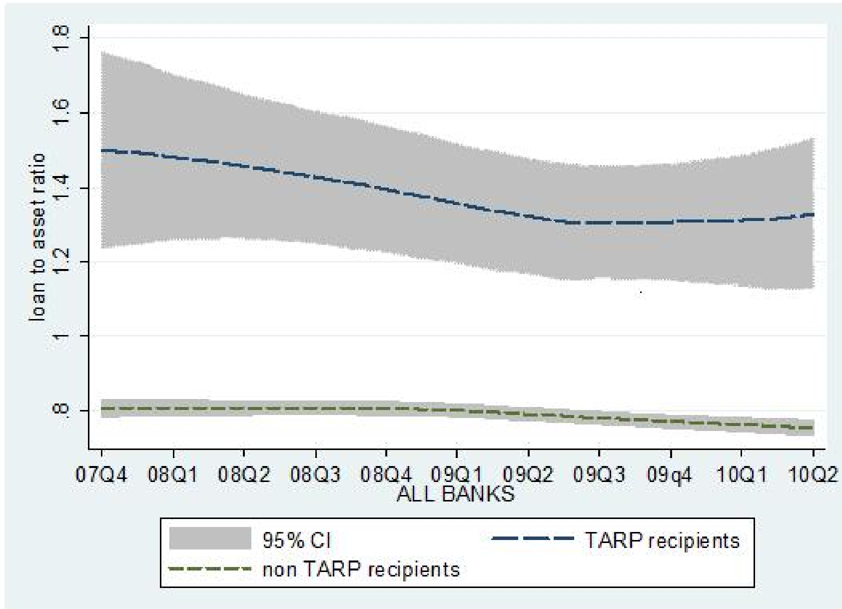

Fig. 1. Fitted Plot of All Banks' LTA from 2007Q4 to 2010Q2

branches all over the country, the definition of local market is not so appropriate; thus I use an additional indicator whether a bank has an interstate office to proxy whether it is a local bank or national bank. Besides, two economic indexes are used: unemployment rate and foreclosure rate. Unemployment rate is got from US Bureau of Labor Statistics. It is a traditional indicator of the economic condition and a higher unemployment often means a need of external funds. Quarterly foreclosure rates are from Realty Trac. It measures the impact of the crisis on the local market.

2.4. Graphic Analysis

2.4.1. Quarterly LTA change

Fig. 1 is a nonparametric fit of LTA by quarter for all banks in my sample. The long dashed line shows the LTAs for the TARP recipients and the short dashed line

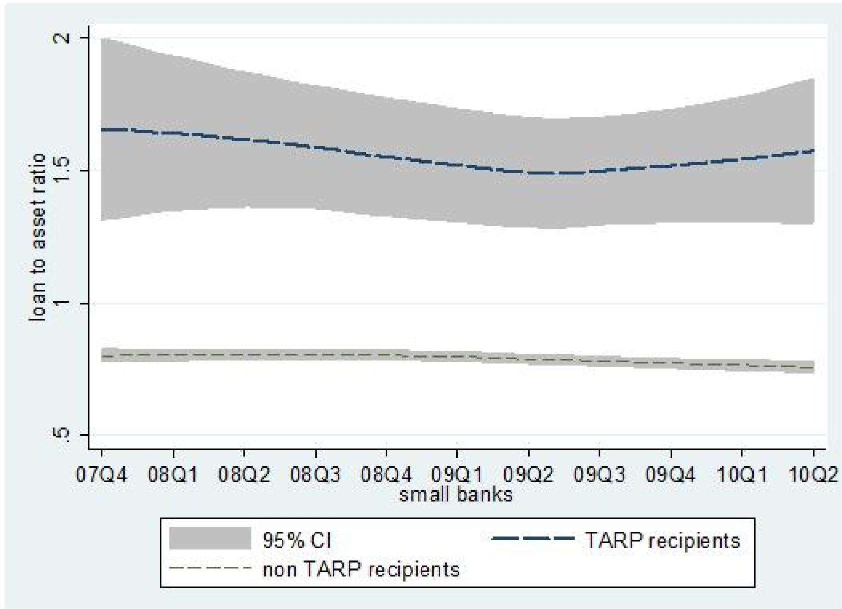

Fig. 2. Fitted Plot of Small Banks' LTA from 2007Q4 to 2010Q2

shows that of non-TARP recipients. Additionally, the grey areas indicate the 95% confidence intervals for each line. From the figure, the LTA of TARP recipients are much higher than that of the non-recipients, even at beginning of the sample (4th quarter of 2007) when TARP was not available. Apparently, which bank gets TARP is not random. A cross-section study to compare banks with and without TARP will most likely result in overestimates of the TARP effect.

Further, when I take a closer look at the TARP recipients, their LTA falls all the way until 2009Q3 and remain stable afterwards. In contrast, the non-recipients are quite steady before 2009Q1, but began to slide down since then. The figure shows that the recipients were more affected by the crisis but they seem to be recovering from the crisis; in contrast, the trend of LTA for non-recipients was quite smooth with a slight decrease when the economy became worse.

If I draw the same figure for different sizes of banks, the trend of LTA varies substantially across different sizes of banks. I divide all banks into three groups, small, medium, and big. The small banks are those banks with assets below 1 billion, medium banks are those with assets between 1 billion to 10 billion, and big banks are those with assets greater than 10 billion. In my sample, there are more than 90% banks are small banks.

Fig. 2 is the fitted plot of LTA by quarter for small banks. I can see that the trend is quite similar to that in Fig. 1, especially for the non-recipients. However, the average LTA of small TARP recipients are a little bit higher than the average LTA of all the TARP recipients, which suggests that the Treasury may have a higher criterion for small banks when it makes the TARP decision. Additionally, the turning point of recipients is one quarter earlier than that in Fig. 1, and the rise is more significant after 2009Q1, that is when small banks began to get TARP investments.

Fig. 3 shows the change of LTA for medium banks over time. The trend of medium banks is quite different from the overall trend and from that of small banks. Both TARP recipients and non-recipients have a declining curve of LTA. Although the LTA of recipients is much higher than that of non-recipients before the peak of crisis (2008Q4), their difference in LTA is shrinking over time. During the last quarter (2010Q2) both of their LTA have decreased to less than 0.7, on average. Obviously, medium banks have been severely affected by the crisis. And I see that there is overlapping area between the two confidence intervals, which implies the difference between LTAs of the two groups may not be significant.

Further, the LTA pattern of big banks is quite different from that of small banks or medium banks. In Fig. 4, the non-recipients' average LTA is above that of the recipients but their difference may not be significant because a large part of the confidence interval of TARP recipients is overlapped by that of the non-recipients.

