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Author
Schroeder, Aaron A.

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Essays on Consumer Behavior

A dissertation submitted in partial satisfaction of the
requirements for the degree
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in

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by

Aaron A. Schroeder

Committee in charge:

Professor Gordon B. Dahl, Chair
Professor James Andreoni
Professor Julie B. Cullen
Professor Thad Kousser
Professor Craig McKenzie

2012

The dissertation of Aaron A. Schroeder is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

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Chair

University of California, San Diego

2012

DEDICATION

To Rusty, who helped me enjoy the highs and make it through the lows.

EPIGRAPH

To see what is in front of one's nose needs a constant struggle.

—George Orwell

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VITA

2002	B.A. in International Affairs, The George Washington University, Washington, DC
2008-2011	Teaching Assistant, University of California, San Diego
2011-2012	Research Analyst, Consumer Financial Protection Bureau
2012	Ph.D. in Economics, University of California, San Diego

ABSTRACT OF THE DISSERTATION

Essays on Consumer Behavior

by

Aaron A. Schroeder

Doctor of Philosophy in Economics

University of California, San Diego, 2012

Professor Gordon B. Dahl, Chair

Individuals' consumption decisions constitute a key foundational block of economics. Although some intrinsic factors behind consumer decisions can be evaulated in a controlled setting, learning about the role of preferences and availability of information in other decisions requires changes by outside actors. The first chapter of my dissertation uses wagering choices made by individuals for an uncertain gamble to measure their attitudes toward risk. The second chapter looks at how characteristics of loans taken out by consumers change when a large supplier, with an atypical set of incentives, leaves the market. The final chapter looks at how increased demand for volunteers during elections, along with increased awareness by all consumers of election-related issues, impact individuals' takeup and intensity of volunteering, a consumption good.

Chapter 1

Re-Jeopardized: Examining Individual Risk Attitudes Among "Jeopardy!" Winners

Abstract

Using data from the game show "Jeopardy!", I find moderate and significant levels of risk aversion under uncertain gambles of sizeable wealth (mean \$2,500-\$5,000) among a population previously believed to show evidence of risk-neutrality. I then find that incorporating a loss aversion parameter from classical prospect theory better explains player behavior. Earlier papers attempting to estimate risk preferences using game shows have historically either relied on CARA utility, estimation of probabilities with large amounts of measurement error, or complex forward and backward induction. I analyze 12 years of games to both estimate risk preferences under expected utility theory with a CRRA specification as well as under the assumptions of prospect theory, incorporating both CRRA utility curvature and loss aversion. These risk preferences are estimated under a one-shot environment, using probabilities of winning based on either the best linear estimator of actual outcomes as well as a binomial Bayesian estimate adjusted for differences in general question difficulty between rounds of the game. Results are robust to measurement error in the estimation of probabilities.

1.1 Introduction

In the lab, behavioral economists such as Holt and Laury (2002), as well as psychologists in Kahneman and Tversky (1979) and Tversky and Kahneman (1992), have used a variety of mechanisms and assumptions of functional form to estimate individuals' risk aversion parameters. Outside of the lab, researchers beginning with Gertner (1993), through Metrick (1995), and more recently Post et al. (2008), have used data from game shows to test hypotheses regarding risk aversion. Typically, these papers rely on contestants making some binary decision, and then using the expected option or continuation value of each choice to estimate risk preferences via some maximum likelihood estimator. Although many of these papers arrive at relatively sensible estimates, they also rely on techniques that may not accurately reflect human behavior. In particular, the earlier Metrick study of "Jeopardy!" (hereafter referred to without quotes) indicated that individuals do not successfully make strategic wagering decisions when doing so becomes complicated. Meanwhile, Post et al., Fullenkamp et al. (2003) and Beetsma and Schotman (2001) rely on individuals' understanding of future probabilities of success and backward induction of multiple rounds of games as part of their assumptions. If individuals rely on rules of thumb and intuition to guess at these calculations, then many of the biases of prospect theory come into play, and the estimated outcomes may not accurately reflect pure risk preferences.

While almost all of the laboratory-based literature, as well as most of the game-show literature, finds some statistically significant measure of risk aversion, the Metrick paper is unable to reject the hypothesis of risk neutrality under the assumption of constant absolute risk aversion (CARA) utility. This paper will use data from the same source as Metrick, but estimate risk parameters using a more realistic utility specification, as well as a more precise methodology to attempt to correct for potential sources of bias present in Metrick's specification. Instead of assuming individuals can easily calculate and discount future outcomes, or perfectly predict the future, I instead make the assumption that individuals use recent results to estimate their probability of success in a one-shot game in the final round. Measuring the estimated probability of success using this assumption, along with the actual wager made by the contestants, allows me to directly calculate the risk parameter under both constant absolute and relative risk aversion. Finally, I incorporate a basic loss-aversion parameter (with the status-quo as the referent) to test the relative importance of risk versus loss aversion in describing individuals' behavior. With this new data, I find slight evidence to reject the null of constant absolute risk neutrality in a subpopulation of the data, but find more evidence of risk aversion assuming CRRA utility among the same group as well as a larger sample. Incorporating the idea that individuals weight losses more heavily than gains allows me to both measure the size of this weighting as well as check the robustness of the CRRA parameter estimate relative to this other possibility, and compare my results to those of earlier groups using certainty equivalents. Here I find incorporating the loss aversion parameter eliminates both the magnitude and significance of the CRRA risk aversion estimate, and cannot reject the hypothesis of a piecewise linear utility function. Section 1.2 will discuss the Metrick results and the potential source of its weakness with regard to statistical power, Section 1.3 explains the data source and collection, Section 1.4 explains the estimation strategy plus methodological concerns, and Section 1.5 provides results and discussion.

1.2 Previous Research on Jeopardy! and Risk Aversion

In a paper published in the *American Economic Review* in 1995, Metrick accumulated data on wagering decisions made by individuals playing in the game show Jeopardy!, and used these wagering decisions to estimate the CARA risk aversion parameter. In particular, Metrick's data set included 104 observations where individuals went into the final round of the game with a score greater than two times that of the next closest competitor; i.e., $x_1 \geq 2x_2$. In these rounds, individuals could wager up to the difference between their score and twice their next closest competitor's score with no risk of losing the game (This difference is hereafter referred to as the "cover"). Using the structure of the CARA utility function and expected utility maximization, Metrick estimated the risk aversion parameter using the actual question outcomes via the logit specification

$$Corr_{ig} = \frac{exp(2\alpha_{ig}y_{ig})}{1 + exp(2\alpha_{ig}y_{ig})} + \varepsilon_{ig} \tag{1.1}$$

where $Corr_{ig}$ represents a correct answer in the final round by individual i in game g, and y represents the wager made. Using these actual outcomes as a proxy for individuals' probability of answering correctly, and also omitting wagers of zero and the maximum possible amount, Metrick found a point estimate of 0.000066 with a standard error of 0.000056, and was unable to reject the null hypothesis of risk neutrality. Using the sample of similar individuals from the data set available for this paper (N=543) results in a similar, also statistically insignificant estimate of 0.000013 with a standard error of 0.000015 (t=0.88).

The similarity of the null result across both groups may arguably strengthen the case for risk-neutrality; however, the choice of utility specification could also explain the inability to find evidence of risk aversion. Few argue for real world applicability of CARA utility, for reasons discussed in Rabin (2000), and an experimental study using real stakes by Levy (1994) found support for decreasing absolute risk aversion, but could not reject the hypothesis of constant relative risk aversion. Maximizing CARA utility with respect to the actual wager results in an optimization function implying that individuals do not consider the size of their endowment when making wagering decisions, unless their ideal wager falls outside that endowment. If two individuals each believed they held the same high probability of answering a question correctly, and each decided to wager \$2,000, given no other information one might assume both individuals were equally risk-averse. If we later discover that one individual could have wagered up to \$2,500 and the other individual up to \$25,000, it becomes more difficult, though still plausible, to maintain the belief that both individuals display similar levels of risk aversion. As a result I will also attempt to measure risk aversion parameters while making the different assumption that individuals make risk-related decisions instead based on the relative size of their endowments.

Although the CARA specification neatly lends itself to empirical estimation, it also relies on the assumption that actual outcomes provide a reasonable approximation of individuals' *ex ante* expectations of success. Hausman et al. (1998) shows that, for nonlinear specifications such as the logit and probit, misspecification of the left hand side variable (in this case, an individual answering correctly when they did not expect to do so, or the reverse), will result in an attenuated estimate of

$$\frac{\partial P(Corr=1)}{\partial y_{ig}} = (1-\gamma_0-\gamma_1) f\left(2\alpha_{ig} y_{ig}\right) 2\alpha_{ig} y_{ig}$$

(as opposed to the true value of $f\left(2\alpha_{ig} y_{ig}\right) 2\alpha_{ig} y_{ig}$) for the Metrick specification provided above, where γ_0 and γ_1 equal the rate at which incorrect and correct answers were unexpected and $f\left(\right)$ is the pdf of the distribution. If individuals have a difficult time clearly estimating their future results, then this would attenuate the parameter estimates and could partially explain the insignificant result found earlier by Metrick.

In order to improve upon previous results, I first need a better way to specify the probability of answering the question correctly. In an ideal world, researchers could ask individuals to estimate their probability of answering the final question correctly at the time they make the wager; using this information, along with the endowment and the wager, we could then directly estimate individuals' risk aversion parameters. Unfortunately, this data does not exist, but we can use information about performance before and during the period of interest, information the contestants themselves would use, to estimate individuals' perceptions of $P(Corr = 1|X)$ with a level of accuracy that improves upon that of the logit-based specification.

1.3 Game Background and Data

1.3.1 Game Show Rules

In order to better understand how the data relates to the outcomes measured in this paper, some background information on the game used to collect the data, as well as some basic summary statistics, will be useful. Jeopardy! is an American game show presented in its current format since 1984. 3 individuals compete against each other to provide trivia "answers" by responding in the form of a question. Only one individual may correctly answer each question. The game is divided into 3 rounds, with the first two rounds ("Jeopardy!" and "Double Jeopardy!") consisting of 30 questions divided into 6 categories, where the second round questions are worth double those in the first round, and all question values are denominated in US dollars. Due to the 30 minute format of the show, some rounds may not reveal all 30 questions, with some remaining unasked on the board. Within these first two rounds lie 3 Daily Doubles, questions where the contestant who reveals the clue can wager any amount between \$100 and their score and receives the sole right to answer the question. In the final round ("Final Jeopardy!", or FJ), individuals are given the category of knowledge from which the question derives, and then may wager any amount between zero and their current within-game winnings, inclusive. Correct answers receive the wager amount, while incorrect answers result in the subtraction of the wager amount from the player's score. The player in first place after the final round wins the game and gets to keep the money won during that game as well as (typically) compete again in the next game. Second and third place win \$2,000 and \$1,000, respectively, or prizes worth the same nominal amount in the early version of the game. Given the average winning player usually does so with a score around \$17,000, this amount plus the ability to play again places a high value on winning the game relative to other outcomes.

1.3.2 Data Source, Scope, and Summary Statistics

This analysis uses data derived from the J-Archive, a fan-organized web site that stores detailed microdata regarding in-game statistics for many Jeopardy! games, including almost all of seasons 14 through 26, with approximately 230 games played each season. This time period starts on Sept. 1, 1997. For unknown reasons, the database excludes half of season 20 (9/2003 through 7/2004). Shows aired before May 24, 1989 tend to exist in the database due to their anomalous nature, so I exclude them from analysis. The database specifies whether a game occurred as part of regular play or as part of a tournament or special event. Within each game, the database provides information on players, questions, and the course of the game. A screen shot of a chart demonstrating the in-game scoring dynamics appears as Figure 1.1. In particular, this paper will use aggregated data on correct and incorrect responses by each player in the first two rounds of the game, the number of questions revealed, and wagering decisions and outcomes from the final round of the game. Although I cannot retrieve the category, text, or content of each FJ question due to restrictions placed by holders of the data, that information is not required for this analysis. I can also obtain information on the amount of money wagered when contestants are permitted to do so, and also use the relative value of a question as a proxy for difficulty. For purposes of my analysis, I will restrict the scope of my sample, like Metrick, to games under regular play where $x_1 > 2x_2$. For reasons discussed in the estimation strategy section, I also restrict my analysis of CARA to individuals with cover bets below $4,000 or $8,000, depending on the date the game takes place.

Table 1.1 provides some basic summary statistics regarding players. In particular, the relevant contestants answer correctly approximately 52-55 percent of the time. Individuals who answered an extremely high number of correct answers might do so because of easier game material, and so there might be a bias in terms of question content across groups. One way to test this would be to look at the total number of questions answered correctly in each game, and compare the totals across the games with a high and low maximum wager. A comparison of total questions answered across the two groups in the main (non-Bayesian) sample shows that in both types of games contestants answered approximately 51 of the questions combined, with a lower share of the questions going to leaders with the lower maximum possible wager. Although the high cover individuals do answer a statistically significantly higher number of questions, the overall games do not appear to be too different in terms of difficulty, as the total number of questions answered correctly across both groups differs by less than 1. The group of individuals used in the CARA analysis, on average, can wager up to $2,400, with a large variation in the cover bet across individuals. The CRRA sample, meanwhile, can wager almost double that amount. The sample of games with no unrevealed questions initially appears to have a higher number of answered questions by all contestants; however, after accounting for the difference in questions asked this difference shrinks considerably. The large overall dollar value held by individuals going into the final round hints at the high option value of playing the game again; of the individuals with insurmountable leads, only three wager more than the critical value, with one appearing to do so due to an arithmetic error in wagering. Figure 2 provides some intuition as to whether individuals behave in a risk averse manner by providing a scatter plot of potential and actual wagers and a locally linear line of best fit for the full sample. Visually, individuals appear to be deviating from the risk-neutral behavior represented by the 45 degree line, assuming that most individuals have p>.5.

1.4 Estimation Strategy

This section first covers the functional forms used to estimate risk aversion parameters, then focuses on the methods used to estimate individuals' beliefs about the probability of answering a question correctly, and concludes by discussing possible econometric and methodological issues of the estimation strategy.

1.4.1 Utility Specification

Utility Specification and Wealth

This paper will use two different utility specifications to estimate coefficients of risk aversion. Earlier papers using game shows to measure risk aversion assumed CARA utility; in order to compare our estimates to earlier results I will use a similar functional form, $U(x) = 1 - e^{-\alpha x}$. These older papers favored a CARA utility specification for two main reasons, both related to its maximization properties. First, as shown by the Metrick result earlier, maximization of CARA utility results in an easily measured logit specification that lends itself to modeling binary choices. Secondly, traditional maximization of most other expected utility specifications requires knowledge about individuals' lifetime wealth in addition to the income at stake in the bet. Regarding wealth, a good deal of research, beginning with that of Binswanger (1981) and summarized by Rabin and Thaler (2001), instead points out that modeling risk preferences in the absence of lifetime wealth integration–that is, modeling the wager using only the endowment at stake in the wager–more accurately generates reasonable estimates of risk aversion. As a result, more recent research such as Beetsma and Schotman (2001) has used the CRRA power utility function, $U(x) = x^{\alpha}$, using only the endowment within the game as an input.

Expected Utility

After playing two rounds of a game and generating enough money to create an insurmountable lead, I assume that individuals treat the Final Jeopardy! round as a one-shot game where individuals can wager up to the amount that leaves them tied for first place as a worst case scenario, and choose a wager based on their estimated probability of answering correctly. Under the theory of expected utility, we should reasonably expect individuals to choose y to maximize their expected value from the gamble, $E(V) = \hat{p}U(x+y) + (1-\hat{p})U(x-y)$, where x equals the total amount of money that can be gambled without risk of losing (the "cover"), and y equals the amount individuals choose to wager. For each of the above specifications, maximizing expected utility with respect to the wager results in the following conditions for individual i in game g:

$$\alpha_{ig}^{CARA} = \frac{ln\frac{\hat{p}_{ig}}{1-\hat{p}_{ig}}}{2y_{ig}} \tag{1.2}$$

$$\alpha_{ig}^{CRRA} = \frac{ln\frac{\hat{p}_{ig}}{1-\hat{p}_{ig}}}{ln\frac{x_{ig}-y_{ig}}{x_{ig}+y_{ig}}} \tag{1.3}$$

These conditions are arranged in a manner that allows estimation of a sample-wide α using standard OLS regression on a constant, under the assumption that individuals make their decisions using the estimate $\hat{p}$, without any concerns over ability of individuals to look forward. Additionally, the above solution functions optimize utility subject to a negative second derivative of utility with regard to the wager size. When the CRRA solution above finds a value for $\alpha > 1$, this results in a positive second derivative, with the above function finding a local minima. Although the value of the parameter is greater than 1, its exact value is censored, and I must use a tobit specification to generate sample estimates of α^{CRRA}.

1.4.2 Measuring p

Best Linear/Polynomial Estimate

Given that the amount of money at their disposal is observable and measured without error for all individuals, the main concern in correctly estimating parameters of risk aversion comes from correctly estimating individuals' *ex ante* beliefs about their abilities, and also making sure that these estimates of ability do not bias or skew the resultant estimates of risk aversion.