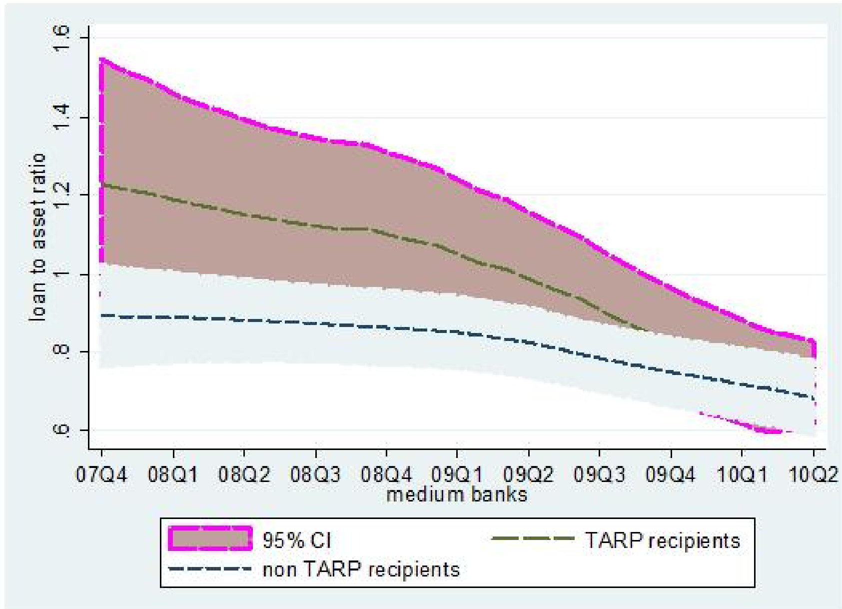

Fig. 3. Fitted Plot of Medium Banks' LTA from 2007Q4 to 2010Q2

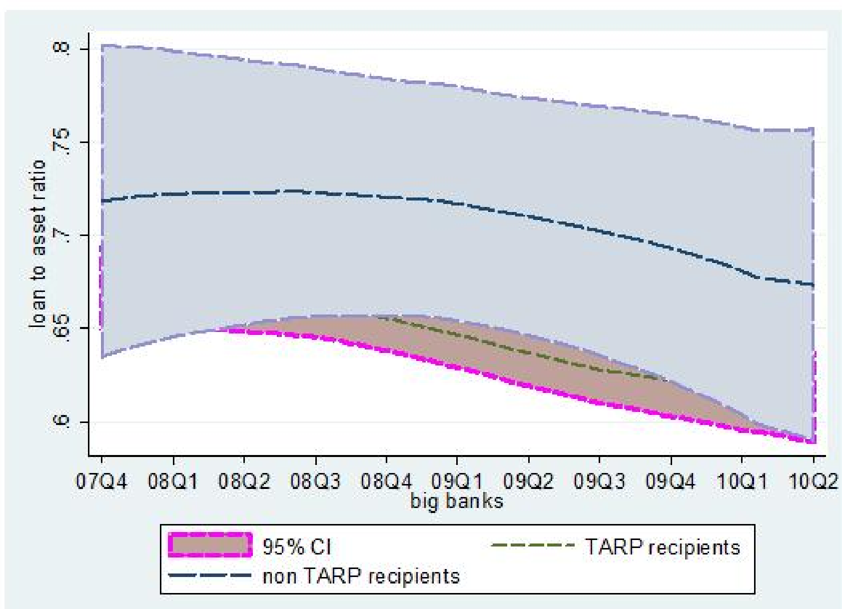

Fig. 4. Fitted Plot of Large Banks' LTA from 2007Q4 to 2010Q2

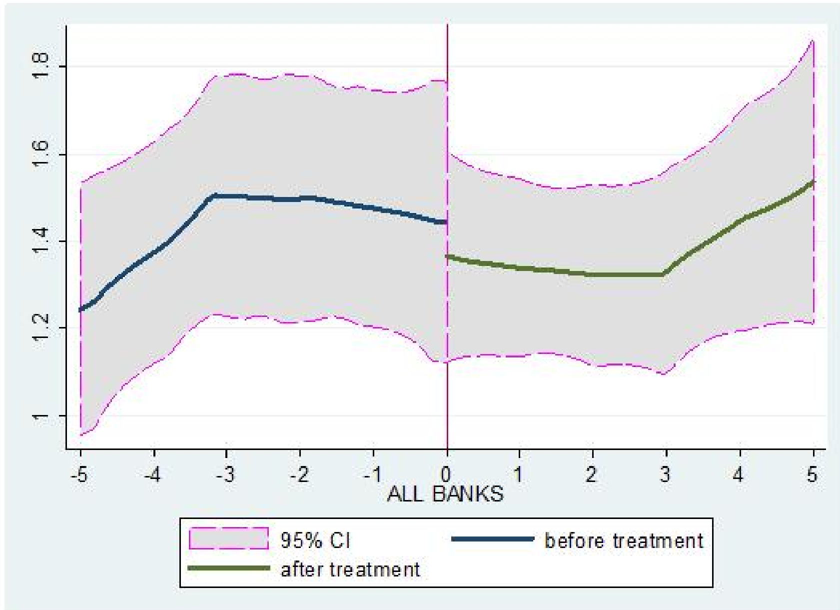

Fig. 5. Fitted Plot of All Recipient Banks' LTA by Treatment Period

Besides, the LTAs for big banks, regardless of receiving TARP or not, decreases over the time. Moreover, I see that the average LTA of big banks is only half of that of small or medium banks. This indicates that big banks' lending behavior is quite different from smaller banks.

2.4.2. Treatment Effect

One problem from the previous graphs is that I ignore the timing of receiving TARP. Next I explicitly incorporate the timing effect. I redefine the quarter of receiving TARP to be the zero period of treatment, the first quarter before that to be the -1 period of treatment, the second quarter before that period to be the -2 period, etc.. Further, I define the first quarter after that to be period 1, and 2nd quarter after that period to be period 2, etc., until the period 4. All periods after the 5th period

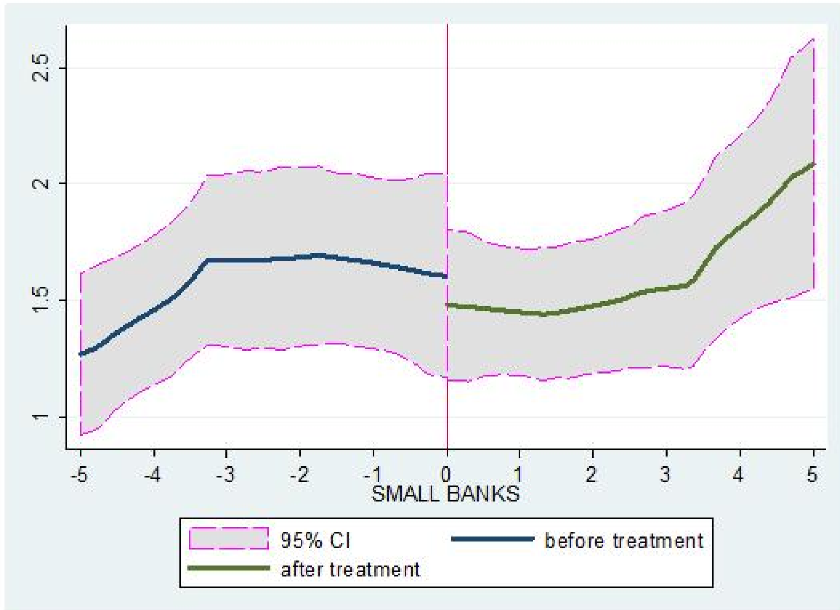

Fig. 6. Fitted Plot of Small Recipient Banks' LTA by Treatment Period

(including the 5th period) are grouped to be period 5. For non-recipients, I do not know when they will be treated, so I exclude them in the graphs and only focus on the TARP recipients.

This enables us to see the average treatment effect of each quarter before and after the recipients receive TARP funds no matter which quarter they actually receive it. Figs. 5-8 show the average treatment[2] in the TARP banks' LTAs before and after receiving the TARP funds.

Fig. 5 plots the sample for all TARP banks, and Fig. 6, Fig. 7 and Fig. 8 plot LTAs for small, medium and large TARP banks, respectively. From Fig. 5, the overall pattern is that LTA goes up 3 quarters before treatment and then goes down, and goes up again 3 quarters after the treatment. The local average treatment effect

[2]Treatment period is period when the bank first receives TARP money.

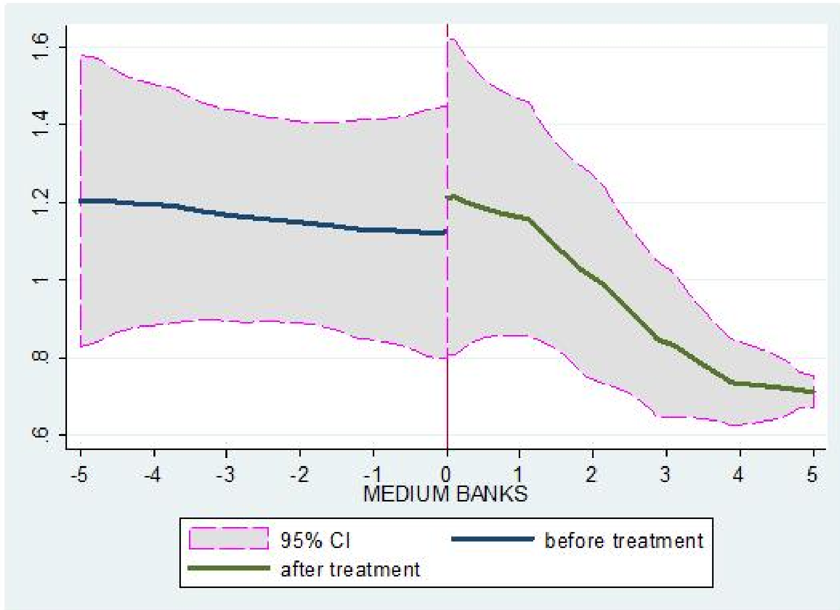

Fig. 7. Fitted Plot of Medium Recipient Banks' LTA by Treatment Period

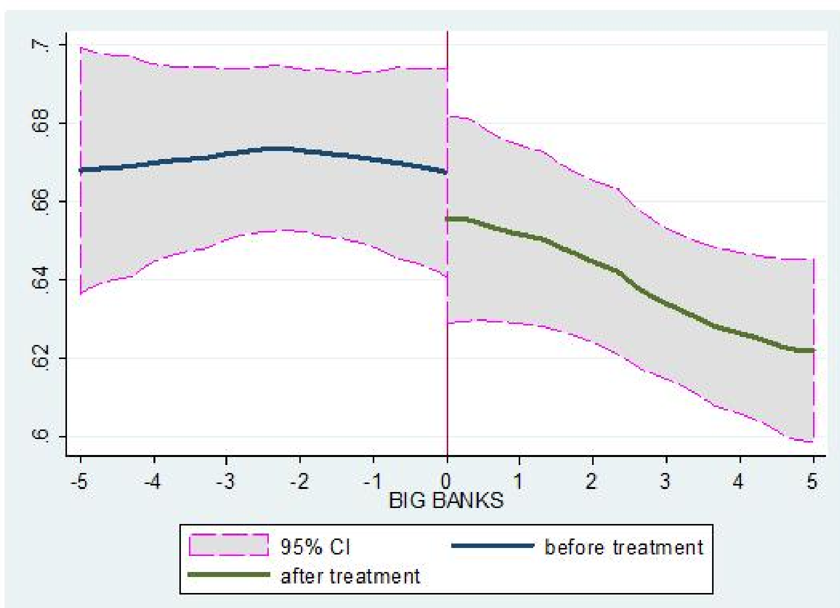

Fig. 8. Fitted Plot of Large Recipient Banks' LTA by Treatment Period

during the treatment period is negative.

A similar pattern for small banks can be found in Fig. 6. The difference between the overall pattern and the one from the small banks is that small banks turn "up" after the first period while for all TARP banks, the recovery did not occur until the third period after treatment.

The pattern for the medium banks, however, is a totally different story. The TARP banks' LTA is declining over time. There is a jump during the treatment period and the declining rate is even faster after the treatment. This implies that the capital injection of TARP provides the medium bank a positive shock but the banks were reluctant to lend when the crisis turns from bad to worse.

For large banks, their LTAs are going down slowly as a whole and there is a turning point during the 3rd period after TARP. Ever since then, LTA goes up straight. I also see that there is a small drop comparing the LTAs before and after treatment.

I also plot fitted log loan change before and after receiving TARP in Fig. 9, Fig. 10, Fig. 11, and Fig. 12. I do not observe significant jump during the treatment period except a slight one for medium TARP banks. An important fact is that after 3 quarters of treatment, small banks have an increasing trend in loans, but both medium and big banks keep their loan almost the same level as the treatment quarter. Combined this fact with the asset growth of TARP banks trend in each category (there are steady growth in assets for small and medium banks, but big banks' assets remain unchanged through the sample), I expect that TARP should have no effect on big banks' LTA, some negative effect on medium banks' LTA, and an unknown effect on small banks' LTA.

Although I see a negative local average treatment effect in LTA around the treatment period, the real treatment effect could be a lagged one on loans. Moreover, I do not control all the other important factors described in Section 2.3.. I will take

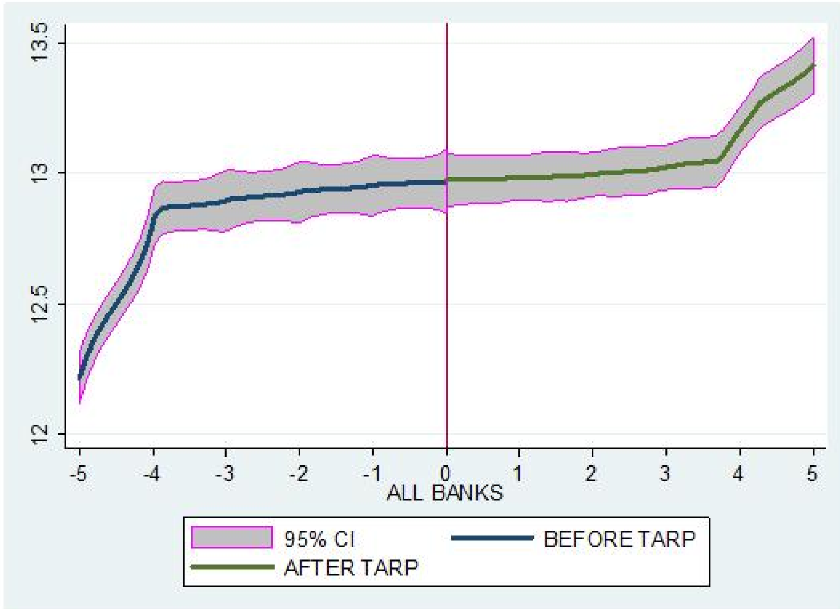

Fig. 9. Fitted Plot of All Banks' Log Loans by Treatment Period

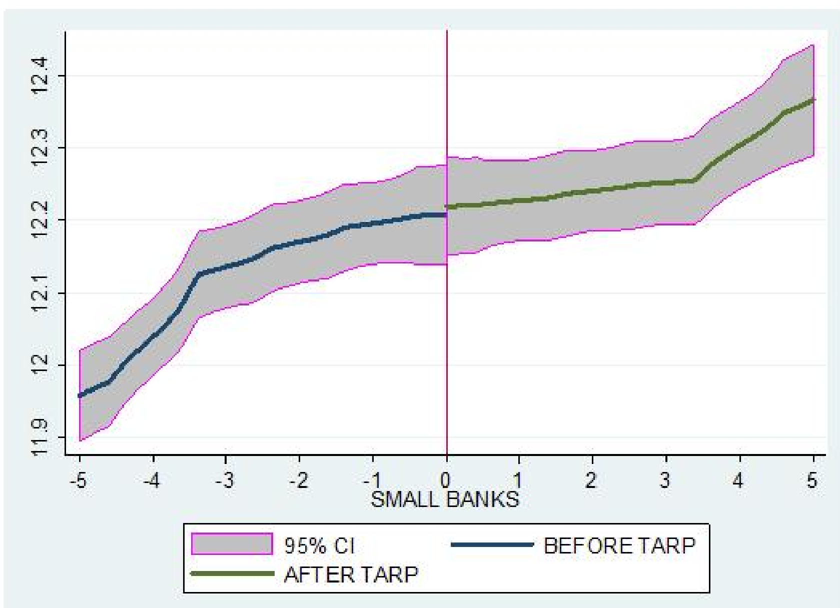

Fig. 10. Fitted Plot of Small Banks' Log Loans by Treatment Period

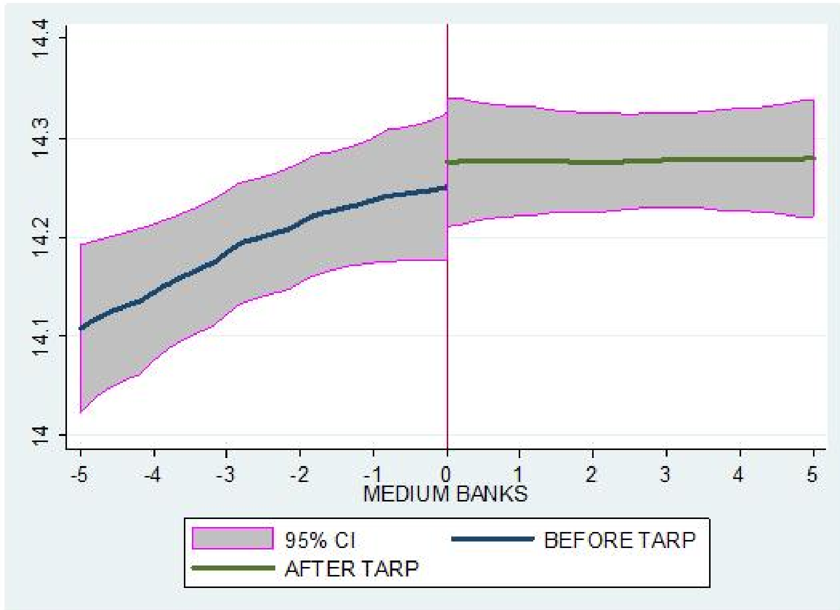

Fig. 11. Fitted Plot of Medium Banks' Log Loans by Treatment Period

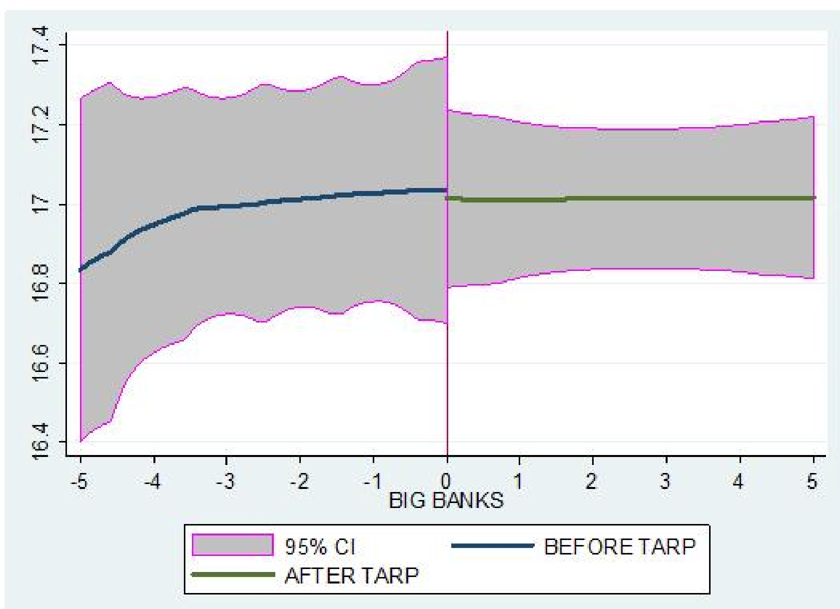

Fig. 12. Fitted Plot of Large Banks' Log Loans by Treatment Period

care of these concerns and try to identify the local treatment effect for each period in the next section.

2.5. Regression Analysis

The figures above suggest a clear link between the treatment of receiving TARP and the LTA, but they do not provide a framework for formal statistical inference. In this section, I will apply different regression models to find out the average effect of TARP on LTA. First, I assume the Treasury's TARP decision is random, i.e. there is no selection to be a TARP bank or not. With this assumption, I use the difference-in-difference model to identify the treatment effect of TARP on LTAs. To deal with the individual bank effect, I apply fixed effect model and dynamic panel model. Since the Treasury's TARP decision might be correlated with loan supply and demand for banks, TARP investments are endogenous to LTA. I then relax the assumption made in difference-in-difference model and take care of the endogeneity problem. I report the results of the above regressions in the subsections.