With that said, how can I plausibly estimate $\hat{p}$ in the population of interest (Individuals with an insurmountable lead as well as extra wagering cash available), and how well can individuals predict their own abilities and realistically use $\hat{p}$ to make their decision? As to the first question, the only observables available include the number of correct and incorrect answers from individuals, the possible range of non-losing wagers, the actual wager, possibly the difficulty of the question as measured by its cash value, the order of revelation of questions, the number of questions revealed/used during the time-limited first two rounds, and no information about the content of the category in Final Jeopardy! or any previous questions. Given the lack of structural knowledge regarding the effect of these variables on the outcome, the method of estimating the likelihood of answering correctly that allows for the most structural flexibility involves a simple polynomial expansion of the number of questions answered correctly and incorrectly for each player, as well as a variable representing the number of questions seen during the game. Although this specification provides no structure or intuition for the relationship between past performance and future results, if I believe individuals can accurately infer their future abilities from their past results, and that the best predictor of actual results best predicts individuals' beliefs, then this will be the best approximation for $\hat{p}$. In the most basic form, a second order polynomial expansion attempting to estimate this relationship takes the form

$$\begin{aligned} p_{ig} = \beta_0 + \beta_1 C_{ig} + \beta_2 W_{ig} + \beta_3 N_g + \beta_4 C_{ig}^2 + \beta_5 W_{ig}^2 + \\ \beta_6 N_g^2 + \beta_7 C_{ig} W_{ig} + \beta_8 C_{ig} N_g + \beta_9 W_{ig} N_g + \varepsilon_{ig} \end{aligned} \tag{1.4}$$

where C_{ig} and W_{ig} represent the number of correct and incorrect answers given by individual i in game g, and N_g equals the number of permanently unrevealed questions in a game. Additionally, I can also include a term in the expansion counting the number of revealed questions in a game that go unanswered by all individuals and/or divide correct and incorrect answers into groupings based on whether the question was one of the last two out of the five total in each category; these questions should be more difficult and would more reasonably approximate the depth of knowledge required to answer questions in the final round.

Given a method that serves as the best linear predictor, can one reasonably argue that individuals see the same probability? Although numerous papers such as Kruger and Dunning (1999) and Ehrlinger et al. (2008) show that all individuals have difficulty measuring relative ability, they then find that experienced individuals do an excellent job of predicting their actual future performance on a task. In the Kruger and Dunning example, talented individuals overestimate their future performance by only 3 percent, a magnitude not significantly different from zero. One could also reasonably argue, though, that instead of using their past performance within the game as a tool for estimating p, players might form their baseline estimate by considering how well similar individuals have performed in the final round of the game. Generating this value is straightforward, and can be done as a robustness check to compare to the result generated using the polynomial expansion.

Bayesian Estimate

As an alternative, I can instead assume that players begin each game under beliefs described by a degenerate prior with a binomial beta distribution that they update with correct and incorrect responses as they play the game. Before the final round individuals would expect to correctly answer a question to which they choose to respond with a probability equal to the center of mass of a Beta$(1+\sum_{t=1}^{T} Corr_t,\, 1+\sum_{t=1}^{T}(1-Corr_t))$ distribution. I can then regress this expectation, along with other game characteristics such as the general distribution of scores among players and whether the player in question is a returning champion, on actual Final Jeopardy outcomes to generate an estimate of $\hat{p}$ that incorporates individuals learning about their abilities as well as weighting their expectations for the final round by the general increase in difficulty of the questions.

1.4.3 Methodological Issues in Estimating α

Concerns with Measures of p - Relationship Between $\hat{p}$ and y

The flexible structure of the polynomial expansion provides the ability to best approximate p, but the same covariates may also be able to explain other variables that help measure parameters of risk aversion. In particular, upon examination of the estimation function under the CARA assumption, if the same covariates can also help in predicting the size of the maximum possible wager individuals can make without losing the game, or if they can predict the actual wager size, then a straightforward use of the above estimate of $\hat{p}$ in estimating risk aversion along with these other variables becomes problematic. In fact, taking a polynomial expansion of our observables across all individuals does indeed result in statistically significant predictions of the cover bet and the actual wager; as a result I am unable to simply use our estimates to measure CARA risk aversion directly using the entire sample, and must rely on an alternative methodology. Given the lack of available instruments in the data set to eliminate any endogenous variation between the two variables, I can only attempt to use a subset of the sample for whom the non-risk related relationship between predictors of answering correctly and the actual amount wagered is minimized. Specifically, I argue that individuals with relatively low cover wagers face variations in these wagers not due to their own performance, but instead in variation in scores generated by the other players. For players with cover wagers below \$4,000 in the original game, and \$8,000 in later versions, concerns about endogeneity are low enough where I can generate reasonable estimates of CARA risk aversion. Discussion of the rationale for this cutoff is provided as an appendix to this paper, available by request.

Although the CARA utility assumption results in derivation of risk parameters using the actual wager in addition to $\hat{p}$, the CRRA assumption instead relies on the proportion of the cover wagered. Rearranging the optimization condition shown earlier results in

$$\frac{y_{ig}}{x_{ig}} = \frac{1 - \left(\frac{p_{ig}}{1-p_{ig}}\right)^{\frac{1}{\alpha_{ig}-1}}}{1 + \left(\frac{p_{ig}}{1-p_{ig}}\right)^{\frac{1}{\alpha_{ig}-1}}} \tag{1.5}$$

implying that instead of worrying about the ability of our predictors of $\hat{p}$ to predict the absolute wager, CRRA utility requires examining these covariates' ability to predict the relative wager. In practice, the number of correct and incorrect answers, again used in a polynomial expansion, do a fairly poor job of predicting the relative wagers of contestants, with a statistic of F(5, 533)=1.13 (p-value = .34). As a result, I can use individuals with cover wagers of all sizes greater than zero to estimate CRRA risk coefficients using this methodology.

Potential Concerns with Sample Choice

Given the choice to restrict the sample for CARA utility, what are the possible consequences? First, if the purpose of this paper is to reproduce and test results from the laboratory in a more realistic setting with real-world stakes, then I might be concerned about eliminating the high-stakes wagers from the sample. At the same time, remaining individuals will still have a mean average possible wager of $2,400, an amount almost 1.5x the author's current monthly salary. This leaves a typical wager in the remaining sample lower than those found in Post et. al., but not wildly different from the relative wagers offered by Kachelmeier and Shehata (1992), and still half of the median pretax household monthly income of roughly $4,000 reported by the US Census Bureau as of 2006.

Similarly, individuals removed from the sample might display different risk profiles than those in the sample, possibly resulting a biased estimate. The first response would be that the direction of any potential bias from this phenomena would depend on the specification of the utility function. In fact, given the relatively large differences in wages and small differences in probabilities, the nature of this bias means I can only generalize the CARA results to individuals who face wagers of similar value (Further discussion located in appendix, available by request from the author).

Additionally, if a player participated in enough iterations of the game, the results from earlier games may begin to disproportionately inform their probabilities and wagering decisions in later games. In general, an "experienced" player would perhaps employ a different strategy throughout the game, or the cover limit might provide a low-end distribution of a player's performance. In this vein, including segments of Ken Jennings's and David Madden's (individuals who appeared in more than 50 and 20 consecutive episodes of regular play, respectively) appearances in the data could potentially overweight the results of one individual under any utility specification, so their performances do not appear in the final sample under any specification.

Finally, a change in the rules of the game over the course of the sample also affects the definition of a "low cover" for the CARA sample. Beginning with show 3966, aired November 26, 2001, the dollar values of all clues in the game doubled, with scores of all players in turn. Given the higher scores across the board due to the doubling of question values, a game that earlier would have resulted in a fairly small cover bet would instead most likely result in a larger possible bet, though this would not change any estimate of the probability of answering the final question correctly given the number of answers given. This explains the use of multiple cutoff points under the CARA specification, which depends on absolute values of the wager. In total, all observations for individuals with a maximum possible "guaranteed win" wager above zero, who do not exceed this cover threshold, and who are not Ken Jennings or David Madden are used to create parameter estimates.

Changes in Behavior During Games

Another concern besides those stemming from structural assumptions and endogeneity is that players who generate insurmountable leads with many questions remaining will behave differently afterward. Players lose money every time they answer a question incorrectly, and that loss of money could potentially lose them a "guaranteed" victory in some cases. Players in this situation may become more unlikely to answer, potentially biasing the estimates of $\hat{p}$ generated for these games. Since typically players don't find themselves in a runaway game until only a few questions remaining, testing their performance against some baseline would be relatively difficult. I can, however, test what percentage of the last ten questions on the board (excluding unrevealed questions from calculation) are answered correctly, incorrectly, and overall for each individuals who obtains a runaway game early, and compare these results to the population who lock up a guaranteed victory on the last revealed question of the game.

1.5 Results

1.5.1 Sample Validity

First, I discuss whether the sample chosen for each utility specification meets the conditions described above. The first two columns of Table 1.2 provide OLS results from the polynomial expansion of the number of correct and incorrect answers and unrevealed questions on the probability of answering the final questions correctly. The first column shows results for the CARA sample of individuals with low endowments and scores greater than two times that of the next closest competitor going into the final question and the second column shows results for the full sample of players with a guaranteed victory and a nonzero wager above the threshold amount. Column 3 restricts the sample to games with no unrevealed questions, and column 4 provides estimates under the Bayesian specification. In all models the covariates jointly provide an improvement in predicting outcomes over regression on a constant. Other covariates, including those incorporating question difficulty, do not further improve the predictive power of any of the models listed. Table 1.3 provides results for a regression of the same coefficients on the absolute wager and cover ratio, respectively, for the groups of interest. The main statistic of interest here is the F-test for joint significance of the model, which can reject neither the null of the null hypothesis of no relationship between the covariates and the endowment for the CARA sample nor the ratio of wager to endowment for the full sample. Results show that concerns delineated by equation (1.5) do not affect the samples used in estimation.

1.5.2 CARA Results

Before analyzing sample results under CARA utility, I must first consider how to treat observations that result in a corner solution for risk parameters under this utility specification. For CARA utility, this includes 2 sets of individuals: those who bid their maximum and those who bid zero. For the first group, since the CARA specification does not allow for consideration of the maximum possible bid when evaluating risk parameters, a non-zero (non-risk neutral) value for α will be generated even when I cannot rule out risk-neutral behavior among these individuals. Similarly, there is no reason to assume these are risk-loving individuals, given that they respect the option value of winning provided by the right to play again the next day. Assuming that these are actually risk-neutral individuals who are constrained by the maximum value of the wager allows us to create a relatively more conservative sample, and one that most likely accurately reflects attitudes. For the second group, those individuals who bid zero but have the ability to wager a positive amount without risk of losing the game, the implications of their behavior with respect to risk preferences depends on their probability of answering the question correctly. For those individuals who are expected to answer the question with a probability less than fifty percent, choosing not to bid any amount reflects, conservatively, risk-neutral behavior equivalent to holding an α of zero. Among individuals expected to answer the question with probability greater than fifty percent, wagering zero implies a high, possibly even infinite coefficient of absolute risk aversion. Given that these individuals display risk-averse behavior, how can we incorporate this into any analysis of data? One possibility would be to assign these individuals the highest risk parameter revealed in the data, and then run a censored tobit regression on the sample. Alternatively, we may worry that this estimate is unrealistic, and that these individuals may display high levels of risk aversion, but choose to bid zero due to additional factors unavailable in the data.

Finally, we might worry that non-risk related factors might have extremely small, though nonzero, effects on the amount of money individuals decide to wager. Although most individuals make bids rounded to some multiple of one hundred, a sizeable number tweak their bid slightly so that, if they win/lose, some personally or culturally significant number will appear. Similarly, contestants are primed by program employess to avoid a tie when possible, because the revealed quality of their main opponent is greater than the unconditional mean. Contestants will frequently wager \$1, \$5, or \$25 less than their full endowment in order to avoid this possibility, whereas they would likely bid the full amount in the absence of the competitor. Due to this I evaluate parameter estimates using both the actual wager as well as an adjusted wager rounded to the nearest \$50 increment.

The first row of Table 1.4 presents results under the CARA utility specification. The first column shows results with no changes made to the wager size. The second column shows results using the adjusted wager, and the third does the same and also assumes individuals at the corner solutions who display risk-neutral behavior have a risk parameter of zero. The fourth column shows results similar to 3, but also includes individuals with a nonzero maximum possible wager who bid zero coded with risk parameters equivalent to the 90th percentile of the remaining population. The first three columns provide weak or no statistically significant evidence of CARA risk aversion, whereas the last demonstrates statistically significant estimates with a high magnitude. One of the earliest estimates of CARA utility from game shows, that of Gertner, provided a lower bound estimate for alpha of 0.00031; even though our estimates of CARA utility are biased away from zero relative to the likely population of our data, the only statistically significant estimate is still approximately one-third the size. Figure 3 shows the estimated and predicted wagers under the CARA specification, with predicted values capped at the endowment size. Even with the larger sample and more precise estimates of the probability of answering correctly, only weak evidence for CARA risk aversion appears in contestant wagers unless fairly strong assumptions are made about individuals who appear to display risk aversion, but for whom we cannot determine an exact parametric value representing their behavior.

1.5.3 CRRA Results

OLS/Main Results

Upon examination of the above results, it should not be surprising to see a creep toward risk neutrality when considering the CARA estimate. Given the risk parameter depends on the wager's cardinal values, any increase in wagering explained by the doubling of question values or other outside factors occurring while holding probability constant would result in an artificial change in tastes toward risk-neutrality. Indeed, few laboratory experiments make use of CARA utility, resulting in few potential comparisons, and field studies such as Levy fail to find evidence of constant absolute risk aversion. Instead, many papers in the behavioral literature, including Holt and Laury and Harrison and Rutström (2009), use the CRRA utility function. Here we face a similar problem as in the CARA case involving corner solutions; again I choose to consider those who bid their maximum with $\hat{p} > .5$ to be risk neutral and those who bid zero with an estimated probability of less than .5 to be risk neutral as well. I also code individuals wagering zero with a probability of answering correctly greater than .5 with risk parameters of zero, which is near the 90th percentile of all individuals. As stated earlier, individuals with risk parameters greater than one do not actually maximize utility with this parameter; instead the equation finds the value that minimizes expected utility. As a result estimates are tested under a tobit model with an upper bound of one.

Results are shown in the second row of Table 1.4. The first column provides results for all individuals in the sample for whom a risk parameter can be calculated using the above equation for CRRA utility maximization and the unadjusted wager. Examination of the standardized residual errors created by regressing the parameter estimates on a constant reveals two observations in particular where players with high estimated probabilities of success and large endowments wagered amounts close, but not equal to zero. This results in parameter estimates of -265 & -182. These observations illustrate how small changes in the wager amount near zero, due to the structure of the CRRA utility function, can result in impractical, unrealistic estimates of α .

The second column on uses the same sample as the first, but instead uses parameter estimates from the adjusted wagers described earlier. This change provides similar observation level estimates for the vast majority of the sample population, and more realistic estimates of parameters that describe the behavior of contestants who wager an amount substantially similar to zero. Using this adjustment of the wager results in estimates significantly different from the null of risk neutrality, even after including risk neutral and risk loving individuals at a corner solution (column 3) and especially after including the most risk-averse individuals who bid zero (column 4). The estimate from column 4, α =.83, implies a certainty equivalent of \$4,351 for a (.5, \$10,000) wager, similar to the CRRA result found in Post et al.. This value is more realistic than the CARA estimate found above, and points to a more reasonable level of risk aversion. Figure 1.4 provides a kernel density of the CRRA risk parameters estimated in Row B, Column 2, showing a parameter distribution with high kurtosis that appears to reach its peak near the value listed earlier.

Row C features the same estimates as those in Row B, but only for the portion of the sample that reveals all the questions in the game. Results for this sample, are analogous to those in the row above, and appear similar to and slightly more risk averse than those from the full sample. Row D features estimates using the Bayesian method of calculating $\hat{p}$. The sizeable difference in these estimates from those above results from the wider dispersion of probabilities and increased measurement error between estimates and outcomes generated from the methodology. After accounting for the most extreme observations, and including the risk-neutral and highly risk-averse individuals, the Bayesian estimates also result in a significant estimate of α, though with a smaller magnitude of risk aversion than the polynomial estimates.

1.5.4 Extensions to the Basic Model

Loss Aversion

Even though the above results provide evidence of risk-aversion under certain structural specifications, how do they hold up under extensions of the model? Individuals might not make their wagering decision based on some curved utility function, but instead decide to wager less than the total cover amount due to some stronger psychic cost that comes from losing money. Under expected utility, using the CRRA utility function, I can also fairly easily model a loss aversion parameter encapsulating this phenomenon. This model assumes that individuals place an additional weight λ on the utility gained from the losing wager, resulting in the need to maximize $E(V) = \hat{p}U(x+y) + \lambda(1-\hat{p})U(x-y)$. Maximizing this function with respect to y results in the formula

$$\alpha_{ig} = \frac{ln\frac{\hat{p}_{ig}}{\lambda(1-\hat{p}_{ig})}}{ln\frac{x_{ig}-y_{ig}}{x_{ig}+y_{ig}}} + \varepsilon_{ig} \tag{1.6}$$

where ε represents the individual error made in evaluating one's own risk profile. When rearranged, this equation suggests that individuals may choose to wager a given amount based both on the traditional concept of risk aversion as well as hedge their emotional bets and reduce the wager. This specification can be estimated using maximum likelihood. Table 1.5 shows the results of running this regression using both the raw and adjusted wager for the polynomial estimate of $\hat{p}$ as well as the Bayesian estimate using adjusted wagers. All results provide strong evidence of loss aversion, with a risk-aversion parameter for the last two columns small in magnitude and, in the case of the Bayesian estimate, weakly statistically significant relative to risk neutrality, and significant loss aversion parameter estimates ranging from 1.27 to 1.41. This result implies that individuals do not bet the maximum due to weighting losses at a rate 27 to 41 percent percent higher than they rate gains, and show evidence of weakly risk-loving utility for money. Figure 1.5 compares the actual wagers made against the predicted wagers under Row B of Table 1.4 and Table 1.5. Although the red dots, representing estimates with loss aversion, allow for curvature similar to that of the blue dots, it appears that assuming individuals hit some breaking point beyond p=.5 where the probability of gain more than makes up for the pain of losing picks of most of the burden of explaining the variation in the sample. This estimate is actually much smaller than the standard assumption of losses weighted twice as highly as gains, which is supported by Sprenger and Tversky and Kahneman. Of course, the small size of the loss aversion parameter could simply come from the relatively even odds of answering the question correctly provided by the fitted estimates.