2.5.1. Difference–in–difference Model

In the difference-in-difference model, before I estimate the effect of TARP investments on LTA, I need to make an assumption on the treatment-to be treated or not is a random experiment. In my case, I assume the Treasury randomly chooses banks among each category to enter the TARP.

The Treasury wants to promote credit floating in the economy by injecting capital into banks, expecting that, with a strengthened capital base, TARP banks would be able to make more loans to business and consumers.

Table XII. Difference-in-difference Model, Dependent Variable LTA_{it}

VARIABLES	All banks	Small banks	Medium banks	Large banks
Lag LTA	0.577***	0.171*	0.499***	0.742***
4th period after TARP	0.150*	0.124***	-0.152	0.0707
3rd period after TARP	0.0663	0.0775*	-0.205	0.0466
2nd period after TARP	0.0172	0.0499*	-0.138	0.0753
1st period after TARP	-0.00976	0.0181	-0.0673	0.123*
1st period before TARP	0.0607	0.0288	-0.231*	0.0673
2nd period before TARP	0.0805	0.0384	-0.260*	0.0529
3rd period before TARP	0.00681	0.0116	-0.175	0.0407
4th period before TARP	-0.0707	-0.02	-0.274**	-0.00925
Ever TARP	0.105*	-0.036	0.309**	-0.0313
Log asset	-0.0799***	-0.0479***	-0.162***	-0.0278**
Log insider loan	-0.00138	0.00138	-0.0224***	0.00879**
ROA	-0.332	-0.165	18.88***	9.253*
Cash to asset	4.304***	1.080*	-1.428	3.252*
Loan to deposit	0.251***	0.682***	0.0965*	0.000774
%Real estate loan	0.226***	0.0387	0.135***	-0.0088
Tier 1 ratio	-1.048***	-1.879***	-3.081***	0.196
Troubled asset ratio	0.00987	-0.00756	0.175**	0.126**
Unemployment rate	-0.000924	0.00226*	0.00286	0.0115
Foreclosure rate	-0.0219	-0.0502*	0.181**	-0.00267
Quarter 3	0.0124	0.0132	-0.0524	-0.0371
Quarter 4	-0.0238	-0.00184	-0.103**	-0.0722
Quarter 5	-0.0119	-0.00132	-0.0832	0.00442
Quarter 6	-0.00218	0.00696	-0.0695	-0.122
Quarter 7	0.0157	0.00685	-0.059	-0.0684
Quarter 8	-0.0118	0.000909	-0.149**	-0.0499
Quarter 9	-0.0116	0.00268	-0.102*	-0.101**
Quarter 10	-0.011	0.00531	-0.184**	-0.0699
Quarter 11	0.0133	0.0141*	-0.132**	-0.126**
Constant	0.991***	0.706***	2.879***	0.456**
Observations	67,256	61,605	4,881	770
R-squared	0.83	0.955	0.87	0.711

For the i^{th} bank, its t^{th} quarter LTA can be written as:

$$LTA_{it} = \lambda LTA_{it-1} + \alpha X_{it} + \beta EverTARP_i + \sum_{k=-5}^{5} \gamma_k D_{ik}$$

$$+quarter\ dummies + \mu_i + e_{it} \quad where \quad \gamma_0 = 0$$

where LTA_{it-1} is the lagged loan to asset ratio of i^{th} bank. LTA has a lagged response to change, thus LTA of the t^{th} quarter should be partially determined by its historical LTA. X_{it}, is a set of control variables, including the bank characteristics and local economic environment. $EverTARP_i$ is a dummy variable that equals 1 if bank i is a TARP recipient, and 0 otherwise. The coefficient of $EverTARP_i$ shows the average difference of LTA of TARP recipients and non TARP recipients. I also add quarter dummies to control for the trend in each quarter. The treatment period dummies are added to capture the adjustment in each period. I define D_{ik} equal to 1 if it is the i^{th} TARP bank t^{th} quarter after receiving the TARP funds, and zero otherwise. Additionally, I normalize D_{i0} equal to 0 for all so that the treatment period is the benchmark case for comparison. Also, I allow individual fixed effect and an idiosyncratic error term. The result is reported in Table XII.

There is no significant effect for the overall sample until the 4th period after they received TARP funds. When I go to sub cases, it seems that TARP investments only have effect on small banks. The effect becomes significant from the 2nd quarter after treatment. For medium banks, there is a huge jump up during the period of treatment and LTA decreases since then, which is consistent with what I find in section 2.4.. Besides, for large banks, there is an increase in LTA during the 1st period of treatment, and it is marginally significant.

Table XIII. Fixed Effect model, Dependent Variable LTA_{it}

VARIABLES	All banks	Small banks	Medium banks	Large banks
Lag LTA	0.200***	0.0734*	0.326***	0.0675**
4th period after TARP	0.0706	0.114**	-0.223*	-0.014
3rd period after TARP	0.059	0.0814	-0.156	0.0236
2nd period after TARP	0.0369	0.0526*	-0.056	0.018
1st period after TARP	0.00509	0.0199	-0.0121	0.000881
1st period before TARP	0.0408	0.0169	-0.253**	0.0223
2nd period before TARP	0.0348	0.0115	-0.286*	0.0394
3rd period before TARP	-0.0197	-0.0182	-0.231**	0.0352
4th period before TARP	-0.0483	-0.0653	-0.309***	0.0883*
Log asset	-1.039***	-0.407*	-1.035***	-0.354***
Log insider loan	-0.00745	-0.00133	0.00234	-0.00499
ROA	0.145	-0.0731	20.02***	11.26**
Cash to asset	1.429	-0.55	-1.668	1.714
Loan to deposit	0.244*	0.634***	0.1	-0.000973***
%Real estate loan	-0.0805	-0.0955	-1.130*	-0.238
Tier 1 ratio	-4.014***	-4.549***	-8.588***	-0.543
Troubled asset ratio	-0.0214	-0.0183	0.0263	0.324**
Unemployment rate	-0.0021	-0.00910**	-0.0282	0.0102
Foreclosure rate	-0.0559	-0.156**	0.0996	-0.00234
Quarter 3	0.0315***	0.0306*	-0.0201	-0.0326
Quarter 4	0.0246	0.0256*	-0.0362	-0.0254
Quarter 5	0.0482***	0.0360**	0.0249	0.016
Quarter 6	0.0662***	0.0594***	0.117	0.00579
Quarter 7	0.0896***	0.0694***	0.168*	-0.0198
Quarter 8	0.0815***	0.0705***	0.114	-0.0392
Quarter 9	0.0933***	0.0742***	0.202*	-0.0372
Quarter 10	0.0878***	0.0728***	0.186	-0.0533
Quarter 11	0.107***	0.0734***	0.282**	-0.0558
Constant	13.42***	5.534*	16.98***	6.796***
Observations	67,256	61,605	4,881	770
R-squared	0.509	0.835	0.697	0.742
Number of banks	6,728	6,162	489	77

2.5.2. Fixed Effect Model

One immediate problem in applying the difference-in-difference model, is that LTA_{it-1} is endogenous to the error term, which gives rise to "dynamic panel bias". To see this, consider the possibility that a bank has some behavioral characteristics, which we did not observe, so that the shock goes into the individual bank effect. For example, in Fig. 1 and Fig. 2, the TARP banks are with a higher LTA than the non TARP banks, and it could be the case that some unobserved variables lead to such a difference. The positive correlation between treatment of TARP and the unobserved individual bank effect implies that the OLS estimator is over-estimated for all banks case and small banks case. I do not observe significant difference in LTAs between TARP banks and non TARP banks in Fig. 3 and Fig. 4, so the OLS estimators are biased to an unknown direction for medium banks and big banks.

I use the fixed effect model to remove the individual fixed effect. Since $EverTARP_i$ is a time-invariant variable, it will be dropped after demeaning. The result is reported in Table XIII. I see a significant and positive effect of TARP on small banks' LTA in the 2nd and 4th quarter after they received TARP investments. For medium banks, the jump in the treatment period persists and the declining trend of LTAs becomes marginally significant at the 4th period of treatment. And there is no significant effect on big banks.

Fixed effect regression does the within group transformation, but this does not eliminate dynamic panel bias. Under the within group transformation, the demeaned lagged dependent variable $LTA_{it-1} - \frac{1}{10}\sum_{t=2}^{11} LTA_{it-1}$ is still correlated with the demeaned error term $e_{it} - \frac{1}{11}\sum_{t=1}^{11} e_{it}$.