Repeat Players & Reference Points in Probabilities

Although the previous section displayed evidence of players exhibiting loss-averse behavior, one might wonder whether some of this behavior comes from previous results by returning players. For example, if an individual expected to do well in the last game and instead answered the final question incorrectly, that could cause the player to wager differently in the subsequent game, either because they use information about the previous game to weight their beliefs about the current game, or because they may be making their risk decisions from a reference point away from the origin. Table 1.6 provides CRRA risk estimates by groups using the full sample based on how players performed in the final round of previous games relative to their expectations, using both the polynomial and Bayesian esitmates. It appears that deviations in previous expectations did not generate markedly different risk preferences, especially considering that regressions of past results on future outcomes do not provide statistically significant predictive power. Using the Bayesian estimates, though, first time players who found themselves with a guaranteed win did behave in a more risk-loving manner than repeat players. Given these individuals do not possess any wealth from previous games, if players did integrate wealth over the course of their time on the program we would expect to see them behave in a more risk-averse manner in our methodology.

While under this specification first time players exhibit more risky behavior, they appear to do so in a way that might not necessarily come from different risk preferences on the whole. A re-examination of Table 1.2 shows that players who play as a returning champion have an eight percent greater probability of answering the Final Jeopardy question correctly, even though their outcomes from the previous game do not otherwise predict current game outcomes. Evaluating first time players' risk preferences after incorporating this extra "champion's edge" results in estimates more in line with those of returning players. One possible explanation for this behavior could be that first time players set their expectations based on how they perform relative to players they see on TV; however, they do not take into account the stress involved with the time limit associated with answering the final question (the show changes the game environment during the final question, with dimmed lights and "thinking" music). Under this explanation first time players are actually overestimating their ability, and so their true risk preferences generated from their beliefs would be those found in the last column of Table 1.6.

1.5.5 Robustness Checks

In-game Behavioral Changes

Thankfully, the presence of the two wildcard "Daily Double" questions in the second round of the game, where individuals may bid up to their current score on one questions, appears to delay the point at which individuals mathematically guarantee victory. Table 1.7 shows that more than half of the players of interest do not receive a guaranteed win until the last question of the game, meaning most players do not feel any impact from this phenomenon. In fact, over 90 percent of the players do not see more than 3 questions after guaranteeing victory. Additionally, the rapid fire pace of the game (drilled and exhorted onto contestants by program employees) leaves little time for players to sum the value of remaining questions and compare them to current scores, meaning that many may not understand the extent of their lead until the end of or after the round.

To examine behavior, I performed a t-test on the difference in percentage of questions answered correctly, incorrectly, and overall during the last ten questions on that board that are revealed versus the earlier portion of the game, by when contestants crossed the threshold of guaranteed victory. I compare contestants who faced more than X questions after crossing the threshold to those who did not guarantee victory until the end of the round. Results are shown in Table 1.8. No sizeable, statistically significant (at the 5 percent level) difference appears across groups until I restrict the former to those contestants with more than four questions heard after guaranteeing victory. Some weak evidence exists for a small difference for those individuals hearing more than three questions after this point. Even then, estimates excluding those who see three or more questions in this manner do not differ substantially in magnitude from the main results (equivalent to Row C, Col. 4 of Table 1.4: .891 [SE=.03]).

Measurement Error in $\hat{p}$

Another concern about the validity of results comes from the realization that if individuals are not wagering based on $\hat{p}$ itself, but instead some value measured with error $\tilde{p} = \hat{p} + \eta$, then this would incorporate non-linear measurement error into the estimated model. Any noisiness might result in more risk loving estimates. Unfortunately, the impacts of this type of measurement error are difficult to predict; however, simulations using the actual data as a template can potentially help describe how this phenomenon could impact the main results. In particular, one way to examine the impact would be to assume that $\hat{p}$ actually equalled the real probability of answering correctly, and then add an error term with a normal distribution of mean zero and measure how estimates change as the variance of the error term increases. Table 1.9 shows the mean and standard error of CRRA parameter estimates across 1000 simulations for the probability of answering correctly measured with normal errors with standard deviations of .1, .15, and .2. The estimate increases at a decreasing rate as the error term increases, biasing our results away from risk aversion. While measurement error can increase the variance and bias the overall sample, simulations provide evidence that the estimates provided earlier may be lower bound estimates.

Alternatively, one might also worry that instead of revealing risk-averse preferences, players in the game are actually behaving in a risk-neutral or risk-loving manner, and measurement error in p appears as risk aversion. Since individuals see more information about their ability in a category than the researcher, they might use this private knowledge to wager a smaller amount than predicted because they know their actual probability of answering is less than it appears. If $\tilde{p} = \hat{p} + \eta$, then in this case we would believe that omitted variable bias from knowledge of the category would lead to $\eta > 0$ in cases of what the researcher sees as risk-loving individuals, and $\eta < 0$ for those who appear risk-averse. In a simulation to test the effects of this, I assume that all individuals with coefficients of risk aversion below .83 (the estimate from Table 1.4) have $\eta < 0$, distributed under a half-normal distribution with mean zero and standard deviation of .1, and all individuals above the mean hold $\eta > 0$ under the same distribution. This attenuates the parameter estimates generated by risk-averse individuals, but at the same time also moves some risk-loving individuals out of the censored portion of the distribtuon, reducing the size of the estimated variance of the distribution. Simulating results in a manner similar to the non-linear measurement error case listed above leads to the results shown in Table 1.10. Errors distributed in this manner can potentially explain the main result; however, this explanation requires a relatively sizeable standard deviation of .2 for the error term in order to fully explain the observed departure from risk neutrality.

1.6 Conclusion

Although the wagers in the final round of Jeopardy! do not typically generate large changes in lifetime wealth, they involve significant amounts of money few individuals would consider lightly. Individuals have as much time as they like to choose their wagers, and are given paper and pencil. Given the large number of questions recently presented, contestants have a fresh reminder of their abilities along with any information gained from previously watching the program. In short, individuals playing the final round of Jeopardy! with little to no risk of losing face a simple monetary decision and have ample time and information to make a rational choice. Few, if any, papers from the field or lab can combine the simplicity and real-world salience of this decision. Although many papers have used game shows and price lists to elicit parameters of risk aversion, this paper provides reasonable estimates resembling earlier papers' using a different methodology, while also pointing out that much of the deviation from the risk-neutral pattern can be explained by loss-aversion as well. In particular the traditional CRRA expected utility result of approximately .8 assuming utility of income is smaller than that estimated in Beetsma and similar to the CRRA parameter estimate in Post et al. The CARA estimate, meanwhile, though less reliable, falls within the range of certainty equivalents for a (.5, \$1,000) gamble estimated by Gertner. The ability of a linear utility function with loss aversion to explain much of the variation among those who exhibit non-risk neutral tendencies, however, leads to questions of how much individuals actually interpret the final gamble as a monetary wager vs. an emotional wager.

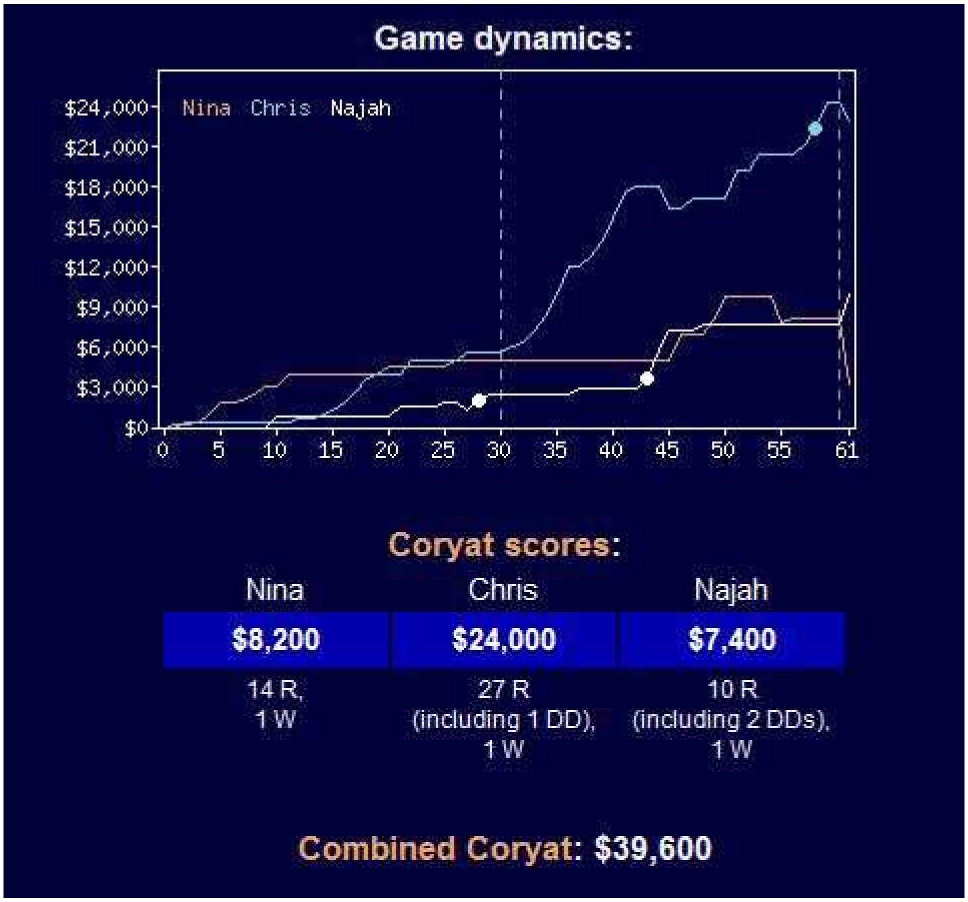


Figure 1.1: Screenshot from "J-Archive" Showing Available Information

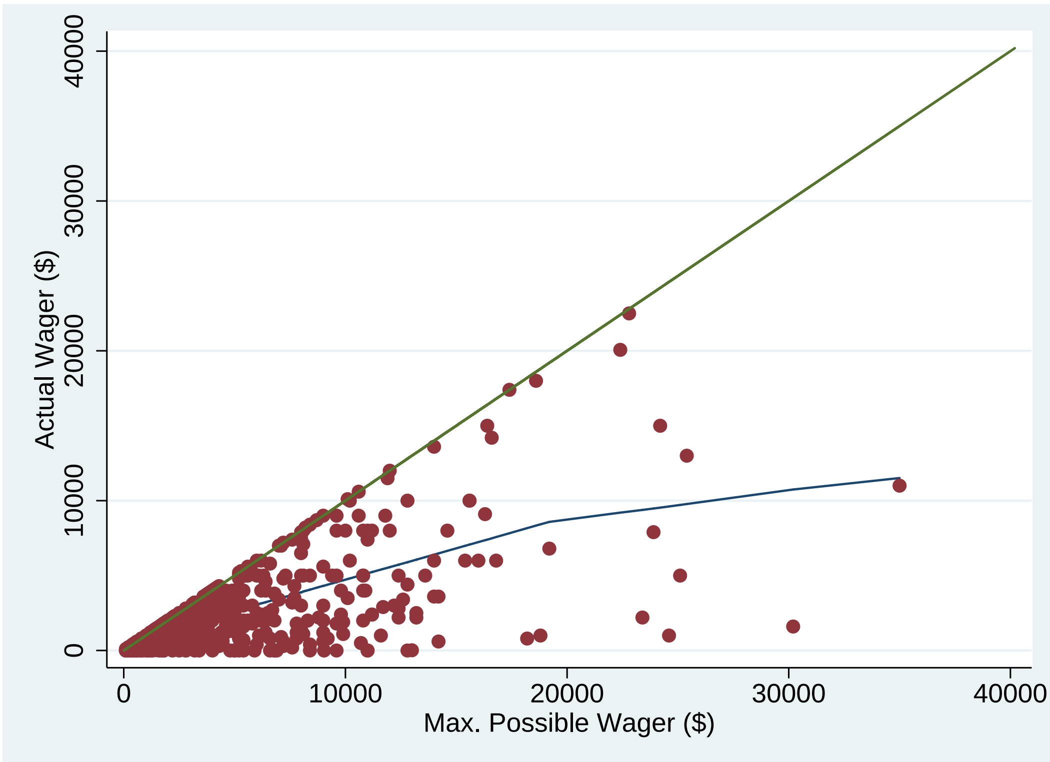
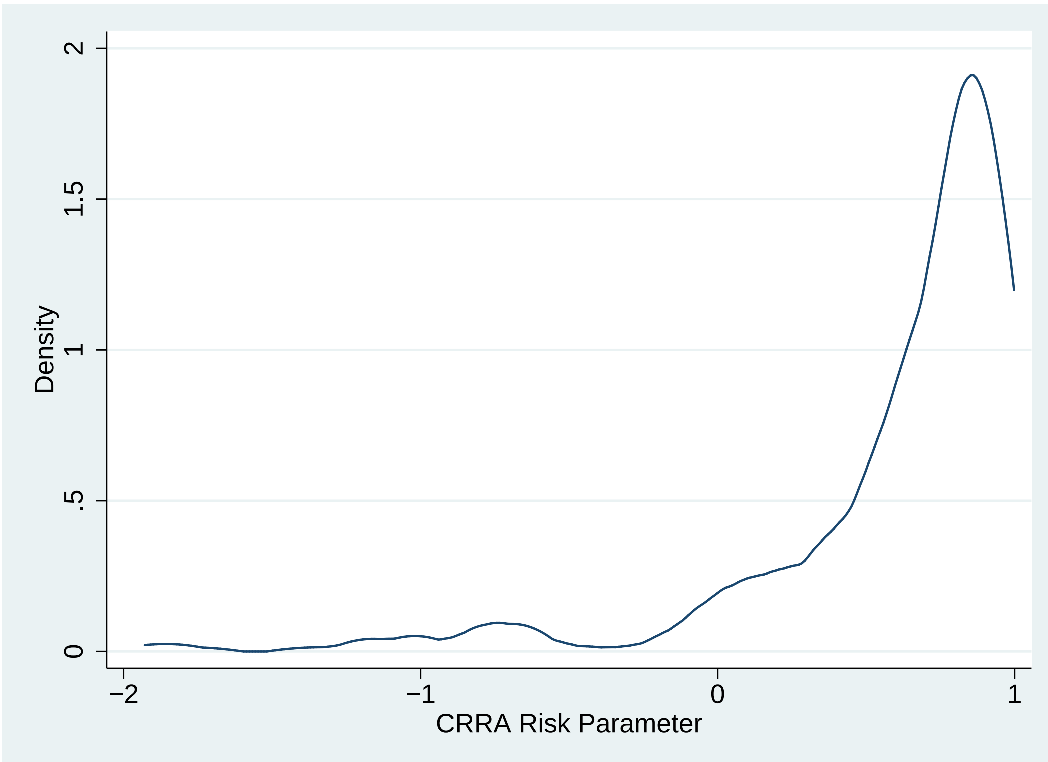
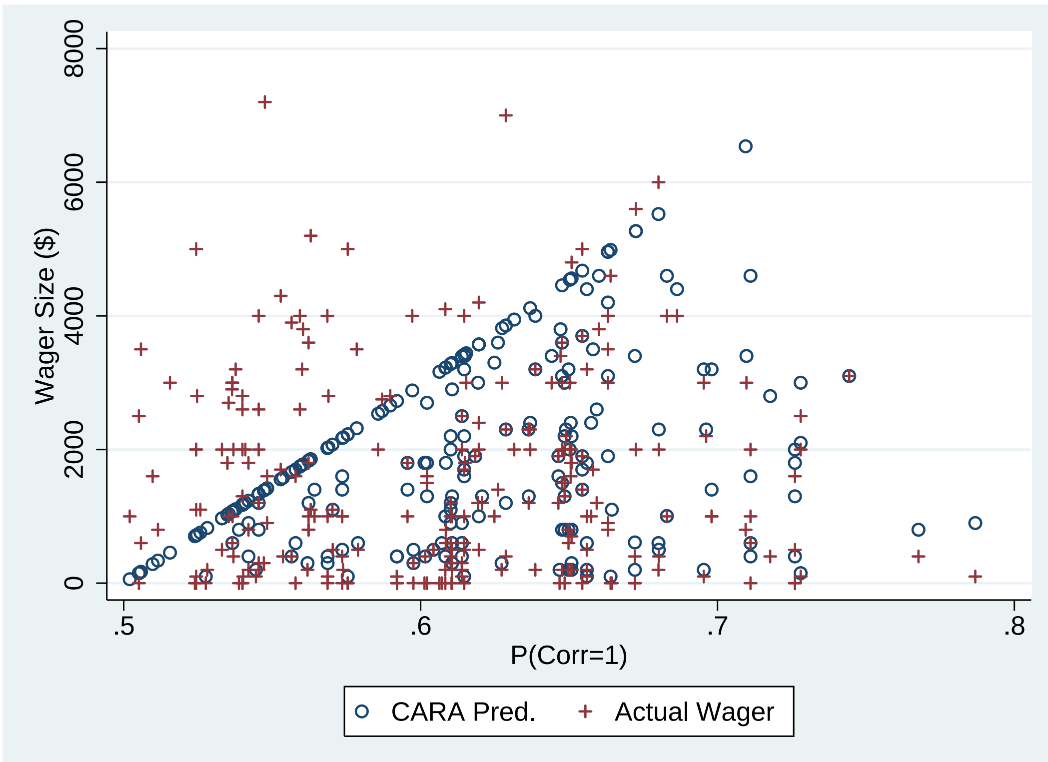


Figure 1.2: Possible and Revealed Wagers for $x_1 \geq 2x_2$: CRRA Sample



Note: 23 percent of sample censored

Figure 1.3: Kernel Density of Revealed CRRA α



Note: Size of CARA predictions are capped at endowment

Figure 1.4: Comparison of Predicted and Actual Wagers Under CARA Utility

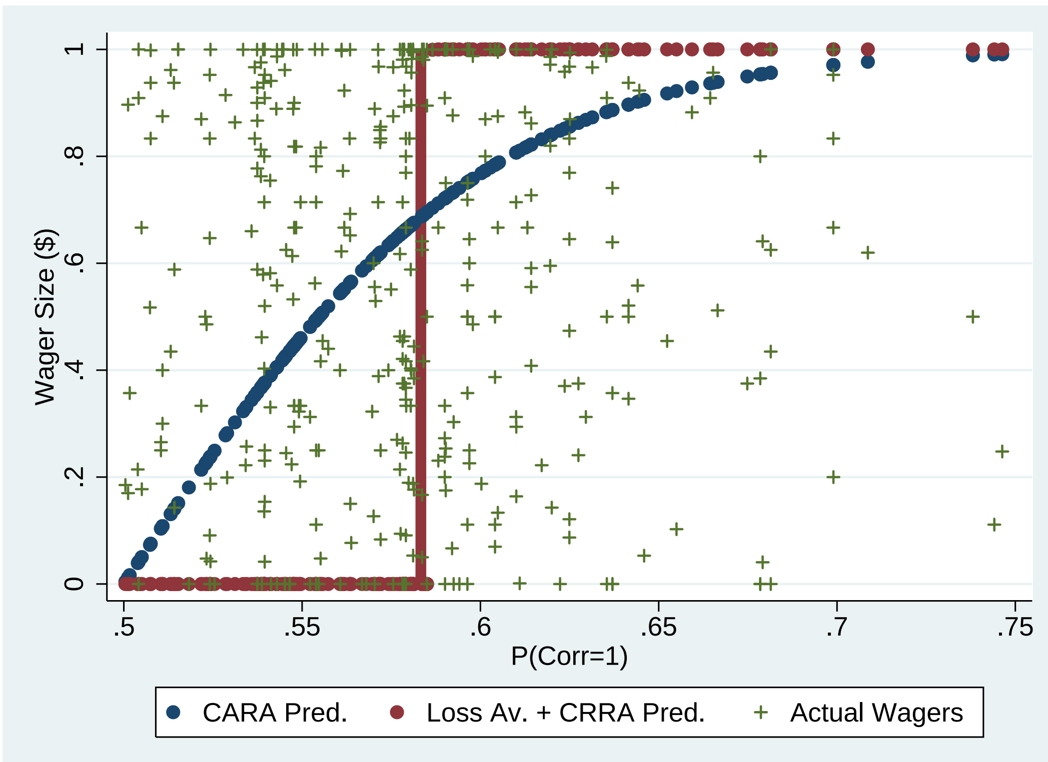


Figure 1.5: Comparison of Predicted and Actual Wagers Under CRRA and Loss Aversion

Table 1.1: Summary Statistics for Eligible "Jeopardy!" Contestants

	All Indiv.	Low Cover (<$4/8,000)	High Cover (>$4/8,000)	Complete Games
P(Corr=1)	0.521	0.531	0.5	0.551
	(0.5)	(0.5)	(0.502)	(0.498)
# Correct	24.9	23.7	27.61	25.98
	(4.862)	(4.468)	(4.634)	(4.568)
# Wrong	2.586	2.626	2.494	2.432
	(1.633)	(1.603)	(1.701)	(1.612)
$2^{nd} Place Correct$	13.55	14.24	11.99	13.92
	(3.438)	(3.305)	(3.225)	(3.443)
$2^{nd} Place Wrong$	3.247	3.313	3.096	2.791
	(1.818)	(1.872)	(1.685)	(1.657)
$3^{rd} Place Correct$	10.73	11.23	9.59	11.34
	(3.615)	(3.555)	(3.499)	(3.681)
$3^{rd} Place Wrong$	3.516	3.531	3.482	3.266
	(1.917)	(1.999)	(1.722)	(1.836)
Unrevealed	1.243	1.151	1.452	
	(1.805)	(1.726)	(1.962)	
Max. Wager	$4,844.50	$2,523.90	$10,114.70	$4,737.00
	($4,852.90)	($1,866.50)	($5,401.40)	($4,932.70)
Actual Wager	$2,432.50	$1,442.60	$4,680.60	$2,434.20
	($2,970.70)	($1,409.60)	($4,139.70)	($3,069.10)
Lead Score (Pre-FJ)	$16,052.90	$14,883.60	$18,708.70	$17,826.10
	($6,952.40)	($6,299.70)	($7,623.60)	($6,775.70)
Lead Score Final)	$16,268.90	$14,999.90	$19,150.90	$18,075.60
	($8,258.90)	($6,647.10)	($10,551.60)	($8,275.60)
Obs.	543	377	166	301

Note: Sample Incl. all individuals with non-zero cover
wagers who make rational wagers, excluding Ken Jennings and Dave Madden.

Table 1.2: First Stage Estimate of Pr(Corr.)

	(1) CARA Sample	(2) CRRA Sample	(3) CRRA - Complete Game	(4) Bayesian Sample
#Correct	-0.0584	-0.0485	-0.0823	
	(0.0584)	(0.0392)	(0.0539)	
#Wrong	-0.144	-0.139*	-0.172	
	(0.106)	(0.0842)	(0.117)	
Unrevealed	-0.138	-0.120		
	(0.119)	(0.0786)		
# Correct^2	0.000979	0.000682	0.00118	
	(0.00115)	(0.000721)	(0.000990)	
# Wrong^2	-0.0103	-0.00917	-0.0149*	
	(0.00782)	(0.00615)	(0.00808)	
Unrevealed^2	-0.00898	-0.00391		
	(0.00693)	(0.00491)		
# Corr. x # Wr.	0.00531	0.00571*	0.00845**	
	(0.00394)	(0.00293)	(0.00415)	
# Corr. x Unrev.	0.00371	0.00349		
	(0.00455)	(0.00278)		
# Wr. x Unrev.	0.0236*	0.0109		
	(0.0120)	(0.00847)		
Bayesian Est.				1.388***
				(0.401)
Prev. Champ				0.0812*
				(0.0431)
Constant	1.521**	1.396**	1.875**	-0.756**
	(0.754)	(0.546)	(0.744)	(0.355)
Observations	377	543	301	543
R-squared	0.083	0.051	0.047	0.031
adj. Rsq	0.0606	0.0351	0.0312	0.0271
F-test	3.695	3.192	2.935	8.536

Standard errors in parentheses, Robust errors are smaller
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: Sample Incl. all individuals with non-zero cover wagers
who make rational wagers, excl. Ken Jennings and David Madden.

Table 1.3: Covariates As Predictor of Wagering Decisions

	Initial Cash Values		Double Cash Values		
Sample:	Wager - Full	Wager - CARA	Wager - Full	Wager - CARA	Cover Ratio
#Correct	-715.6***	-44.34	-336.4	284.0	-0.0409
	(217.1)	(195.2)	(364.0)	(258.6)	(0.0281)
#Wrong	419.2	-31.32	108.8	-177.9	0.0367
	(475.3)	(364.6)	(761.9)	(458.1)	(0.0602)
Unrevealed	-806.0**	116.1	-103.5	431.3	-0.00807
	(365.5)	(320.7)	(970.6)	(671.2)	(0.0563)
# Correct^2	17.68***	1.559	9.881	-5.069	0.000705
	(4.047)	(3.915)	(6.555)	(5.020)	(0.000516)
# Wrong^2	29.36	17.71	-106.3**	16.55	-0.00399
	(37.71)	(27.06)	(53.56)	(34.24)	(0.00440)
Unrevealed^2	18.90	-24.29	-11.28	-27.31	0.00270
	(21.11)	(16.79)	(74.85)	(47.33)	(0.00352)
# Corr. x # Wr.	-28.39*	-6.073	21.51	-1.529	-0.000423
	(16.15)	(13.21)	(26.88)	(17.19)	(0.00210)
# Corr. x Unrev.	41.85***	-4.250	17.72	-14.05	-0.000540
	(12.93)	(12.63)	(34.19)	(25.28)	(0.00199)
# Wr. x Unrev.	-40.46	31.68	-36.94	14.23	-0.000670
	(43.06)	(34.83)	(88.06)	(59.75)	(0.00606)
Constant	8,608***	1,517	4,105	-1,722	1.099***
	(2,967)	(2,471)	(5,163)	(3,389)	(0.391)
Observations	252	174	291	203	543
R-squared	0.263	0.037	0.112	0.021	0.019
adj. Rsq	0.235	-0.0158	0.0832	-0.0244	0.00209
F-test	9.583	0.700	3.924	0.465	1.126

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Columns 1 & 2 are for early versions, 3 & 4 are for doubled clue values.
Sample Incl. All individuals with non-zero cover
wagers who make rational wagers, excluding Ken Jennings and David Madden.

Table 1.4: Risk Parameter Estimates Using Tobit Specification

VARIABLES	(1) Raw Wager	(2) Adj. Wager	(3) Adj. Wager RN Incl.	(4) Adj. Wager All Incl.
A. CARA Estimates				
α	-0.000334	9.10e-05*	6.83E-05	0.000121***
	(0.000324)	(5.17E-05)	(4.67E-05)	4.36E-05
CE(.5, $1,000)	$541.56	$488.63	$491.46	484.88
CE(.5, $10,000)	$8028.97	$3899.71	$4162.35	3571.66
Observations	329	325	341	373
B. CRRA Estimates - All Games				
α	4.653***	0.880**	0.914**	0.833***
	(0.915)	(0.0525)	(0.0423)	(0.0396)
σ	18.12***	0.977	0.878***	0.865***
	(0.715)	(0.0427)	(0.034)	(0.0318)
CE(.5, $1,000)	$861.60	$454.90	$468.43	$435.13
Observations	472	406	500	542
C. CRRA Estimates - Complete Games				
α	1.453	0.703***	0.777***	0.708***
	(0.543)	(0.0944)	(0.0779)	(0.0719)
σ	8.459***	1.370***	1.251***	1.207***
	(0.41)	(0.0725)	(0.0596)	(0.0548)
CE(.5, $1,000)	$620.61	$373.07	$409.80	$375.68
Observations	266	227	278	301
D. CRRA Estimates - Bayesian Est.				
α	4.345***	0.937	0.965	0.898***
	(0.637)	(0.0414)	(0.0331)	(0.0323)
σ	12.21***	0.751***	0.673***	0.690***
	(0.505)	(0.0347)	(0.0274)	(0.0267)
CE(.5, $1,000)	$852.55	$477.23	$487.59	$462.14
Observations	473	407	507	543

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Note: Sample Incl. All individuals with non-zero cover wagers within threshold, excluding Ken Jennings and David Madden.

Table 1.5: CRRA Risk Parameter and Loss Aversion Estimates Using Tobit Specification

	(1) Raw Wager	(2) Adj. Wager	(3) Bayesian - Adj. Wager
α	1.520***	1.064**	1.040*
	(0.119)	(0.0283)	(0.0248)
λ	1.410***	1.417***	1.277***
	(0.00387)	(0.0209)	(0.0165)
σ	2.556***	0.556***	0.487***
	(0.0914)	(0.0195)	(0.0178)
Observations	543	543	543

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Sample Incl. All individuals with non-zero cover wagers within threshold, excluding Ken Jennings and David Madden.

Table 1.6: Tobit Reg. of CRRA Risk Parameters by Prev. Experience

Prev. Result rel. to $E(*)$	*Poly Exp.* Repeat Players	*Poly Exp.* All Players	*Bayesian Est.* Repeat Players	*Bayesian Est.* All Players	*Bayesian Est.* New Players - Adjusted $\hat{p}$
$Corr_{t-1} = 1 \mid E(*) = 0$	0.0831	0.0831	-0.0251	-0.0252	
	(0.159)	(0.15)	(0.116)	(0.114)	
$Corr_{t-1} = 0 \mid E(*) = 0$	0.293	0.291	0.159	0.159	
	(0.192)	(0.181)	(0.139)	(0.137)	
$Corr_{t-1} = 1 \mid E(*) = 1$	0.0484	0.0535	0.0552	0.0554	
	(0.154)	(0.146)	(0.113)	(0.111)	
1^{st} *Time*		0.18		0.489***	0.805***
		(0.132)		(0.103)	(0.063)
Baseline	0.717**	0.706**	0.677***	0.676***	
	(0.125)	(0.118)	(0.091)	(0.0896)	
σ	0.911**	0.863***	0.677***	0.668***	0.918
	(0.0429)	(0.0317)	(0.0306)	(0.0257)	0.0518
Observations	303	542	303	543	240

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Baseline case includes individuals with previous experience where $Corr_{t-1} = 0 \mid E(*) = 1$.

Table 1.7: Count of Games by Number of Questions Asked After Lock

Questions Asked	Count of Games	Pct.	Cum. Pct.
0	313	57.64	57.64
1	102	18.78	76.43
2	59	10.87	87.29
3	24	4.42	91.71
4	17	3.13	94.84
5	14	2.58	97.42
6	11	2.03	99.45
8	2	0.37	99.82
9	1	0.18	100.00
Total	543	100.00	

Note: Cell C4 of Table 4 would be approx. .86 (SE .035) if only games with 3 or fewer questions asked after a lock occurs are included

Table 1.8: T-test of Gameplay Changes Over Last 10 Questions by Questions Asked After Lock

	Lock with $Q_{rem} > 3$ v. $Q_{rem} = 0$	Lock with $Q_{rem} > 4$ v. $Q_{rem} = 0$
Δ% Correct	-0.0507	-0.0684*
	(0.0326)	(0.0408)
Δ% Wrong	-0.0136	-0.0244
	(0.0133)	(0.0167)
Δ% Answered	-0.0643*	-0.0928**
	(0.0329)	(0.0410)
Observations	358	341

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: $H_0 : n_1 = n_2$.
Sample Incl. All individuals with non-zero cover wagers
who make rational wagers, excluding Ken Jennings and David Madden.

Table 1.9: Risk Parameter Estimates with Errors in $\hat{p}$

	(2) Adj. Wager
A. $\hat{p} = p + \varepsilon, \varepsilon \sim N(0, .1)$	
α_{CRRA}	1.078*** (0.003)
B. $\hat{p} = p + \varepsilon, \varepsilon \sim N(0, .15)$	
α_{CRRA}	1.243*** (0.006)
C. $\hat{p} = p + \varepsilon, \varepsilon \sim N(0, .2)$	
α_{CRRA}	1.423*** (0.008)
D. $\hat{p} = p$ (Table 1.4 [B,4])	
α^{CRRA}	0.833** (0.032)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Sample Incl. All individuals with non-zero cover wagers
who make rational wagers, excluding Ken Jennings and David Madden.

Table 1.10: Risk Parameter Estimates with Nonstandard Errors in $\hat{p}$

(1)	(2) Adj. Wager
A. $\hat{p} = p + \varepsilon, \varepsilon \sim \begin{cases} +\lvert N(0,.1)\rvert & \alpha > \bar{\alpha} \\ -\lvert N(0,.1) & \alpha < \bar{\alpha} \end{cases}$	
α_{CRRA}	0.909***
	(0.001)
B. $\hat{p} = p + \varepsilon, \varepsilon \sim \begin{cases} +\lvert N(0,.15)\rvert & \alpha > \bar{\alpha} \\ -\lvert N(0,.15) & \alpha < \bar{\alpha} \end{cases}$	
α_{CRRA}	0.941***
	(0.002)
C. $\hat{p} = p + \varepsilon, \varepsilon \sim \begin{cases} +\lvert N(0,.2)\rvert & \alpha > \bar{\alpha} \\ -\lvert N(0,.2) & \alpha < \bar{\alpha} \end{cases}$	
α_{CRRA}	1.001
	(0.004)
D. $\hat{p} = p$ (Table 1.4 [B,4])	
α^{CRRA}	0.833***
	(0.032)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Sample Incl. All individuals with non-zero cover wagers
who make rational wagers, excluding Ken Jennings and David Madden.

Chapter 2

Is Bigger Better for Reverse Mortgages? How Large Banks' Presence Impacts HECM Loan Characteristics

Abstract

This paper evaluates the role of lenders in determining the average loan characteristics of a popular type of reverse mortgage loan, the FHA Home Equity Conversion Mortgage (HECM). Shortfalls between current levels of retirement savings and individuals' need to insure themselves against unexpected income, asset, and health shocks after leaving working age mean products such as the HECM will become increasingly relevant over time. Despite the existence of counseling programs to promote proper use of this financial instrument, over time HECM loans have taken on characteristics that lengthen the term of the loan and restrict the financial flexibility these loans are meant to provide. Anecdotal evidence exists that the market structure of HECM suppliers incentivizes them to promote these undesirable characteristics. I use the departure from the HECM market of a diversified financial institution not facing these incentives to test whether this phenomenon indeed exists, and find the departure of this institution associated with an increase in the probability of borrowers choosing a fixed rate loan, a decrease in the mean borrower age, and a decline in the amount of assets set aside to

maintain the loan in good standing.

2.1 Introduction

As the "baby boom" generation in the United States approaches retirement, policymakers' interest in how these households will finance their retirement grows. The shift from "Defined Benefit" (DB) retirement plans, where pensions guarantee a specified payout based on tenure and/or contribution, to "Defined Contribution" (DC) plans, such as 401(k)s, have shifted the burden of planning for retirement onto employees (Beshears et al., 2011). Laibson (1997) points out that this may result in undersaving relative to households' targets, as people generally have difficulty allocating consumption rationally between the present and distant future. Indeed, Beshears et. al. point out that the shift from DB to DC plans have left significant numbers of public sector employees needing to save at levels higher than the present in order to finance their goal retirement lifestyle. The impact on household retirement savings assets from the current recession provides added strain for households near their planned retirement age to find ways to afford their current standard of living for years to come.