Table XIV. Dynamic Panel model, Dependent Variable LTA_{it}

VARIABLES	All banks	Small banks	Medium banks	Large banks
Lag LTA	0.109***	0.0469***	0.324***	0.0602***
4th period after TARP	0.014	0.00939	-0.140***	-7.43E-05
3rd period after TARP	0.0245**	0.0119	-0.0728***	0.00498
2nd period after TARP	0.0283**	0.00529	-0.0235	-0.000445
1st period after TARP	0.012	0.005	-0.0101	-0.0105
1st period before TARP	-0.0242*	-0.00684	-0.120***	0.0126
2nd period before TARP	-0.0337**	-0.00366	-0.143***	0.0308***
3rd period before TARP	-0.0295	-0.00299	-0.127***	0.0317**
4th period before TARP	-0.0561**	-0.0496**	-0.146***	0.0385***
Log asset	-0.400***	-0.211***	-1.669***	-0.360***
Log insider loan	0.00262	-0.000286	0.0378***	-0.0114***
ROA	-0.172***	-0.206***	13.91***	12.18***
Cash to asset	0.0416	-1.072***	-1.246***	3.064***
Loan to deposit	0.587***	0.704***	0.170***	-0.000668**
%Real estate loan	-0.0264	-0.011	-1.126***	-0.434***
Tier 1 ratio	-4.783***	-2.500***	-10.21***	0.130*
Troubled asset ratio	-0.0119	-0.000636	0.165***	0.435***
Unemployment rate	-0.00292	-0.000994	-0.0381***	-0.00681***
Foreclosure rate	-0.0316	-0.0497	0.128**	0.0481***
Quarter 3	0.0154***	0.0111***	0.0214	-0.0168***
Quarter 4	0.0101	0.00868**	0.0427**	-0.0077
Quarter 5	0.008	0.0117**	0.119***	0.0233***
Quarter 6	0.0174	0.0183**	0.252***	0.0613***
Quarter 7	0.0158	0.0229**	0.302***	0.0505***
Quarter 8	0.0159	0.0243**	0.320***	0.0311***
Quarter 9	0.0196	0.0292***	0.381***	0.0253**
Quarter 10	0.0206	0.0289***	0.369***	0.00779
Quarter 11	0.0249*	0.0294***	0.482***	-0.00302
Observations	60,524	55,439	4,392	693
Number of banks	6,726	6,161	488	77

2.5.3. Dynamic Panel Model

To address the endogeneity of both the lagged LTA with unobserved factors, we apply the two step GMM regression, which uses further lags of LTA as instruments for lagged LTA. The result is shown in Table XIV.

Under dynamic panel model, there is a positive and significant effect in 2nd and 3rd quarter after treatment for the recipients as a whole. And there is also a 2 percentage point increase in LTA during the treatment period.

For small TARP banks, there is no significant effect of TARP. From Table XI, I see that the TARP recipients under this category are selected using a stricter criterion and it could be that these TARP banks are more aggressive than the others. Ivashina and Scharfstein (2010) suggest that more vulnerable banks cut lending more than others because these banks lend to firms whose loan demand fell more during the crisis. Small banks, most of which are local banks (5% of small banks have interstate offices), usually rank high in the local market share. One of the possible reasons for no significant effect on small TARP banks' LTAs, is that their loan demand is relatively stable and they were having a steady growth in both loan and asset.

For medium banks, I also observe a jump in the period that they got the TARP funds, but the size of the jump is much smaller than that in difference-in-difference model or fixed effect model-an average 12 percentage points increase in LTA from the previous period. There is highly statistically significant and negative effect of TARP on recipients' LTAs in 3rd and 4th quarter of treatment. The LTA of TARP banks decreases by 14 percentage points after a year of investments, and the LTA stays at a similar level with 4th quarter before TARP, that is two years ago. The result implies that the TARP banks in this category sit on the TARP investment and reluctant to lend. One of the possible reasons is that these banks spend the money to enrich their capital base. When I compare the TARP banks with the non TARP banks, I find TARP banks' assets has a lower growth rate with a stable loan level, while non TARP banks' loans grow at a positive rate. This implies that these TARP recipients might be the ones that need help.

For large banks, there is no significant effect on average. In terms of large banks, the TARP investments were more targeting on the goal to stabilize the financial system, because of the systemic risk. Comparing TARP banks with the non TARP banks, I see almost no growth in either loans or assets for the recipients. And inversely, the non TARP banks were able to have growth on both loans and assets.

I also run a Sargan/Hansen test for joint validity of the instruments. For all banks, the Sargan test of chi-square statistic is 80.26, which reject the null hypothesis at 1% significance level. For the small and medium banks, the Sargan test of chi-square statistics are 74.84 and 104.0806, both of which reject the null hypothesis at 1% significance level. And the statistic is 55.84 under cases of big banks, for which I cannot reject the null.

Another concern is the autocorrelation in the idiosyncratic disturbance term. So I run an autocorrelation test. I can reject the null for small, medium and large banks at 1%, 5% and 10% significance level, respectively. But I cannot reject the null for the whole sample.

In terms of a dollar amount, if I replace the treatment dummy with the TARP investment amount to asset ratio during the five periods after TARP (Table XV), the effect on LTA becomes clearer. One thing to notice is that now I no longer use the treatment period as the benchmark, instead, I compare the LTA level after TARP with the average level of LTA before TARP. For small banks, one dollar of TARP funds leads to 0.04 and 0.02 dollar fewer loans in treatment quarter and the 1st quarter after treatment, respectively, but it turns out to be 0.02 dollar more loans

Table XV. Dynamic Panel Model with TARP Investment/asset

VARIABLES	All banks	Small banks	Medium banks	Large banks
Lag LTA	0.108***	0.0468***	0.327***	0.0588***
Log asset	-0.397***	-0.209***	-1.393***	-0.358***
Log insider loan	0.00253	-0.000223	0.0569***	-0.0108***
ROA	-0.157***	-0.193***	15.56***	12.41***
Cash to asset	0.114	-0.958***	-2.727***	2.875***
Loan to deposit	0.589***	0.705***	0.153***	-0.000630***
%Real estate loan	-0.0264	-0.0111	-0.765**	-0.426***
Tier 1 ratio	-4.794***	-2.496***	-9.415***	0.103
Troubled asset ratio	-0.012	-0.000477	0.0687**	0.436***
Unemployment rate	-0.00282	-0.000927	-0.0340***	-0.00660***
Foreclosure rate	-0.0296	-0.0493	0.0583	0.0512***
4th period after TARP, TARP investment/asset	-2.84E-06	2.43e-05**	0.00771***	7.82E-05
3rd period after TARP, TARP investment/asset	-1.09E-05	-1.54E-06	0.00938***	-8.40E-05
2nd period after TARP, TARP investment/asset	-4.59E-06	-2.61E-06	0.0127***	-0.000503
1st period after TARP, TARP investment/asset	-4.93E-05	-2.69e-05**	0.0104***	-0.00115**
0 period after TARP, TARP investment/asset	-7.22E-05	-4.35e-05**	0.00773***	-0.000257
Quarter 3	0.0152***	0.0109**	0.0171	-0.0175***
Quarter 4	0.01	0.00886*	0.0370**	-0.0177***
Quarter 5	0.00857	0.0116**	0.0884***	0.00808
Quarter 6	0.0195*	0.0190***	0.201***	0.0516***
Quarter 7	0.0191	0.0238**	0.241***	0.0388***
Quarter 8	0.0199	0.0253**	0.238***	0.0171
Quarter 9	0.0232	0.0302***	0.296***	0.00743
Quarter 10	0.0241	0.0302***	0.277***	-0.0124
Quarter 11	0.0282**	0.0306***	0.367***	-0.0226**
Observations	60,524	55,439	4,392	693
Number of banks	6,726	6,161	488	77

Table XVI. Dynamic Panel Model, Dependent Variable: Real Estate Loan/asset

VARIABLES	All banks	Small banks	Medium banks	Large banks
5th period after TARP	0.00377	0.00835	-0.0195	0.00674
4th period after TARP	-0.00241	0.0029	-0.00193	0.0139*
3rd period after TARP	5.20E-05	0.00109	0.00478	0.0102
2nd period after TARP	0.0035	0.00597	-0.000518	0.00199
1st period before TARP	-0.00186	-0.00262	-0.0127*	0.0192***
2nd period before TARP	-0.0114	-0.00877	-0.0249***	0.0306***
3rd period before TARP	-0.0138	-0.0136	-0.0187**	0.0334***
4th period before TARP	-0.0331**	-0.0231	-0.0307**	0.0338***
Observations	59,632	54,646	4,302	684
Number of banks	6,626	6,072	478	76

Table XVII. Dynamic Panel Model, Dependent Variable: Residential Loan/asset

VARIABLES	All banks	Small banks	Medium banks	Large banks
5th period after TARP	0.00108	0.0038	0.000205	0.0123**
4th period after TARP	0.00424	0.00342	0.000489	0.0105
3rd period after TARP	0.00186	0.000218	0.00133	0.00616
2nd period after TARP	0.00429	0.00244	0.000674	-0.00191
1st period before TARP	-0.00158	-0.000795	-0.00332	0.00372
2nd period before TARP	-0.00936***	-0.00774*	-0.00543**	0.00676
3rd period before TARP	-0.0107**	-0.00966**	-0.00519	0.00128
4th period before TARP	-0.0176***	-0.0211***	-0.00566	-0.00942
Observations	59,632	54,646	4,302	684
Number of banks	6,626	6,072	478	76

Table XVIII. Dynamic Panel Model, Dependent Variable: Farmland Loan/asset

VARIABLES	All banks	Small banks	Medium banks	Large banks
5th period after TARP	0.00031	0.000959	0.000337	-0.00688***
4th period after TARP	0.00193*	0.00256*	0.0015	-0.00361***
3rd period after TARP	0.00141	0.00232	0.000778	-0.00368***
2nd period after TARP	0.00056	0.000744	0.000225	-0.00343***
1st period before TARP	-0.00152	-0.000678	-0.00240***	0.00224***
2nd period before TARP	-0.00258**	-0.00185	-0.00231***	0.00365***
3rd period before TARP	-0.00356**	-0.00243*	-0.00232**	0.00712***
4th period before TARP	-0.00416**	-0.00398*	-0.00197**	0.0131***
Observations	53,540	49,337	3,654	549
Number of banks	5,955	5,488	406	61

after a year of treatment. This boosting effect is more noticeable for medium banks. There is an annually 7.71 dollar more loans being generated for every TARP dollar invested. Beside, the effect is positive and significant since the treatment quarter. Still, there is no significant effect on big banks.