Due to the need for increased self-reliance in making long-term financial decisions, the current depressed levels of savings assets relative to previous expectations, and the typical tendency for individuals to undersave for long-term goals using traditional mechanisms, financial industry and policy experts have looked for potential products that bridge the gap between end of life savings and spending. One of these products, the Home Equity Conversion Mortgage (HECM), commonly referred to as a reverse mortgage, offers the ability to accomplish this by exploiting the dual nature of housing as both a consumption and investment good. The consumption aspect of housing purchased with a traditional "forward" mortgage ensures that individuals consistently make payments over time, while the property's status as a durable good allows it to be sold after usage is complete, with the reverse mortgage serving as a futures contract between the borrower and the lender. Though the HECM product has a long history dating back to the early 1990s its potentially confusing structure, distant repayment date, and financially vulnerable target market shares much in common with more infamous mortgage innovations of the housing boom, such as the "Pick and Pay" Option ARM, a forward mortgage that allowed for negative amortization contingent on a large future payment. Features of these products, combined with behavioral biases such as hyperbolic discounting, can result in a net reduction of consumer welfare. Agarwal et al. (2012) point out that loans they describe as predatory have default rates 6-7% higher than other loan types, and legislation restricting access to these loans most heavily impacts the most at-risk borrowers.

Some academics, such as Posner and Weyl (2013), recommend the creation of an agency that would test, examine, and regulate consumer financial products with high upside and unknown risks before allowing them into the market. Without commenting on the viability of the concept, in the absence of its presence we must rely on exogenous changes to the existing market when attempting to evaluate potential explanations for characteristics of a good at equilibrium. This paper evaluates potential concerns regarding current usage of the relatively obscure, but quickly growing reverse mortgage, then uses an exogenous change in the supply of this product to the market in order to examine the impact of market structure on equilibrium loan characteristics. I find that the departure of a large, diversified lender from the HECM market is associated with an increase in the proportion of loans with fixed rates, impacting the flexibility of borrowers to use their housing equity; a decrease in the average age of the borrower, which lengthens the typical loan term; and a mildly significant decrease in the setting aside of funds that help prevent foreclosure. The next section provides an overview of characteristics of the product constituting the vast majority (>98 percent) of the US reverse mortgage market, the FHA-insured HECM loan, followed by a discussion of the product's potential pitfalls. Section 2.3 will discuss characteristics of the current equilibrium in the HECM market and the exogenous shock that allows for examination of the role of supply in maintaining that equilibrium. Section 2.4 explains the data and estimation strategy, Section 2.5 provides results, and Section 2.6 will give commentary on the results and comments on potential further research.

2.2 Reverse Mortgage Fundamentals

2.2.1 What is a Reverse Mortgage?

After the decline in use of exotic forward mortgages following the 2008 crisis, for consumers reverse mortgages now arguably constitute one of the hardest to understand financial products in the market. The vast majority of reverse mortgages originate through the FHA-backed HECM program. Reverse mortgages allow homeowners older than 62 to borrow against the equity in their home. Given a significant portion of asset growth through retirement comes through house price appreciation and mortgage payments, this mechanism could help resolve the retirement saving puzzle (Nakajima and Telyukova, 2011). Though reverse mortgages do not require a credit check, potential borrowers must go through mandatory counseling with a HUD-approved organization before originating a HECM loan. After completing the loan, borrowers can immediately access funds up to a predetermined limit based on the value of the home, and defer repayment until the borrower dies, sells, or moves out of the house. Although different payment options exist, most borrowers receive the funds as a lump-sum payment at time of closing with a fixed interest rate. Loans with an adjustable rate typically work similarly to a line of credit, with borrowers able to withdraw against the limit at multiple intervals. Interest on the amount borrowed accrues over time, but borrowers do not have to repay any amount above the predetermined limit, and may prepay at any time without penalty. While residing in the home, borrowers must stay current on insurance and property taxes, and maintain the home in good condition at risk of foreclosure. Given basic assumptions, reverse mortgages can allow older Americans to tap into their single-largest asset for funding while also allowing them to simultaneously maintain it as their single largest consumption good. Papers such as Merrill et al. (1994) have attempted to estimate the realistic potential size of the real estate market, as well as explain the relatively low take-up rate. The difficulty in explaining the product to consumers, along with a strong tendency to treat homes as different from other asset types, likely accounts for its lower than predicted use by homeowners. Though half of homeowners age 62 and older had more than 55 percent of their net worth tied up in their home, only between 2 and 3 percent of eligible individuals 65 and over take out a reverse mortgage (Nakajima, 2012).

2.2.2 Concerns with Reverse Mortgages

While the above section provides a description of how the reverse mortgage product works in an ideal world, the lengthy explanation also provokes as many concerns as it resolves. First, the confusion regarding the product means that consumers likely rely heavily on financial advice from professionals, and may not necessarily understand the full range of options at their disposal. For example, an older borrower looking for short-term liquidity could instead take out a home equity line of credit (HELOC), or even a second mortgage. Alternatively, those burdened by a hefty mortgage and subsequent collapse in housing prices could use the HECM to pay down their mortgage, when instead refinancing or selling and moving to a more appropriately sized house could enhance welfare in the long run. As Michelangeli (2010) points out, this moving risk can mitigate a large portion of the welfare gains provided by reverse mortgages. Financial professionals' incentives, due to their payment and salary structure derived from the size and type of transaction, likely do not precisely match those of their customers. Research on retirement saving only magnifies those fears. Mullainathan et al. (2012) used an audit study of financial professionals to show they appeared to exploit the biases of their customers when it benefited them, even when it affected the customer negatively, at a statistically significant level. Chalmers and Reuter (2012), in a similar study on retirement saving, found those using brokers to allocate their retirement funding had riskier portfolios that underperformed those using more passively managed target retirement date funds. The same risky funds, however, provided higher fees to the brokers who recommended them. Finally, Shi (2012) used state-level variation across states over time in the licensing and lending standards for forward mortgage brokers to show that lending quality characteristics, such as loan to value (LTV), debt to income (DTI), and credit score (FICO), decline in areas with looser licensing and lending standards. The accumulated research on the incentives of retirement and mortgage product suppliers show that they impact the equilibrium characteristics of these products' usage, and that policymakers must consider the role of financial product suppliers and their incentives in generating their equilibrium usage characteristics.

On the consumer side, one of the primary purposes of the product – bridging the gap between retirement savings/earnings and expenses – concentrates its appeal toward individuals with the highest difference between those two values. This means those most interested in the product display the highest tendency toward hyperbolic preferences toward spending, as well as the smallest set of alternatives. HECMs require no credit check, and do not base pricing on credit history. As a result HECM loans become most attractive to individuals with poor credit histories and those who do not understand the full range of available financial products; most likely these individuals do not fully understand the implications of the HECM loan, nor the implications of choosing the high initial-payout, closed-end fixed rate mortgage currently popular in the market. The CFPB report on reverse mortgages uses American Housing Survey data from 2009 to show that approximately 85 percent of reverse mortgage borrowers have an annual household income less than \$50,000, with over half maintaining incomes less than \$25,000 (CFPB, 2012). Behrman et al. (2012) point out that even among the subset of these individuals with high education, lack of financial literacy regarding these products can impact wealth management strategies. Lusardi's research (Lusardi 2012,Lusardi et al. 2012) identifies the elderly and those with the lowest levels of assets as the sets of individuals with the lowest levels of financial literacy and numeracy, meaning that these individuals, more than others, will need to rely on the advice of the financial professionals discussed earlier when evaluating their retirement financing options.

2.3 Current HECM Equilibrium and Market Structure

2.3.1 Trends in Characteristics of the Reverse Mortgage Market

Given the difficulty in understanding a product that functions in the opposite manner from more familiar mortgages, it should come as no surprise that consumers increasingly tend to choose certain features of the product at rates not predicted by rational economic theory. In particular, analysis based on FHA data for its federally insured HECM product of trends since the mortgage crisis point to three anomalies. First, eligible borrowers take out reverse mortgages at younger ages over time; as noted by Shan (2011) and the CFPB the median age of a reverse mortgage borrower has decreased from 76 to 70 years since 1990, as shown in Figure 1. Tapping into this good at an early age leaves homeowners without emergency assets available in the future for unexpected expenses such as medical care, etc. Risks associated with these potential emergencies feature heavily in explaining why the elderly save for retirement in the first place (Nardi et al., 2010). As stated earlier, the HECM mortgage comes due when the borrower leaves the house, either through sale or death. Taking out the HECM at the earliest eligible age locks these younger households into their current location, unable to leave and unable to insure themselves against future emergencies. Even in this case, the note holder can then foreclose on the home if it can prove that the borrower is not properly maintaining the house as a collateral asset. This means increasingly younger HECM consumers, many of whom take out the product due to shortfalls in savings, need to make sure they set-aside enough proceeds to continue to maintain the home, and ensure they live in an environment where they can receive future medical care.

Second, borrowers have shifted their loan types from an adjustable loan similar to home equity lines of credit to closed-end, fixed rate mortgages that provide only one payout per transaction and create volatile real interest rate costs. As noted by Campbell (2012), this preference for the fixed-rate loan matches the environment found in the forward mortgage market, where consumers prefer fixed-rate loans despite the real benefits offered by adjustable products. Research on present bias such as that of Laibson and Hastings and Mitchell (2011) explain why consumers might prefer these products even though they do not necessarily improve welfare in the long run relative to other options. Use of the fixed-rate product in the reverse mortgage market creates an additional cost on the consumer not found in the traditional market. The lump-sum payout requirement forces consumers to, once again, predict future funding requirements for consumption and possibly take out a larger loan than they would otherwise.

Unsurprisingly, then, borrowers take out more money in the initial (or only, in the case of closed-end, fixed rate loans) withdrawal from the reverse mortgage than before. As shown in Table 2.1, outside of those at the major lenders borrowers withdraw almost all of the available equity from their home when taking out a reverse mortgage. Consumers could rationally take out these large lump sums in order to plan a large-scale retirement funding strategy; however, evidence from private data released to the CFPB hints that consumers in the housing bust use reverse mortgages as a means of paying off heavily burdensome traditional mortgage liens, with approximately 70 percent of borrowers with appraised home values over $400,000 using reverse mortgage funds to pay off existing liens at closing. These three phenomena, when combined, point to an environment where consumers frequently suboptimally use reverse mortgages, tapping and emptying their largest equity asset at an age where they may continue to live for many years. Usage patterns are evolving in a direction that requires greater foresight and planning of long-term consumption, when the product's current purpose is to compensate for the inability of consumers to adequately make these same decisions earlier. The current pattern of earlier withdrawal and larger payout would make more sense if consumers typically chose the loan option where they receive an annuity until death, even if the proceeds exceed the value of the loan, as this would provide a committed stream of payments that overcomes many popular consumer savings concerns, but instead almost all consumers choose an immediate lump-sum payment option, possibly in a way that resolves current debts but leaves nothing for the future. Evidence points to fulfillment of the hyperbolic discounting bias described by Laibson, where individuals do not rationally evaluate the trade-offs between immediate payment and long-term goals.

Although demand-side behaviors can explain all three facts listed above, supply-side structures and behaviors could potentially contribute to these usage patterns. The current reverse mortgage landscape began taking shape in 2007, when the creation of a securitization for closed-end fixed-rate reverse mortgages by Ginnie Mae generated a more favorable private secondary market for these products relative to those with adjustable rates (CFPB Reverse Mortgage Report). For open-ended loans, issuers needed to maintain sufficient funds to finance potential future withdrawals from the line of credit; they also faced risks in the resale market from potential changes in future interest rates. Securitization allowed for the expansion of wholesale lending, which allows for an originator to make a larger volume of loans with less liquidity, but only for closed-end, fixed-rate reverse mortgage loans easily sold on the secondary market. This differs from the more traditional model of retail/portfolio lending, where a loan originator must hold the loan on their books until the contract expires. Even after creation of this product, however, Fannie Mae's continued willingness to purchase adjustable-rate loans from wholesale lenders led to a high proportion of adjustable to fixed-rate loans. In 2009, however, Fannie Mae reduced the price it paid for adjustable rate loans at the same time as the secondary market for all loans shrank after the mortgage crisis and fixed interest rates became more attractive relative to adjustable rates. Unsurprisingly, the confluence of these events correlates with a dramatic shift of the market to the fixed-rate product, as shown in Figure 2.2.

After the departure of Fannie Mae, the set of reverse mortgage originators divided into 2 general categories, each facing different sets of incentives for their ideal mix of loans. Wholesale lenders originated loans with the necessary goal of packaging them to other investors, for securitization or otherwise. The companies typically offer only the reverse mortgage product, giving them little incentive to attempt to optimize and debias a consumer's overall financial portfolio or the type of reverse mortgage chosen, and leaving them facing little impact from long-term negative outcomes of the loan. Although the FHA requires that prospective HECM buyers go through counseling before completing a HECM loan, anecdotally the quality of this counseling varies, and one could imagine certain lenders committing to more rigorous education on aspects of the HECM loan and its alternatives than others. Goda et al. (2012) show that the type of information provided in education interventions can statistically significantly impact consumers' retirement decisions. The second major type of lender, the retail lender (also called an issuer-servicer), issues, services, and holds onto the loan. These lenders will be in touch with the consumer through the life of the loan. In 2010, three large retail lenders, all offering a large, diversified range of financial services, originated and issued 76 percent of all retail loans, while also maintaining a wholesale funding channel. The retail branches of these institutions had greater incentives than similar employees at other institutions to provide consumers information on other, possibly more suitable financial products, which could select out younger homeowners and those looking to payoff a traditional lien. Their large asset base and ability to hold loans in portfolio meant that the retail lenders could more easily fund adjustable-rate loans, and so had little incentive to guide consumers away from these products. Additionally, while the FHA program protects the investor from foreclosure-related losses, customer-facing issuer-servicers will still want to avoid complications associated with the foreclosure process, as well as the inevitable poor public relations that arise from foreclosing on the homes of the elderly. Though a wholesale originator has little incentive to ensure that consumers set aside enough funds to maintain their property, issuer-servicers internalize that cost from the outset. In particular, a diversified institution will likely want a reverse mortgage customer who can retain liquidity and reduce uncertainty in future obligations so that they continue to be a profitable customer in multiple product lines. In short, while the current market structure for loan funding has allowed for expansion of the wholesale lending market for fixed-rate loans, the more traditional issuer/servicer model may result in loan characteristics that policymakers find more favorable.

2.3.2 An Exogenous Change in the Retail Lending Market

Table 2.2 shows the market share of the top 10 largest mortgage funders in 2010, as well as a breakdown of their market share in the Retail and Wholesale lending channels. In the first time period 3 lenders make up 61 percent of all originations, and also supplied funding for 40 percent of the wholesale market. Between February 2011 and March 2012 all three lenders also left the reverse mortgage market, though each did so under different circumstances. Bank of America, the number two lender in the overall space and within each loan subtype, left the market first, ceasing to initiate all reverse mortgage lending after February 4th, 2011. According to its own statement, as recorded by internet-based trade publication Reverse Mortgage Daily, the Bank closed its operations not due to any dramatic changes in market conditions, but instead to focus on improving servicing of its troubled forward mortgage portfolio, which continued to receive both public and regulatory scrutiny (Yedniak, 2011b). In a later article in the same publication, a Bank of America spokesperson stated its reverse mortgage unit was profitable even at the time of exit (Yedniak, 2011a). On June 16 of the same year Wells Fargo, who in 2010 originated approximately one-quarter of all FHA-backed reverse mortgage loans in 2010, announced its own similar exit from the reverse mortgage market, although it did so due to what it perceived as a decline in future market conditions, as well as complaints about government regulation in the market (Lieber, 2011). Finally, in April 2012 Metlife, the largest supplier of wholesale loan funding, announced its exit from all banking services due to what it perceived as stringent regulatory requirements in that area (Carnns, 2012). In particular, Bank of America and Wells Fargo's business models, which heavily relied on their retail channels, differed from the rest of the market. The nature of retail lending meant many of their customers likely had pre-existing relationships with the bank, and many of the loans were brought in through their strong brick-and-mortar branch networks. The high levels of liquidity in each bank also meant that they could hold onto larger amounts of reverse mortgages, allowing for more even marketing of closed fixed- v. open adjustable-rate mortgages. The departure of these institutions from the industry allows for examination of the role of the HECM reverse mortgage's market structure in explaining stylized facts about the market equilibrium.

2.4 Data and Estimation Strategy

2.4.1 Estimation Strategy

Given the concerns listed above and the rapidly changing landscape of the reverse mortgage market, this paper seeks to examine the role of suppliers in explaining current average market characteristics. I will examine their role in explaining the proportion of mortgages originated with a fixed interest rate, the average initial payout of a loan as a percentage of funds available, the amount of money set aside at loan origination to pay for future home maintenance and taxes, and the age of the youngest borrower associated with the loan. The identification strategy for the paper relies of Bank of America's initial market share, as well as their subsequent departure, being exogenous from the portfolio characteristics of their areas served and market share. I will use empirical testing to examine the former case, and must rely on the bank's publicly stated reasons for departure, as well as lack of alternative explanation provided by industry experts, for the latter. Within Bank of America, I will test whether the departure of the retail banking network, which offers a more diverse product portfolio for its customers and has greater incentives to provide wider financial planning for customers, affects the market differently than its departure from the wholesale funding space. Additionally, given that the degree of change is likely a function of market share, since that will indirectly define the size of the short-run gap between quantity demanded and supplied from the initial equilibrium, I will test whether the loan characteristics made within geographic markets change as a function of Bank of America's market share. In some Metropolitan Statistical Areas (MSAs) Bank of America provided zero HECM loans in 2010; these areas should face a smaller impact from the departure of the bank from the reverse mortgage space than MSAs where Bank of America originated and/or funded a large percentage of all reverse mortgage loans. In order to provide a control entity for comparison, I will also include market shares for Wells Fargo and Metlife, both of which did not leave the market until after my period of analysis. The presence of these banks in Bank of America's market area could affect the impact of their departure by providing similar alternative outlets for either funding, origination support, or both.

To test the main hypothesis I run two sets of regressions; the first,

$$Y_{igt} = \beta_0 + \beta_1 I_{2011} + \sum_{n \in N} (\beta_n I_{ng} + \Psi_n I_{2011} I_{ng}) + q_t + \varepsilon_g + \varepsilon_{it} \tag{2.1}$$

answers the question of whether the overall departure of Bank of America from a market (represented by Ψ_{BofA}) is associated with the change in Y_{igt}, the variable of interest for loan i in MSA g in month t. I_{2011} is an indicator variable for whether the loan originated in 2011, I_{ng} is an indicator for the loan originating in a geographic area served by large bank n, and q_t represents time effects at the monthly level for loan application and origination dates, as well as indicators for overall and bank-specific policy changes. The second estimation,

$$Y_{igt} = \beta_0 + \beta_1 I_{2011} + \sum_{n \in N} (\alpha_n I_{ng} + \Psi_n I_{2011} I_{ng} + \Gamma_n S_{2010ng} + \Theta_n S_{2010ng} I_{2011}) + q_t + \varepsilon_g + \varepsilon_{it} \tag{2.2}$$

accounts for the relative market share of Bank of America within an area, and allows for changes in the outcome variable to depend on the ability of the other two large lenders, Wells Fargo and Metlife, to absorb some of the impact felt by the departure of Bank of America from the lending space within each geographic area. Here S_{2010ng} equals the market share for bank n in a given geographic area for 2010. Though I only report results for regressions performed on the loan types of interest specified for each outcome, loans were analyzed separately for each outcome in three ways: where the indicator variables represent the universe of loans funded by a bank ("Sponsored"), where they represent whether a bank provided funding for but did not originate the loan ("Wholesale"), and where they represent whether a bank both originated and funded the loan ("Retail"). I estimate results using standard errors clustered at the MSA level, to allow for correlation in the unobserved errors within geographic areas. Additional controls include indicators for periods in which the HECM loan market changed, or in which Bank of America's product offerings changed relative to other borrowers. For example, In October 2010 the FHA revealed new rules regarding origination, servicing fees, and the minimum rate banks could charge for a fixed-rate HECM loan, as well as a new product called the HECM Saver that offered a different schedule of fees and maximum amount available for withdrawal. In another example, in May 2010 Bank of America's retail branch began to offer a special fixed rate loan with lower servicing fees than those offered by other HECM requirements. Since this changed the mix of loans both in general and within Bank of America for the following three months I include an indicator for this period in the results presented; however, the significant results presented are robust to specification and interactions of this factor with market presence and market share.

2.4.2 Data

The data analysis performed in this paper uses loan-level HECM data compiled by HUD and the FHA. This dataset contains observations from 1989 through November 2011; I use observations of new HECM loans (not including refinances) between January 2010, when the trend toward fixed rate mortgages stabilizes near its current level, and July 2011, when Wells exits the market due to what it sees as changing conditions in the reverse mortgage space. In the data I consider Bank of America's departure to occur at the end of February 2011, since although Bank of America's decision to leave the market occurs during that month, the FHA continued to process applications throughout, leading to a typical number of loans from that bank being stamped with a February date. Meanwhile, zero loans from Bank of America appear with a March

2011 application date. Variables available in the FHA HECM data include 5 digit-zip code (and, thus, MSA), borrower and co-borrower age, HECM type, the initial loan limit, the initial cash payment from the loan proceeds, the rate type of the loan (fixed v. adjustable), the note rate of the loan, the sponsoring lender, and the originating lender. Loans in this timeframe located outside an MSA are not included in the sample. After accounting for all these characteristics, my sample includes 96,984 observations. From these initial variables I construct additional variables used to perform my statistical analysis. Besides preferences and market structure, differences in the magnitude of adjustable interest rates v. fixed interest rates will also likely play a role in the relative distribution of loan types. Since we only have the month in which the loan originates and do not see any rate sheets provided by mortgage lenders to borrowers though rates are set by the FHA, I account for the spread between fixed and adjustable interest rates using a fixed effect for the month in which the loan was originated. In order to understand the potential for impact of Bank of America's departure from the reverse mortgage space in each area, I also need some measurement of the level of market share they hold in each geographic area I consider. Since Bank of America played a role in the financing of mortgages originated by wholesale lenders as well as originated loans through its own branded retail channel, I evaluate the impact of their departure from a market area both through their overall departure as well as their departure from the retail space and the secondary funding market. To measure their overall market share I divide the total number of HECM loans Bank of America sponsored in a given geographic area from January 2010 through February 2011 by the number of all HECM loans originated in that MSA over the same period. For market share held by B of A's retail operations I use a similar process, but only include loans in the numerator that appear to be both originated and sponsored by Bank of America. The wholesale loan share uses loans funded but not originated by Bank of America. I then create variables measuring the market share of Wells Fargo and Metlife, similarly, to compare how conditions changed in markets served more heavily by the large operators remaining after Bank of America's departure. Figures 2.3 through 2.5 provide kernel densities of market share for retail loans, wholesale funded loans, and all funded loans combined. From a total of 961 MSAs from which a loan originated in the period January 2010 - February 2011, Bank of America funded loans in 662, with an overall average market share of approximately 14 percent. Focusing on retail loans, where the bank both originates and funds the loan, Bank of America maintained a presence in 579 of 961 markets, with the retail arm holding an average 9 percent share of the market. Figure 2.6 describes the relationship between retail market share and the number of loans originated and funded during 2010. The largest markets, with up to around 2,500 total loans within a year, generally see a market share between .1 and .2.

Table 2.1 provides basic loan characteristics for loans funded by each of the three large lenders in 2010, compared to the mean for all other loans combined. Cursory analysis shows that, in many cases, characteristics of the large bank loans resemble each other more than they do those of the rest of the population. Bank of America, and in most cases Wells Fargo and Metlife, feature higher percentages of retail loans, lower rates of closed-end, fixed rate mortgages, lower initial withdrawals of equity from the mortgage, higher amounts set aside for future repairs and housing expenses, and lower borrower ages on average.

Before examining the results, I also examined whether the count of loans in an MSA changed as a result of Bank of America's departure. Figure 2.7 presents a histogram of loans originated by month from January 2010 through July 2011. Although the count of loan applications increases as the FHA prepares to release its new rules, products, and rates (since FHA announced older applications would be grandfathered in, and applications themselves cost little, this likely represents regime shopping), the count of applications changes little between February and March 2011, the points immediately preceding and following Bank of America's exit. Though no counterfactual exists, this implies that Bank of America may not have played much of a role in steering individuals toward or away from a HECM reverse mortgage loan.

2.5 Results

As stated earlier, this paper attempts to explain the role of market structure, including funding and customer interaction, in explaining four stylized facts about the US reverse mortgage market. Given the ability to examine loans made in markets before and after Bank of America's departure, how should we interpret the empirical results as they relate to explaining the key drivers of these facts? Each section will begin by explaining how the combined set of results can potentially explain drivers of these stylized facts, followed by explanations of the empirical results.

2.5.1 Distribution of Fixed-Rate Loans

While American consumers tend to prefer fixed-rate loans for financial products generally, market-driven forces also contribute to the high rate of fixed-rates in the HECM reverse mortgage space. For loan originators looking to sell the servicing and securitization rights to the loan in the wholesale market, the more liquid secondary market for the Ginnie Mae closed-end fixed rate loan provides an incentive for wholesalers to either offer only that product or steer customers toward it over their adjustable-rate offerings. Originators directly associated with large banks, who can afford to hold the adjustable-rate loans in portfolio if necessary and fund future withdrawals, would also face these incentives, but with a much smaller impact than it has on others. As a result, I would expect the proportion of loans in an MSA featuring a fixed rate to increase after Bank of America's departure from retail lending, while I would expect to see little to no effect from it's departure from wholesale funding of loans in an MSA, since wholesale originators likely always wanted to package these loans in a more easily securitizable manner to make them more attractive to potential funders.

Table 2.4 presents results from OLS regression on the equations listed above; the first two columns show results for equation (2.1), with the second two columns displaying results from equation (2.2). Though not shown, individuals choosing the HECM Saver loan chose adjustable rate loans with a much higher probability; an increase in the natural log of the home value was also associated with an increase in the choice of an adjustable rate loan. Regarding my earlier predictions, an indicator for the presence and subsequent departure of Bank of America's retail lending from an MSA showed no statistically significant impact across any of the four specifications tested, with the highest magnitude of coefficient equivalent to a 2.5 percent increase in the proportion of fixed rate loans in an MSA after the bank's departure. Adding information about the market share of Bank of America retail - shown in column 3 - does result in a statistically significant impact on the rate of fixed-interest mortgages with a highly significant coefficient of .303, implying an increase of 3 percent in the proportion of fixed-rate loans in an MSA for a 10 percent increase in the market share of Bank of America's retail lending arm. Including information about the remaining major retail lending banks results in a statistically significant, similarly sized coefficient of interest to that shown in column 3, but all three banks display significant positive coefficients on the interaction of a loan process originating post-February 2011 and their market share. A test of joint significance on whether the coefficient for market share plus the post-February interaction equals zero can be rejected for both Metlife and Wells Fargo, while the test cannot reject the null for Bank of America. This implies that while Bank of America's nonzero market share in an MSA predicted the proportion of fixed rate loans before its departure, afterwards the same variable holds no statistically significant predictive power, leaving areas with a high market share and formerly relatively fewer fixed-rate loans statistically indistinguishable from other areas in 2011 after controlling for other factors. For the wholesale space, presented in Table 2.5, as predicted we see no impact from the departure of Bank of America's wholesale funding arm. Here, across all specifications the magnitude of the standard error exceeds that of the coefficient, with Metlife appearing to greatly increase the proportion of adjustable-rate loans in an MSA as a function of market share after Bank of America wholesale's departure.

2.5.2 Borrower Age

As noted earlier, the average age of the youngest borrower associated with a HECM loan has decreased over time, but how could a change in the composition of loan originators affect this outcome? Since a HECM loan in good standing becomes due once the borrower either dies or moves from the home, the utility of the loan relative to alternative options decreases as borrowers' expected remaining healthy life expectancy increases. Firms offering a diversified portfolio of loan options will likely profit from any of the choices made by the consumer, and so have reason to steer relatively younger borrowers to more appropriate products. Wholesale originators and small issuer/servicers typically do not offer a wide variety of financial products, including home equity or other more traditional loans. If consumers come to these providers and may instead benefit from an alternative arrangement, providing this information would reduce or eliminate the payoff to the originator. As a result, I would expect to see the departure of Bank of America's retail branch of the market associated with a decline in the age of the youngest borrower. Since many of Bank of America's wholesale loans come from small providers, I would expect to see little change resulting from the bank's departure from that financial arena.

Results from regression of age on Bank of America retail characteristics appears as Table 2.6. The indicator for Bank of America's former retail presence post-departure is negative, stable in magnitude, and statistically significant across all four specifications, with the bank's departure associated with an average age at origination .7 years younger than in the previous year, after controlling for other factors. Adding market share is insignificant, though does not drastically change the magnitudes for the main indicator. Variables associated with the other large retail lending institutions in 2011 are both smaller in magnitude than those for Bank of America and not statistically significant. Results for the wholesale funding operations show no predictive relationship between variables interacting Bank of America's wholesale lending presence in an MSA and loans occurring after their departure in February 2011. These results, combined, match the hypothesis laid out at the beginning of the section and provide evidence that the departure of Bank of America's retail lending arm is associated with younger borrower ages for FHA HECM loans.

2.5.3 Distribution of Initial Payout Ratio

The third phenomenon discouraging policymakers regarding reverse mortgages is the increase in the initial (and in the case of fixed-rate mortgages, only) amount of equity withdrawn from a reverse mortgage. HECM borrowers younger ages, when combined with high initial payout ratios, results in borrowers with longer remaining life expectancies and less equity than ever with which to protect themselves against negative financial shocks, e.g., hospitalization. Wholesale originators and many retail operators, with their limited product portfolios, have no incentive to provide comprehensive long-term financial planning for their clients, meaning they are less likely to advise clients to take out less than the maximum amount possible. Similar to the prediction for borrower age, I expect to see the departure of Bank of America's retail branch of the market associated with an increase in the proportion of home equity paid out at loan origination. Since many of Bank of America's wholesale loans come from small providers, I would expect to see little change resulting from the bank's departure from that financial arena.

Examination of results across retail loans, shown in Table 2.8, show little to no impact either from the presence of the large banks or the subsequent departure of Bank of America. Overall, the model explains little to no variation in the payout ratio, suggesting that the presence of the large banks do not appear to impact the outcomes. Table 2.9 , displaying wholesale results, tells a similar story. The overall fit continues to be poor, with the overall lack of impact across all variations of considering market structure pointing toward a demand-side explanation, such as the use of HECM mortgages to pay off traditional liens, for the increase in payout ratios.

2.5.4 Repairs and Insurance Set-Aside

Younger borrower ages and longer tenure in homes with HECM liens raises concerns that a previously less important condition of maintaining the loan in good standing will become more troublesome in the coming years. While HECM loans become due in good standing when the owner leaves or dies, the loan can also go into default if the property is not maintained "in a condition equal to when the loan was closed," or if the borrower fails to pay property taxes and insurance in a timely manner. In order to prevent this occurrence, HECM mortgages allocate funding to a "Repair/Insurance Set Aside" to pay for these expenses; however, no formal guidance exists on the proper amount of money to allocate to this fund. In equilibrium we should expect the funders of loans to price in the potential cost of default conditional on the amount of money set aside for these costs, some loan funders might face higher costs than others. Since the onset of the housing crisis in 2007-2008, Bank of America in particular has faced heightened scrutiny over its mortgage loss mitigation practices; in fact it used the need to concentrate additional resources toward managing its forward mortgage portfolio as an explanation for leaving the HECM origination and servicing markets. Even before this decision, however, we might believe that all of the three major retail lenders and wholesale funders, with their large public profile and customer-facing suite of products, would face higher costs in terms of bad publicity from having to foreclose on delinquent elderly borrowers. This would likely lead to them preferring to service loans with higher set asides to prevent this occurrence, lead the market overall to price the cost of default at a higher rate than otherwise, and result in higher set-asides for repairs, insurance, and taxes.

Table 2.10 presents results for a regression with indicators for whether Bank of America or the other two major lenders held the servicing rights for a loan. Column 1, which includes only an indicator for whether the loan originates in an area with at least one loan serviced by Bank of America, is only mildly statistically significant, but becomes statistically significant at the 95% level after including information on the other two major HECM lenders. This implies that loans originated after Bank of America's departure in areas where it formerly serviced loans set aside approximately $235 dollars less than in the previous year. Including information about market share does not markedly improve the fit of the model nor show any statistically significant impact from Bank of America's departure as a function of it's earlier market share. Separating out results by retail lending and wholesale funding (not shown, though available on request) do not provide any evidence on whether this phenomenon comes from the retail or wholesale channels.

2.5.5 Robustness Checks

While examining the results above, two econometric concerns arise. First, identification in this case assumes that Bank of America's presence and market share across MSAs is random with respect to demand-side preferences. Specifically, if Bank of America chose to market itself and build share heavily in areas with unique tastes regarding the loan characteristics tested above, then this could bias the results. Secondly, the difference-in-difference methodology across time used requires that overall trends of the characteristics tested above were not changing at different rates between areas as a function of Bank of America presence or market share.

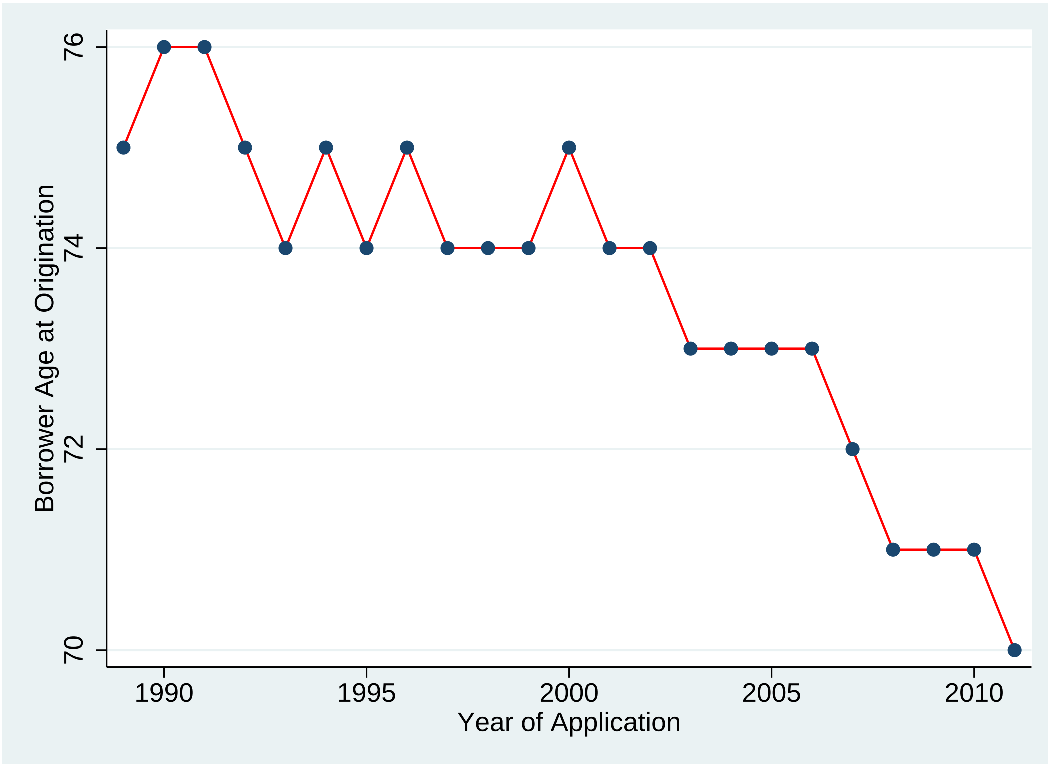
To test whether Bank of America deliberately entered markets with specific preferences I regress the outcomes examined earlier against Bank of America's presence and market share in 2010, along with other basic controls, but examine loans originated and funded between January 2007 and April 2007, when Bank of America entered the HECM market via its purchase of Seattle Mortgage Company's reverse mortgage business. Even this time-frame is arguably vulnerable to the same argument it is intended to solve, since one could argue that Seattle Mortgage, at the time of purchase one of the largest originators and servicers of HECM loans in the country, may have selected into markets with particular characteristics. Given that it entered the HECM market in its infancy, 1995, such an argument is realistically unlikely. Results in Table 2.11 show no statistically significant relationship between our characteristics of interest in early 2007 and Bank of America's later presence or market share, with the exception of a relationship between the level of funds and later bank presence that is statistically significant at the 10 percent level.