As a whole, I see a stimulating effect of TARP for all the recipients. And this stimulating effect is particularly significant for medium banks. In my sample, 30% medium banks and 62% big banks have interstate offices, which implies that there is possible variation in the loan demand. With the capital injection of TARP, banks might be able to stabilize their capital base and adjust their loan supply as a whole.

I further probe into the sources of loan change by checking different categories of loans, including real estate loans, 1-4 family residential loans, farmland loans, commercial and industrial(C&I) loans, consumer loans and credit card loans(Tables XVI-XXI). I do not have data of C&I loans in 2009Q2, so a couple of treatment quarter dummies are dropped. For small banks, there is only an increase in farmland

Table XIX. Dynamic Panel Model, Dependent Variable: C&I Loan/asset

VARIABLES	All banks	Small banks	Medium banks	Large banks
5th period after TARP	-0.0105	-0.000636	-0.00901	-0.0203
4th period after TARP	-0.00596	0.00165	-0.00562	0
3rd period after TARP	-0.00294	0.00243	-0.00833	
2nd period after TARP	-7.67E-06	0.00474	-0.00358	-0.00413
1st period before TARP	0.00138	0.00329	-0.00606***	0.00604*
2nd period before TARP	0.00297	0.00905**	-0.00879***	0.00631*
3rd period before TARP	0.00198	0.00698	-0.00775***	0.00629
4th period before TARP	0.000321	0.003	-0.00783**	0.00395
Observations	39,754	36,430	2,868	456
Number of banks	6,626	6,072	478	76

loans. For medium banks, no significant effect is found after treatment except an annual 0.21 percentage point decrement in credit card loans. For large banks, the evidence is mixed. A marginally significant increment in real estate loans, an annual 1.23 percentage point increment in residential loans, 0.81 percentage point increment in consumer loans and 0.653 percentage point increment in credit card loans are found significant in the result. But I also find an annual decrement of 0.688% in farmland loans.

2.6. Robustness Check

In this section, I conduct several robustness checks to make sure my results are not driven by other potential confounding factors.

Table XX. Dynamic Panel Model, Dependent Variable: Consumer Loan/asset

VARIABLES	All banks	Small banks	Medium banks	Large banks
5th period after TARP	0.00161	0.00174	0.000111	0.00807***
4th period after TARP	0.00145*	0.00154	0.000445	0.00573***
3rd period after TARP	0.000199	7.29E-06	9.11E-05	0.00151
2nd period after TARP	0.000557	0.00051	0.000219	0.00116
1st period before TARP	-0.00115*	-0.000723	-0.00462***	-0.00185*
2nd period before TARP	-0.00308***	-0.00284**	-0.00555***	-0.00138
3rd period before TARP	-0.00377***	-0.00282**	-0.00621***	-0.000183
4th period before TARP	-0.00352***	-0.00298*	-0.00556***	0.00414**
Observations	59,632	54,646	4,302	684
Number of banks	6,626	6,072	478	76

Table XXI. Dynamic Panel Model, Dependent Variable: Credit Card Loan/asset

VARIABLES	All banks	Small banks	Medium banks	Large banks
5th period after TARP	-2.95E-07	1.53E-05	-0.00209***	0.00653***
4th period after TARP	3.09E-05	2.50E-05	-0.000313	0.00362***
3rd period after TARP	4.11E-05	9.05E-06	-0.000112	0.000663
2nd period after TARP	-8.65E-06	1.50E-05	0.000357	0.000816*
1st period before TARP	1.71E-05	-2.53E-05	-0.00281***	-0.00214***
2nd period before TARP	-3.74E-05	-4.94E-05	-0.00339***	-0.000681
3rd period before TARP	-2.46E-05	-3.95E-05	-0.00412***	0.00059
4th period before TARP	-0.000111	-9.84E-05	-0.00397***	0.00274***
Observations	59,632	54,646	4,302	684
Number of banks	6,626	6,072	478	76

2.6.1. Announcement Day

The above results are calculated using the date that TARP banks reported to receive the funds. A potential concern is the self-fulfillment effect: when a bank expects to receive TARP funds some day in the future, it may begin increasing its lending. To address this concern, I use the announcement date instead. The result does not change, since most of the announcement date and receiving date are in the same quarter.

2.6.2. Instruments for Ever TARP

The Treasury's TARP decisions were correlated with bank characteristics and local economic environment, and the unobserved factors in TARP decisions is something I cannot fully control for. Thus, I employ instrument variables to address the endogeneity problem. And the instrument variables I adopt are political and regulatory connections.

Political interference might play a role in the TARP funds distribution, as WSJ reported:"The goal of aiding only banks healthy enough to lend... clearly seems to have shifted ...Part of the problem is that some powerful politicians have used their leverage to try to direct federal millions toward banks in their home states." However, political or regulatory connections were unlikely to directly influence banks' operating strategies or to be correlated with the level of local loan demand. So it is reasonable to assume that political and regulatory connections affected bank loan only through TARP. Still, I will check whether the instruments are weak instruments.

The evaluation of TARP application was not transparent. There were only two guidelines on banks' qualification for TARP investment: (1) Banks were healthy as determined by their regulators, and (2) dividends paid on common stock and compensation packages for bank executives must satisfy certain conditions. There guidelines are difficult for an outsider to tell whether a bank should receive TARP.

It is widely speculated that other factors beside bank health and local economic conditions were involved in TARP funds distribution. Anecdotes suggested that powerful politicians exerted their influence to help weak banks get TARP funds.

One possible channel of political influence on TARP decisions was through Representatives. I use two variables to capture the political influence through the Representative channel. The first one is the percentage of campaign contribution from local Financial Insurance, and Real Estate (FIRE) industry in total contribution received by a Representative in the 2008 election cycle. A larger percentage means a Representative relies more on local FIRE's support in the campaign. In turn, the Representative will probably push harder for the FIRE industries' interest. The second one is a dummy that indicate if a Representative sat on the Subcommittee on Financial Institutions and Consumer Credit, which supervises all federal banking regulators. The Representative would be more effective in pushing federal banking regulators and the Treasury if she sat on the subcommittee.

The House Representatives committee assignment data are obtained from the House website. There are 71 Representatives sitting on the Financial Services Committee in 111th Congress, 45 of which were on the Subcommittee on Financial Institutions and Consumer credit. I identify 321 banks in the sample headquartered in the state of the committee members, and 189 of which are located in the state of subcommittee members.

I obtain the campaign contribution data from the Center For Responsive Politics (CRP). The CRP compiles and publishes PACs and individual political contribution data for each congress member in every 2-year election cycle. Individual contributors' industries are identified in the CRP data based on their employees. I compute the percentage of donation from local FIRE industries(both from individual and PACs) in the total contribution received by each Representatives in the 2008 election.

Another channel that I consider is a bank's connection to the Federal Reserve Banks. The Fed member banks and bank holding companies must submit their TARP applications to the Fed, and the Treasury's TARP decisions would be based upon the Fed recommendations. A bank with Fed connection, thus might be treated more favorably in the Fed evaluation process.

Following Duchin and Sosyura (2011), I assume a bank was connected to the Fed if an executive of the bank served as director of a Federal Reserve Bank (FRB) or of a branch of a FRB. Each of the 12 Federal Reserve Banks has a nine-member board. Representing the banking industry, the three Class A directors are usually senior executives of member banks. By the Fed's rule, three Class A directors of a Federal Reserve Bank have to be from large, medium, and small size banks, respectively. Each of the 24 branches of the Federal Reserve Banks has a board of five or seven directors, which are appointed by its parent bank and the Board of Governors. Usually one or two directors on a Federal Reserve Bank branch's board are bank executives.

The list of directors for each of the 12 Federal Reserve Banks and their 24 branches is obtained from the Fed's website. There are 67 banks in my sample that are considered to have connections to the Fed.

Besides campaign contribution and committee assignments, ideology might also play a role. Republicans were thought to be, in general, more opposed to government bailouts of private firms. To control for the ideology issue, I include a Democrat dummy, which equals 1 if a Representative was a Democrat.