To test the second concern mentioned, whether trends over time differed between MSAs with and excluding Bank of America HECM lending, I again regress the outcomes examined earlier against Bank of America's presence and market share in 2010, this time over loans originated between 2010 and Bank of America's departure and closed by March

2011, but now include an interaction between the closing date of the loan and Bank of America's presence and market share, to see if their impacts change over time in the period leading up to Bank of America's departure. Results, shown in Table 2.12, show little systematic change over time, with the exception of a temporary change in the rate of fixed loans as a function of market share in the period leading up to the FHA's HECM program changes, between May and August of 2010. This relationship comes from a unique offering from Bank of America for a low-fee fixed interest HECM loan later matched by other lenders. Unsurprisingly, this offering increased the proportion of fixed-rate loans originated by Bank of America before its departure, and should, if anything, make its impact of leaving the HECM market appear smaller than the truth. Including an interaction term for this period of exclusivity and Bank of America's market share in the main regression results changes neither the magnitude or significance of any of the results listed in the previous sections.

2.6 Conclusion

As life expectancies grow and individuals expect to retire at similar or earlier ages than previous generations, consumers will need a wide variety of tools to save and tap into equity for retirement. A reverse mortgage, used responsibly, can contribute greatly toward making sure individuals can reasonably achieve their financial goals after their time in the workforce is over. Due to it's extremely unique characteristics, though, consumers are more dependent on the advice of others, including the seller of the reverse mortgage, to fully understand whether the decision to take out a HECM or similar-type loan makes sense. If all of one type of seller of these loans leaves the market, this raises concerns over how this impacts the future market, and what measures might need to be taken to maintain a market equilibrium where reverse mortgages are taken out and sold with all parties fully understanding the potential consequences. Here I use the departure of one large retail bank to understand the potential impacts that may arise from the departure of all similar banks, using a difference-in-difference model based on the presence and market share of the major banks involved in the industry and regressing these characteristics on outcomes of interest. I find consistently significant evidence that the departure of these broad-based institutions' retail lending arms may lead to an increase in closed-end, fixed-rate mortgages, which lock-in consumers and offer the most potential for abuse, and also some evidence that suggests these larger banks' retail operations create a market distribution for financial products that results in a higher average age of HECM borrowers. One possible explanation for this phenomenon is the ability for these institutions to better steer consumers to particular products that match their financial needs; however, this claim cannot be tested with the current data. The departure of these broad-based institutions does not appear to change how much equity borrowers decide the withdraw from their home, however, and mild evidence exists that Bank of America's presence in the market led to higher maintained reserves for funding property taxes, insurance, and maintenance over the life of the loan. In the case of the former, this lack of impact hints that the full withdrawal of funds, and the related issue of consumers using the HECM program as a way to pay off burdensome forward mortgages, is more a function of demand-side preferences than supply. Given the concern in the research literature on whether and how individuals can responsibly save for retirement, monitoring of this helpful yet misunderstood product should continue in the coming years.



Note: For co-borrowers, youngest borrower age used

Figure 2.1: HECM Borrowers' Median Age By Year

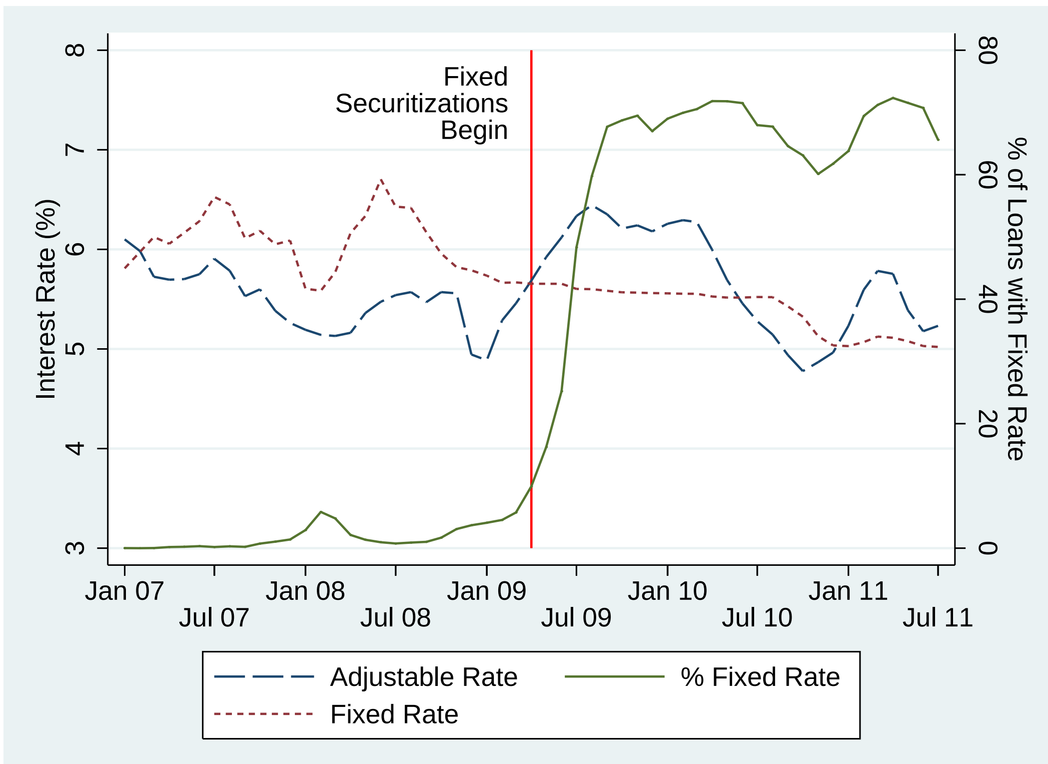
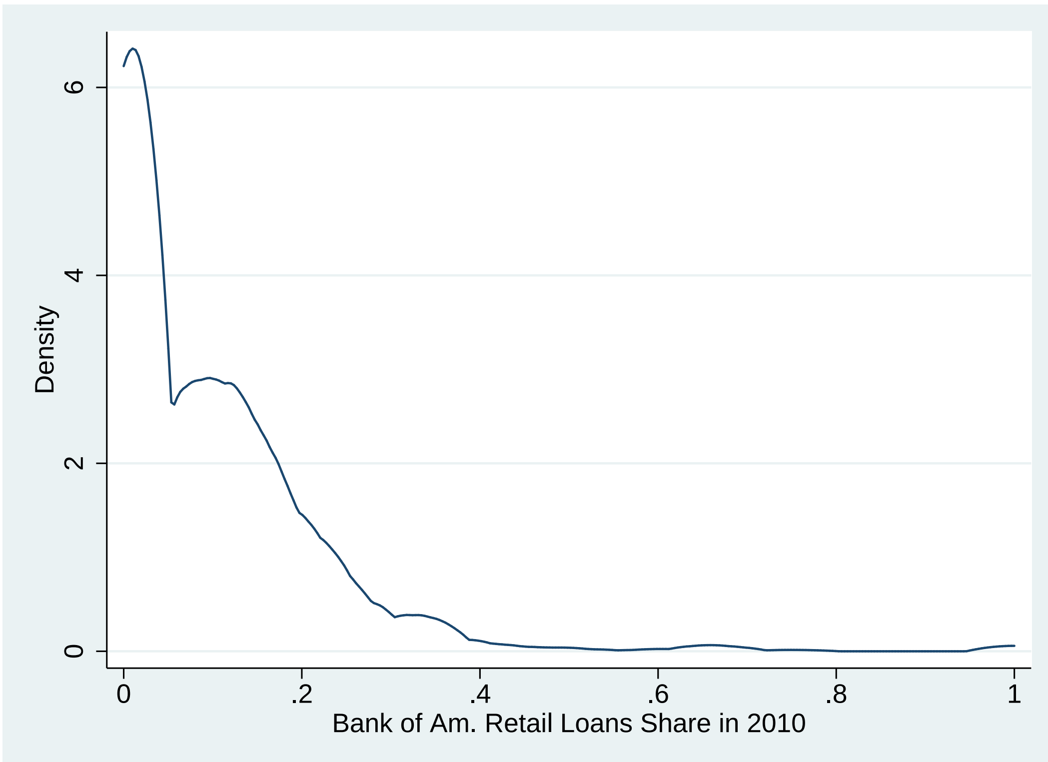
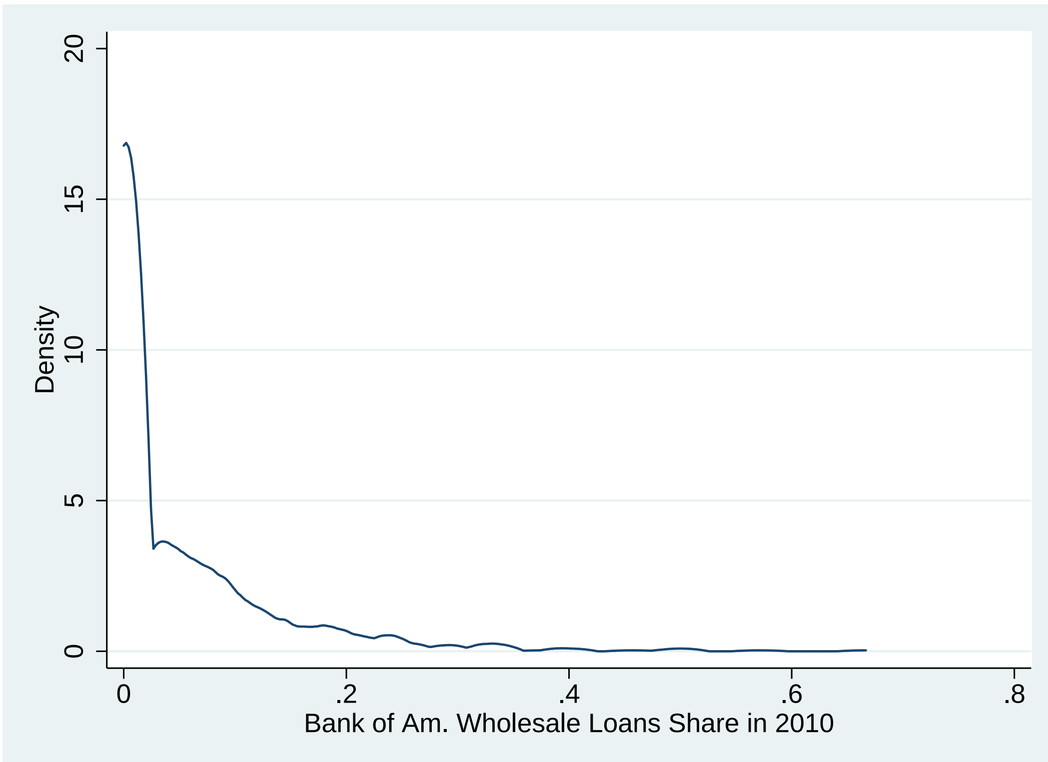


Figure 2.2: Interest Rate by Type



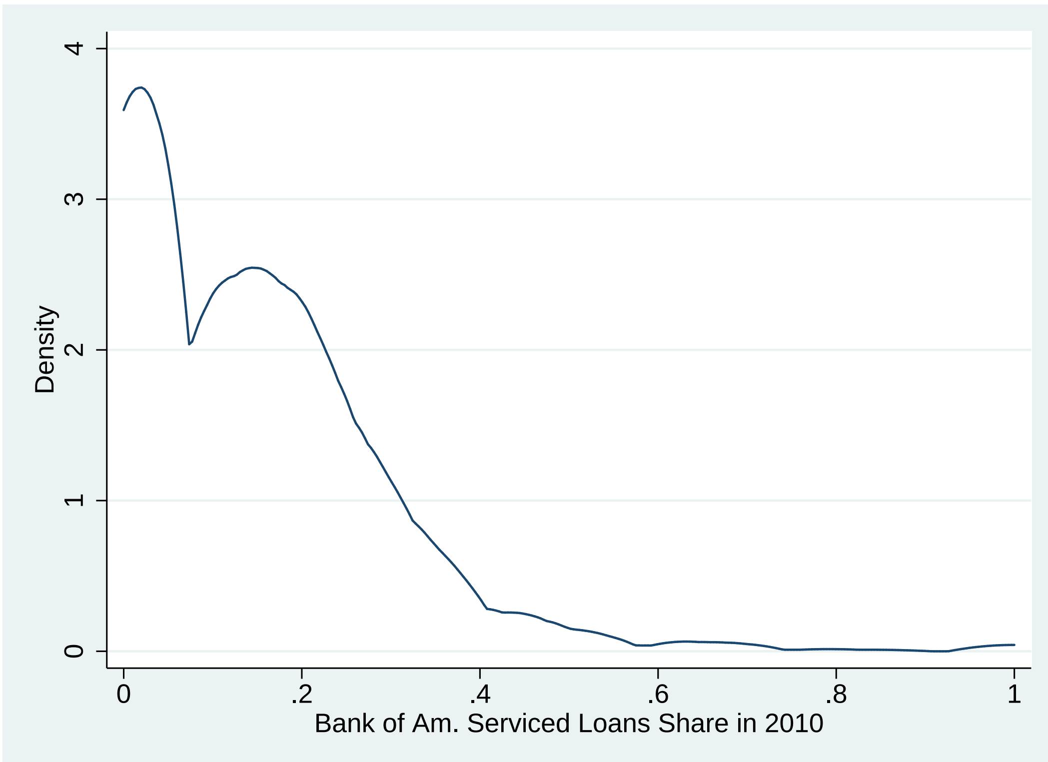
Includes 961 MSAs, 579 with nonzero share. Mean=.09, SD=.122

Figure 2.3: Kernel Density of Bank of America Retail Loans, by MSA



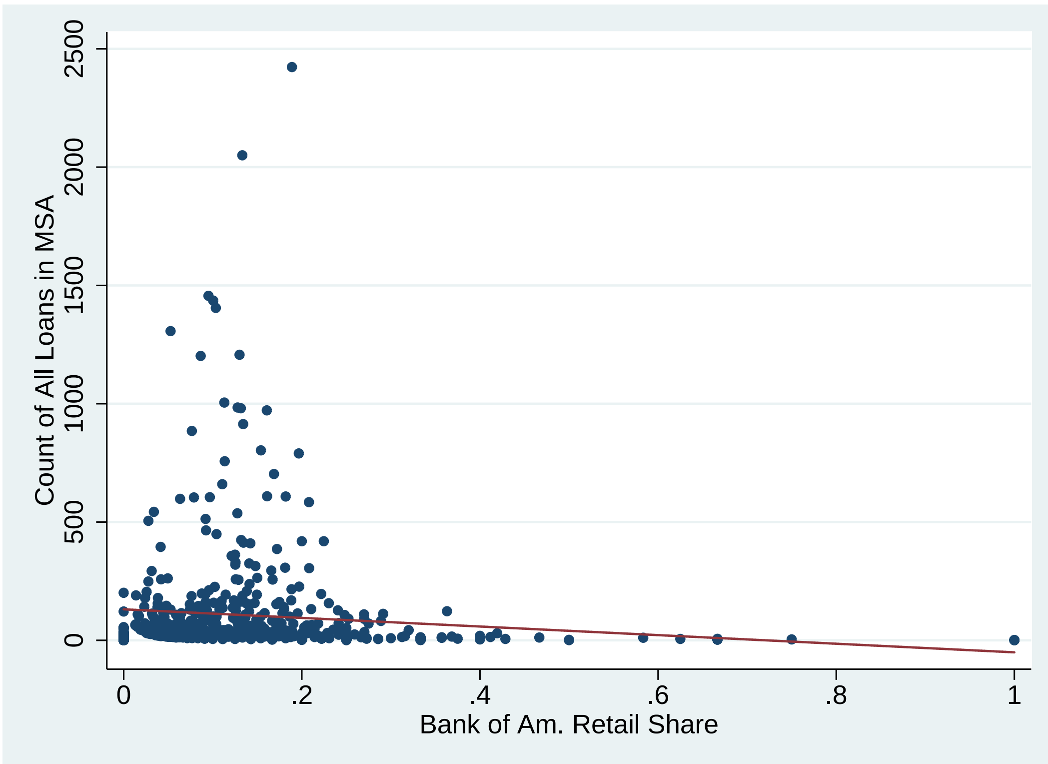
Includes 961 MSAs, 434 with nonzero share. Mean=.05, SD=.082