To address this endogeneity problem, I use the political connection as instruments as explaining the probability of receiving TARP funds. To add variation in time dimension, I interact political and regulatory connections with quarter dummy

Table XXII. Weak IV Test

	All banks	Small banks	Medium banks	Large banks
Chi-squared statistic	14.5	9.36	9.2	12.26
Cragg-Donald Wald F statistic	10.14	5.58	2.37	3
Critical value of 5% maximal IV relative bias		21.42		
Critical value of 10% maximal IV relative bias		11.34		

variables. The equation is written as

$$P(EverTARP_i = 1) = \delta * Z_{it} + \theta * political - connection_i +$$

$$\vartheta * political - connection_i * quarter - dummies + \epsilon_{it}$$

where Z_{it} is bank characteristics variables, used in Section 2.5.. Before proceeding to the second stage of regression, I have to make sure that the instruments are valid and strong. Four instruments are considered here: a dummy for a local Representative having a seat on Subcommittee on Financial Institutions, a local Democratic Representative indicator, local FIRE industries' portion of campaign contribution to a Representative, and a Fed connection dummy. The Weak IV test result is reported in Table XXII. I conduct Cragg-Donald Wald test. Under all cases, I cannot reject the null at the 5% level of significance, which means that there is an issue of weak IV. And that is why I did not include these instruments in my specification in Section 2.5..

Table XXIII. Dynamic Panel Model, Dependent Variable: CTA

VARIABLES	All banks	Small banks	Medium banks	Large banks
Lag	0.659***	0.641***	0.704***	0.0750***
Log asset	-0.592***	-0.373***	-0.528***	-0.208***
Log insider loan	-0.0018	-0.00192	-0.0380***	-0.0182***
ROA	-1.622***	0.245**	3.032***	2.038***
Cash to asset	-0.851**	-2.672***	20.33***	25.97***
Loan to deposit	0.281***	0.557***	-0.00168	0.00607***
%Real estate loan	0.0206	0.0714	0.47	-0.757***
Tier 1 ratio	-1.269***	-1.652***	6.869***	8.612***
Troubled asset ratio	0.00661	0.00883	0.161***	1.037***
Unemployment rate	-0.00038	0.000769	0.00485	-0.0212***
Foreclosure rate	-0.00134	-0.0466*	0.115***	-0.0499***
5th period after TARP	0.0226	0.0174	0.023	0.0728***
4th period after TARP	0.0121	0.0155	-0.00467	0.0133
3rd period after TARP	0.00866	0.0165	-0.00722	-0.0380**
2nd period after TARP	0.0107	0.012	-0.0144	-0.015
1st period before TARP	-0.00343	-0.0126	0.0549***	0.0724***
2nd period before TARP	-0.0216	-0.0274	0.0256	0.127***
3rd period before TARP	-0.0201	-0.0292	0.0434**	0.169***
4th period before TARP	-0.0201	-0.0445	0.0207	0.176
Quarter 3	0.0181***	0.0140***	-0.000848	0.0190*
Quarter 4	0.0252***	0.0101*	-0.0338***	0.0359**
Quarter 5	0.0242***	0.00869	-0.0344***	0.0249
Quarter 6	0.0292**	0.0126	0.00772	0.111***
Quarter 7	0.0373***	0.0145	0.0277	0.0781***
Quarter 8	0.0389***	0.0155	0.00931	-0.021
Quarter 9	0.0452***	0.0260**	-0.0432**	-0.104***
Quarter 10	0.0486***	0.0271**	-0.0215	-0.109***
Quarter 11	0.0574***	0.0306**	0.0107	-0.164***
Observations	53,540	49,337	3,654	549
Number of banks	5,955	5,488	406	61

2.6.3. Alternative Loan Measure

Additional to total on-balance loan value, there is an alternative measure of credit, which is defined as the sum of on-balance sheet loans and off-balance sheet unused loan commitments and letters of credit. Similarly, when I use the credit to asset ratio (CTA) as the dependent variable, and replace LTA with CTA, the result is shown in Table XXIII.

I see a slightly different result from Table XIV. There is no significant effect for small banks compared to what I find in Table XIV. For medium banks, the TARP banks' CTAs decrease by 5.49% during the treatment quarter.

In terms of a dollar amount(Table XXIV), a dollar TARP investment can be translated into 7.8 dollar more of credit for medium banks. Conversely, for large banks, there is an annual increase of 7.28 percentage point in CTA. One dollar of TARP investment can be translated into 1.25 dollar more in large banks' credit.

2.7. Conclusion

The Capital Purchase Program, the core of the Troubled Asset Relief Program, was designed to stabilize the banking system by injecting up to $250 billion into qualifying financial institutions. The stated goal of TARP is to strengthen the capital base of economically sound but financial distressed banks, and to promote bank lending.

This chapter adds to the literature of recent studies on TARP by using a dynamic perspective to see the TARP's effect on banks' LTA. I find that there is no significant effect of TARP on small banks' and big banks' LTA. Taking the treatment period as benchmark, there is a 14 percentage point decrease in medium TARP banks' LTA. Moreover, one dollar of TARP investment leads to 7.71 dollar more loans for them.

When I use credit as an alternative measure, I still find no effect on small banks.

Table XXIV. Dynamic Panel Model with TARP Investment/asset, Dependent Variable CTA

VARIABLES	All banks	Small banks	Medium banks	Large banks
Lag CTA	0.659***	0.641***	0.706***	0.0677***
Log asset	-0.592***	-0.373***	-0.523***	-0.203***
Log insider loan	-0.00176	-0.00179	-0.0370***	-0.0181***
ROA	-1.624***	0.240**	2.784***	1.862***
Cash to asset	-0.856***	-2.688***	20.39***	26.48***
Loan to deposit	0.281***	0.556***	-0.00294	0.00595***
%Real estate loan	0.0213	0.0713	0.308	-0.709***
Tier 1 ratio	-1.279***	-1.645***	6.760***	8.489***
Troubled asset ratio	0.0066	0.00894	0.143***	1.045***
Unemployment rate	-0.000336	0.000832	0.00993**	-0.0165***
Foreclosure rate	-0.0012	-0.0452*	0.133***	-0.0250**
5th period after TARP, TARP investment/asset	2.79E-06	1.70E-06	0.00780***	0.00125
4th period after TARP, TARP investment/asset	2.38E-06	1.62E-06	0.00478***	-0.00205***
3rd period after TARP, TARP investment/asset	1.85E-06	1.11E-06	0.00153***	-0.00424***
2nd period after TARP, TARP investment/asset	1.62E-06	1.00E-06	-0.00484***	-0.00374***
1st period after TARP, TARP investment/asset	1.30E-06	1.03E-06	0.00401***	-0.00303***
Quarter 3	0.0177***	0.0138***	-0.00945	-0.0176***
Quarter 4	0.0251***	0.0101*	-0.0414***	-0.0438***
Quarter 5	0.0247***	0.00928	-0.0551***	-0.0598***
Quarter 6	0.0304**	0.014	-0.0127	0.0164
Quarter 7	0.0389***	0.0166	0.00211	-0.0268
Quarter 8	0.0408***	0.018	-0.0386*	-0.131***
Quarter 9	0.0475***	0.0286**	-0.104***	-0.226***
Quarter 10	0.0514***	0.0298**	-0.0822***	-0.231***
Quarter 11	0.0605***	0.0335***	-0.0464*	-0.279***
Observations	53,540	49,337	3,654	549
Number of banks	5,955	5,488	406	61

For medium banks, the TARP banks' CTAs decrease by 5.49% during the treatment quarter. In terms of a dollar amount, a dollar TARP investment can be translated into 7.8 dollar more of credit for medium banks. And for big banks, there is an annual increase of 7.28 percentage point in CTA. One dollar of TARP investment can be translated into 1.25 dollar more in big banks' credit.

CHAPTER III

SUMMARY AND CONCLUSION

Although a government safety net can help protect consumers and banks and prevent or ameliorate the adverse shocks, like adverse events and financial crisis, it is a mixed blessing. The most serious drawback of the government safety net stems from moral hazard. For example, when consumers encounter adverse events like divorce or a large medical bill, the option of bankruptcy as their last resort provides increased incentives for manipulating their debts which results in a maximized financial benefit from filing. Knowing the government will not leave them to fail, financial institutions(banks) have an incentive to take on greater risks than they otherwise would, with taxpayers paying the bill if the bank subsequently goes belly up. Financial institutions have been given the following bet: "Heads I win, tails the taxpayers loses".

Chapter I investigates consumers' bankruptcy choice with the law of bankruptcy as their last resort. In the literature, two theories, adverse events theory and strategic timing theory, have received particular attention. It is important to distinguish which theory is true, because each theory is based on different assumptions on consumer behavior, and each theory implies potentially different policy responses to reduce bankruptcy filings. If adverse events theory is correct, and if it is determined that bankruptcy filings are too high, then policies to reduce bankruptcy filings could include measures that minimize the impact of adverse events, or increase financial education program for planning for such events. And if strategic timing theory is correct, then policies to reduce filings could include tighten access to bankruptcy courts, make bankruptcy more expensive, lower exemptions divert more debtors to longer repayment plans, lengthen minimum time between repeat filings and require debt management programs outside of bankruptcy.

At the heart of each theory is the role of financial benefit in the bankruptcy filing decision.

In the "strict" interpretation, strategic timing theory holds, if, *ceteris paribus*, filing benefit affects the bankruptcy decision positively, and adverse events theory holds, if, *ceteris paribus*, adverse events variables affect a consumer's decision to file. Using data from the Panel Study of Income Dynamics (PSID), Fay, Hurst, and White (2002), (henceforth, FHW,) show that financial benefit is positively and significantly related to the filing decision, and after controlling for financial benefit, adverse events variables do not affect the bankruptcy decision (except for a marginally significant positive effect of divorce). The strict interpretation implicitly assumes that strategic behavior is the only behavior affecting financial benefit.

In this chapter, we propose that even when financial benefit may affect the filing decision in either theory, the inclusion of financial benefit as an optimizing variable is a testable difference between the two theories. In other words, strategic consumers may additionally manipulate debt before filing, but adverse events consumers do not. We formalize this distinction by inquiring whether financial benefit is exogenous or endogenous to the filing decision. The discussions provide a set of natural instrumental variables, the adverse events. Using both PSID data and SCF data, we show that financial benefit is exogenous to the bankruptcy decision, consistent with adverse events theory. With both datasets, the coefficient on financial benefit from filing is strongly significantly positive. To inquire into the possibility of both types of behavior existing simultaneously, we extend the analysis by estimating a regime-switching model with two types. We find evidence of heterogeneity in types consistent with both behavior. In particular, financial benefit is shown to be endogenous for the strategic type, and exogenous for the adverse events type. The coefficient on financial benefit is significantly positive for the strategic type and insignificant for the adverse event type.

To inquire into the possibility of both types of behavior existing simultaneously, we extend the analysis by estimating a model with two unobserved types. We find evidence of heterogeneity in types consistent with both behavior. In particular, financial benefit is shown to be endogenous for the strategic type, and exogenous for the adverse events type. The coefficient on financial benefit is significantly positive for the strategic type and positive but insignificant for the adverse events type. These results show a role for both hypotheses.

Chapter II explore the effect of government's bailout program on banks during the crisis. The moral hazard created by the government safety net and the desire to prevent financial institution failures have presented financial regulators with a particular quandary. Because the failure of a very large financial institution makes it more likely that a major financial disruption will occur, financial regulators are naturally reluctant to allow a big institution to fail and cause losses to its depositors and creditors.

Although it is not only the "big" banks that get TARP investments, there is a difference between the big TARP banks and other TARP banks. I observe a significantly lower leverage ratio in big TARP banks than the non-TARP banks in the same size category, but a higher leverage ratio in TARP banks than non-TARP banks in other size categories. It implies that the Treasury's choice of TARP investment are not just the "healthy" banks as claimed. The last thing the government wants to see is a failure of a big bank and the domino effects coming after. In order to stabilize the economy, it is wise to save the big banks from failing. On the other hand, there is a "certification effect" of TARP investments among the banks in other size categories, since the Treasury would like to have a positive return or at least not too much losses for the taxpayers. Thus it is a positive signal if a bank in this category gets TARP.

Moreover, I discover that there is a heterogeneous effect of TARP on these two sizes of banks in terms of loan growth. The smaller banks have positive and significant growth in loans no matter they were well-capitalized or under-capitalized. However, the big banks do not use the money in lending out, i.e., they sit on the money and try to shore up their capital base.

To the best of my knowledge, this is the first empirical analysis quantifying TARP's effect on banks' LTA with panel data. It is related and complementary to several recent works. Bayazitova and Shivdasani (2009) study the allocation of TARP capital to public banks, which account for less than 10% of all commercial banks in the US. Taliaferro (2009) studies banks' self-selection into TARP based on bank characteristics only, and examines capital structure decisions of TARP banks by comparing TARP banks with matched non-TARP banks. Duchin and Sosyura (2011) study the political and regulatory influences on TARP funds distribution. There are two major differences between this chapter and the paper mentioned above. First, the panel data allow us to check the dynamic effect of LTA adjustment over time. Second, my models and specifications are more complete by controlling for not only bank characteristics, local economic conditions and time trend, but also the history influence and endogeneity of TARP decision.

This chapter contributes to the literature of financial and banking crisis. Banking crisis have significant negative effects on real economy, especially on sectors dependent on bank financing (Kronzner, Laeven, and Klingebiel, 2007; Dell'Ariccia, Detragiache, and Rajan, 2008). This effect can be largely attributed to the reduction in banks' credit supply in the economy, which could be a result of "capital crunch" of banks (Bernanke and Lown 1991). In this chapter, I test if the injection of capital can boost banks' LTA during crisis.

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APPENDIX A

This appendix presents the joint density of log of $(bank, ln(fb+1))$ if both adverse event type and the strategic type people are potentially present but unobserved. The join density $(file, ln(fb+1))$ is given by:

$$\begin{aligned} & f(file, ln(fb+1)|X, AE, W) \\ = & f((file, ln(fb+1))|T=1, X, AE, W)Pr(T=1|X, AE, W) \\ + & f((file, ln(fb+1))|T=2, X, AE, W)Pr(T=2|X, AE, W) \end{aligned}$$

We assume that the set of W is such that $Pr(T=1|X, AE, W) = Pr(T=1|W) = \Phi(W\alpha)$, and $f((file, ln(fb+1))|T=1, X, AE, W) = f((file, ln(fb+1))|T=1, X, AE)$. In other words, the set of W only affects of probability of being in one of the two types. It does not affect conditional joint density of $(file, ln(fb+1)|T)$.

The join density of $(file, ln(fb+1))$ consists four observed cases, $(file=1, ln(fb+1)=0)$, $(file=0, ln(fb+1)=0)$, $(file=1, ln(fb+1))$, and $(file=0, ln(fb+1))$.

$$\begin{aligned} & Pr(file=1, ln(fb+1)=0) \\ = & Pr((file=1, ln(fb+1)=0)|T=1)Pr(T=1) \\ + & Pr((file=1, ln(fb+1)=0)|T=2)Pr(T=2) \\ = & \Phi(W\alpha) * \int_{-\infty}^{-X\delta_1-\mu_1 AE} \Phi(\frac{X\beta_1+\theta_1 v_1}{\sqrt{1-\theta_1^2\sigma_{v_1}^2}})\frac{1}{\sigma_{v_1}}\phi\frac{v_1}{\sigma_{v_1}}dv_1 \\ + & (1-\Phi(W\alpha)) * \Phi(X\beta_2) * \Phi(-\frac{X\delta_2+\phi_2 AE}{\sigma_{v_2}}) \end{aligned}$$

Similary,

$$\begin{aligned}
& Pr(file=0, ln(fb+1)=0) \\
= \quad & Pr((file=0, ln(fb+1)=0)|T=1)Pr(T=1) \\
+ \quad & Pr((file=0, ln(fb+1)=0)|T=2)Pr(T=2) \\
= \quad & \Phi(W\alpha) * \int_{-\infty}^{-X\delta_1-\mu_1 AE} \Phi(-\frac{X\beta_1+\theta_1 v_1}{\sqrt{1-\theta_1^2\sigma_{v_1}^2}})\frac{1}{\sigma_{v_1}}\phi\frac{v_1}{\sigma_{v_1}}dv_1 \\
+ \quad & (1-\Phi(W\alpha)) * (1-\Phi(X\beta_2)) * \Phi(-\frac{X\delta_2+\phi_2 AE}{\sigma_{v_2}})
\end{aligned}$$

Additionally,

$$\begin{aligned}
& Pr(file=1, ln(fb+1)) \\
= \quad & Pr((file=1, ln(fb+1))|T=1)Pr(T=1) \\
+ \quad & Pr((file=1, ln(fb+1))|T=2)Pr(T=2) \\
= \quad & \Phi(W\alpha) * \Phi(\frac{X\beta_1+\gamma_1 ln(fb+1)+\theta_1(ln(fb+1)-X\delta_1-\mu_1 AE)}{\sqrt{1-\theta_1^2\sigma_{v_1}^2}}) \\
* \quad & \frac{1}{\sigma_{v_1}}\phi(\frac{ln(fb+1)-X\delta_1-\mu_1 AE}{\sigma_{v_1}}) \\
+ \quad & (1-\Phi(W\alpha)) * \Phi(X\beta_2+\gamma_2 ln(fb+1)) * \frac{1}{\sigma_{v_2}} * \phi(\frac{ln(fb+1)-X\delta_2-\mu_2 AE}{\sigma_{v_2}})
\end{aligned}$$

And finally,

$$
\begin{aligned}
& Pr(file = 0, ln(fb+1)) \\
= \quad & Pr((file = 0, ln(fb+1))|T = 1)Pr(T = 1) \\
+ \quad & Pr((file = 0, ln(fb+1))|T = 2)Pr(T = 2) \\
= \quad & \Phi(W\alpha) * (1 - \Phi(\frac{X\beta_1 + \gamma_1 ln(fb+1) + \theta_1(ln(fb+1) - X\delta_1 - \mu_1 AE)}{\sqrt{1 - \theta_1^2 \sigma_{v_1}^2}})) \\
* \quad & \frac{1}{\sigma_{v_1}} \phi(\frac{ln(fb+1) - X\delta_1 - \mu_1 AE}{\sigma_{v_1}}) \\
+ \quad & (1 - \Phi(W\alpha)) * (1 - \Phi(X\beta_2 + \gamma_2 ln(fb+1))) \\
* \quad & \frac{1}{\sigma_{v_2}} * \phi(\frac{ln(fb+1) - X\delta_2 - \mu_2 AE}{\sigma_{v_2}})
\end{aligned}
$$

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