Figure 2.4: Kernel Density of Bank of America Wholesale Loans, by MSA



Includes 961 MSAs, 662 with nonzero share. Mean=.14, SD=.145

Figure 2.5: Kernel Density of Bank of America Serviced Loans, by MSA



β(Retail)=122.43 (p=0), β(Share)=-181.8 (p=.002)

Figure 2.6: Count of Loans by Bank of America Retail Share, Jan. - Dec. 2010

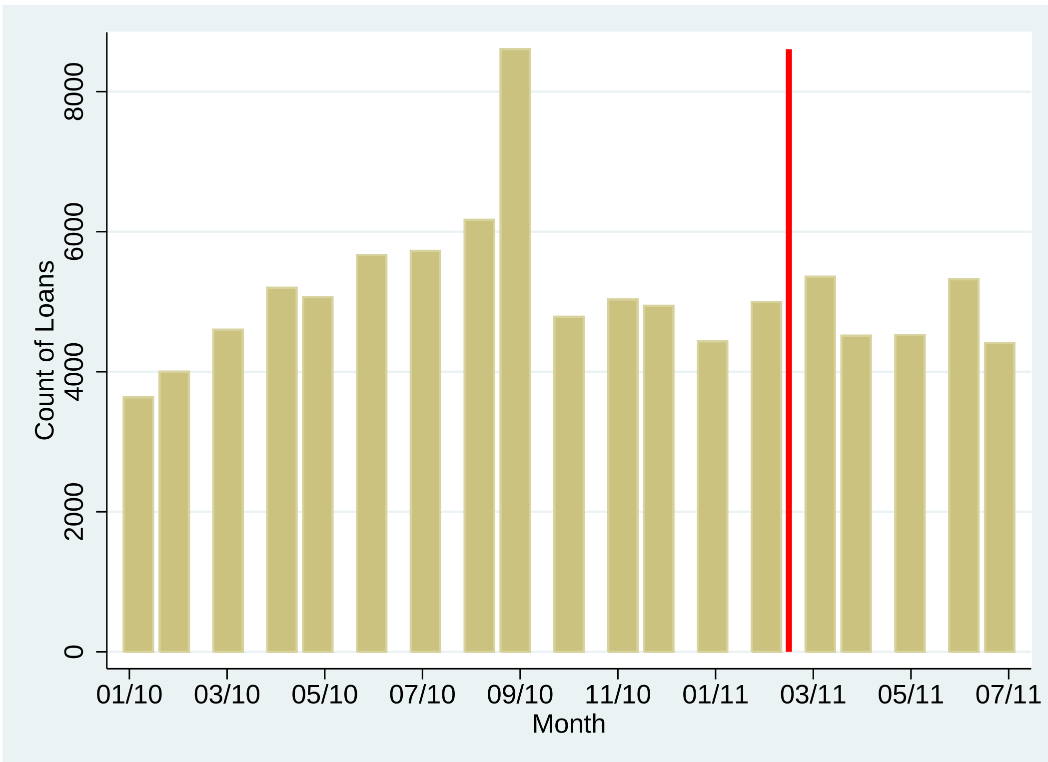


Figure 2.7: Count of HECM Loan Applications, by Month

Table 2.1: Mean 2010 Loan Characteristics By Sponsoring Bank

	Bank of America	Wells Fargo	Metlife	All Other Inst.
	Mean	Mean	Mean	Mean
% Retail Loans	.658***	.929***	.470**	.457
% Fixed Rate	.619***	.449***	.672***	.845
Initial Payout (Rel. to Total Avail.)	.798**	.741***	.917	.976
Initial Payout Size	$132,859	$118,344***	$127,121***	$131,461
Appraisal Value	$286,084***	$275,288***	$264,448***	$241,891
Repairs and Insurance Set Aside	$771***	$587	$871***	$609
Svc. Fee Set Aside	$1,071***	$393***	$757***	$976
Youngest Borrower Age	72.54***	72.56***	71.90***	71.28

Note: Stars represent hypothesis test of difference between individual institution and all institutions in Col. 4
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.2: 2010 HECM Market Share by Channel

	Overall		Retail		Wholesale	
	Count	Pct.	Count	Pct.	Count	Pct.
Bank of America	12830	17.61	8436	18.57	4394	16.02
Wells Fargo Bank	19946	27.38	18523	40.78	1423	5.19
Metlife Bank	11361	15.59	5337	11.75	6024	21.96
Financial Freedom	1830	2.51	655	1.44	1175	4.28
Generation Mortgage Co.	4738	6.50	1652	3.64	3086	11.25
Genworth Financial	4459	6.12	1062	2.34	3397	12.38
One Reverse Mortgage	3677	5.05	3677	8.10		
Security One Lending	1118	1.53	548	1.21	570	2.08
Sun West Mortgage	1141	1.57	144	0.32	997	3.63
Urban Financial Group	5153	7.07	1361	3.00	3792	13.82
Other	6603	9.06	4026	8.86	2577	9.39

Table 2.3: 2011 HECM Market Share by Channel

	Overall		Retail		Wholesale	
	Count	Pct.	Count	Pct.	Count	Pct.
Wells Fargo Bank	6907	28.63	6741	33.05	166	4.45
Metlife Bank	5297	21.95	4361	21.38	936	25.07
American Advisors Group	652	2.70	652	3.20		
Generation Mortgage Co.	1988	8.24	1094	5.63	894	23.95
Genworth Financial	1700	7.05	1141	5.39	559	14.97
One Reverse Mortgage	1707	7.07	1707	8.37		
Reverse Mortgage USA	320	1.33	320	1.57		
Security One Lending	635	2.63	597	2.93	38	1.02
Sun West Mortgage	477	1.98	269	1.32	208	5.57
Urban Financial Group	2219	9.20	1492	7.32	727	19.47
Other	2226	9.23	2021	9.91	205	5.49

Table 2.4: LPM Regression of Retail Bank Characteristics on P(Rate Type = Fixed)

	(1)	(2)	(3)	(4)
Bank of America	0.00254	0.0187	0.0501**	0.0146
	(0.0180)	(0.0187)	(0.0238)	(0.0215)
Wells Fargo		-0.0809***		-0.0410
		(0.0187)		(0.0297)
Metlife		-0.0244		0.00538
		(0.0175)		(0.0212)
Bank of America Market Share			-0.405***	-0.452***
			(0.116)	(0.0974)
Wells Fargo Market Share				-0.367***
				(0.0656)
Metlife Market Share				-0.661***
				(0.107)
Bank of Am. 2011	0.0246	0.0251	-0.0126	0.0106
	(0.0156)	(0.0164)	(0.0183)	(0.0192)
Wells Fargo 2011		0.00625		-0.0236
		(0.0225)		(0.0250)
Metlife 2011		0.00347		0.00692
		(0.0162)		(0.0188)
2010 Bank of Am. Share x 2011			0.303***	0.289***
			(0.0799)	(0.0763)
2010 Wells Fargo Share x 2011				0.183***
				(0.0363)
2010 Metlife Share x 2011				0.200**
				(0.0810)
HECM Saver	Yes	Yes	Yes	Yes
Post Feb. 2011	Yes	Yes	Yes	Yes
Post Fee Change	Yes	Yes	Yes	Yes
Post Rate-Floor Change	Yes	Yes	Yes	Yes
Log House Value	Yes	Yes	Yes	Yes
Closing Month	Yes	Yes	Yes	Yes
Opening Month	Yes	Yes	Yes	Yes
Fee Change x Presence	Yes	Yes	Yes	Yes
Fee Change x Share	No	No	Yes	Yes
H_0: $\beta_{BACShare} + \beta_{BACShare,2011} = 0$				2.243
H_0: $\beta_{WFCShare} + \beta_{WFCShare,2011} = 0$				6.327**
H_0: $\beta_{MetShare} + \beta_{MetShare,2011} = 0$				19.94***
Adjusted R^2	0.090	0.091	0.092	0.102
Observations	96984	96984	96984	96984

Robust standard errors in parentheses, clustered at MSA level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: LPM Regression of Wholesale Bank Chars. on P(Rate Type = Fixed)

	(1)	(2)	(3)	(4)
Bank of America	0.0156	0.0142	-0.0109	-0.00584
	(0.0150)	(0.0148)	(0.0204)	(0.0197)
Wells Fargo		-0.0809***		-0.0538***
		(0.0163)		(0.0185)
Metlife		0.0376***		0.0559***
		(0.0143)		(0.0174)
Bank of America Market Share			0.402**	0.219
			(0.166)	(0.151)
Wells Fargo Market Share				-0.408**
				(0.174)
Metlife Market Share				-0.202*
				(0.109)
Bank of Am. 2011	-0.00201	-0.00479	0.00186	-0.00628
	(0.0135)	(0.0137)	(0.0156)	(0.0157)
Wells Fargo 2011		0.0112		0.000867
		(0.0134)		(0.0156)
Metlife 2011		0.000972		0.0275*
		(0.0140)		(0.0157)
2010 Bank of Am. Share x 2011			-0.0558	-0.0349
			(0.0880)	(0.0841)
2010 Wells Fargo Share x 2011				0.343*
				(0.190)
2010 Metlife Share x 2011				-0.265***
				(0.0637)
HECM Saver	Yes	Yes	Yes	Yes
Post Feb. 2011	Yes	Yes	Yes	Yes
Post Fee Change	Yes	Yes	Yes	Yes
Post Rate-Floor Change	Yes	Yes	Yes	Yes
Log House Value	Yes	Yes	Yes	Yes
Closing Month	Yes	Yes	Yes	Yes
Opening Month	Yes	Yes	Yes	Yes
Fee Change x Presence	Yes	Yes	Yes	Yes
Fee Change x Share	No	No	Yes	Yes
H_0: $\beta_{BACShare} + \beta_{BACShare,2011} = 0$				2.085
H_0: $\beta_{WFCShare} + \beta_{WFCShare,2011} = 0$				0.136
H_0: $\beta_{MetShare} + \beta_{MetShare,2011} = 0$				17.63***
Adjusted R^2	0.090	0.097	0.092	0.099
Observations	96984	96984	96984	96984

Robust standard errors in parentheses, clustered at MSA level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: LPM Regression of Retail Bank Characteristics on Youngest Borrower Age

	(1)	(2)	(3)	(4)
Bank of America	0.937***	0.724***	0.312	0.0798
	(0.234)	(0.236)	(0.277)	(0.295)
Wells Fargo		0.593**		0.964***
		(0.292)		(0.368)
Metlife		0.539***		0.543**
		(0.166)		(0.232)
Bank of America Market Share			5.417***	5.978***
			(1.260)	(1.256)
Wells Fargo Market Share				0.267
				(0.664)
Metlife Market Share				1.877
				(1.190)
Bank of Am. 2011	-0.722***	-0.683***	-0.661**	-0.711**
	(0.254)	(0.261)	(0.284)	(0.295)
Wells Fargo 2011		-0.483		-0.610
		(0.444)		(0.488)
Metlife 2011		0.0278		0.176
		(0.275)		(0.299)
2010 Bank of Am. Share x 2011			-0.441	-0.569
			(1.094)	(1.085)
2010 Wells Fargo Share x 2011				-0.0536
				(0.530)
2010 Metlife Share x 2011				-1.499
				(1.201)
HECM Saver	Yes	Yes	Yes	Yes
Post Feb. 2011	Yes	Yes	Yes	Yes
Post Fee Change	Yes	Yes	Yes	Yes
Post Rate-Floor Change	Yes	Yes	Yes	Yes
Log House Value	Yes	Yes	Yes	Yes
Closing Month	Yes	Yes	Yes	Yes
Opening Month	Yes	Yes	Yes	Yes
Fee Change x Presence	Yes	Yes	Yes	Yes
Fee Change x Share	No	No	Yes	Yes
Adjusted R^2	0.007	0.007	0.009	0.009
Observations	96984	96984	96984	96984

Robust standard errors in parentheses, clustered at MSA level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: LPM Regression of Wholesale Bank Chars. on Youngest Borrower Age

	(1)	(2)	(3)	(4)
Bank of America	0.603***	0.177	1.054***	0.560***
	(0.169)	(0.156)	(0.210)	(0.197)
Wells Fargo		0.642***		0.543*
		(0.240)		(0.283)
Metlife		0.642***		0.694***
		(0.139)		(0.184)
Bank of America Market Share			-6.857***	-5.301***
			(1.482)	(1.343)
Wells Fargo Market Share				0.464
				(2.191)
Metlife Market Share				-1.123
				(1.156)
Bank of Am. 2011	-0.0291	0.249	-0.0344	0.289
	(0.213)	(0.254)	(0.232)	(0.275)
Wells Fargo 2011		-0.0716		0.00201
		(0.144)		(0.181)
Metlife 2011		-0.560**		-0.692***
		(0.231)		(0.253)
2010 Bank of Am. Share x 2011			0.0431	-0.362
			(1.311)	(1.336)
2010 Wells Fargo Share x 2011				-2.597
				(2.158)
2010 Metlife Share x 2011				0.985
				(1.042)
HECM Saver	Yes	Yes	Yes	Yes
Post Feb. 2011	Yes	Yes	Yes	Yes
Post Fee Change	Yes	Yes	Yes	Yes
Post Rate-Floor Change	Yes	Yes	Yes	Yes
Log House Value	Yes	Yes	Yes	Yes
Closing Month	Yes	Yes	Yes	Yes
Opening Month	Yes	Yes	Yes	Yes
Fee Change x Presence	Yes	Yes	Yes	Yes
Fee Change x Share	No	No	Yes	Yes
Adjusted R^2	0.007	0.009	0.009	0.010
Observations	96984	96984	96984	96984

Robust standard errors in parentheses, clustered at MSA level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: LPM Regression of Retail Bank Characteristics on Initial Payout Ratio

	(1)	(2)	(3)	(4)
Bank of America	-0.264	-0.310	-0.225	-0.322
	(0.345)	(0.374)	(0.340)	(0.387)
Wells Fargo		0.111		0.0653
		(0.143)		(0.131)
Metlife		0.124		0.201
		(0.110)		(0.155)
Bank of America Market Share			-0.290	-0.279
			(0.679)	(0.707)
Wells Fargo Market Share				-0.0530
				(0.119)
Metlife Market Share				-0.759**
				(0.365)
Bank of Am. 2011	0.725	0.672	0.368	0.904
	(0.489)	(0.468)	(0.351)	(0.690)
Wells Fargo 2011		-0.0213		-0.120
		(0.154)		(0.267)
Metlife 2011		0.175		-0.490
		(0.269)		(0.425)
2010 Bank of Am. Share x 2011			2.941	3.600
			(2.480)	(3.114)
2010 Wells Fargo Share x 2011				3.153
				(3.148)
2010 Metlife Share x 2011				8.724
				(8.321)
HECM Saver	Yes	Yes	Yes	Yes
Post Feb. 2011	Yes	Yes	Yes	Yes
Post Fee Change	Yes	Yes	Yes	Yes
Post Rate-Floor Change	Yes	Yes	Yes	Yes
Log House Value	Yes	Yes	Yes	Yes
Closing Month	Yes	Yes	Yes	Yes
Opening Month	Yes	Yes	Yes	Yes
Fee Change x Presence	Yes	Yes	Yes	Yes
Fee Change x Share	No	No	Yes	Yes
Adjusted R^2	0.000	-0.000	-0.000	0.000
Observations	96522	96522	96522	96522

Robust standard errors in parentheses, clustered at MSA level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: LPM Regression of Wholesale Bank Chars. on Initial Payout Ratio

	(1)	(2)	(3)	(4)
Bank of America	0.118	0.0911	0.141	0.124
	(0.101)	(0.0822)	(0.104)	(0.0928)
Wells Fargo		-0.0388		-0.0492
		(0.0533)		(0.0724)
Metlife		0.0753		0.0326
		(0.0474)		(0.0617)
Bank of America Market Share			-0.325	-0.376
			(0.405)	(0.484)
Wells Fargo Market Share				-0.107
				(0.253)
Metlife Market Share				0.426
				(0.556)
Bank of Am. 2011	0.350	0.312	0.0207	-0.0383
	(0.379)	(0.341)	(0.118)	(0.128)
Wells Fargo 2011		-0.617		-0.478
		(0.643)		(0.522)
Metlife 2011		0.355		0.864
		(0.374)		(0.808)
2010 Bank of Am. Share x 2011			4.943	3.601
			(4.445)	(3.123)
2010 Wells Fargo Share x 2011				0.912
				(0.905)
2010 Metlife Share x 2011				-4.966
				(4.346)
HECM Saver	Yes	Yes	Yes	Yes
Post Feb. 2011	Yes	Yes	Yes	Yes
Post Fee Change	Yes	Yes	Yes	Yes
Post Rate-Floor Change	Yes	Yes	Yes	Yes
Log House Value	Yes	Yes	Yes	Yes
Closing Month	Yes	Yes	Yes	Yes
Opening Month	Yes	Yes	Yes	Yes
Fee Change x Presence	Yes	Yes	Yes	Yes
Fee Change x Share	No	No	Yes	Yes
Adjusted R^2	0.000	0.000	0.000	-0.000
Observations	96522	96522	96522	96522

Robust standard errors in parentheses, clustered at MSA level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: LPM Regression of Servicer Bank Characteristics on Repair and Insurance Set Aside

	(1)	(2)	(3)	(4)
Bank of America	85.66	67.48	-6.446	-16.56
	(78.67)	(82.70)	(92.57)	(96.42)
Wells Fargo		20.26		119.9
		(133.6)		(141.8)
Metlife		83.83		-19.07
		(75.27)		(89.66)
Bank of America Market Share			546.6*	755.9**
			(304.8)	(340.3)
Wells Fargo Market Share				53.76
				(215.9)
Metlife Market Share				727.0***
				(260.8)
Bank of Am. 2011	-180.2*	-234.8**	-160.4	-218.6*
	(104.9)	(112.7)	(121.4)	(131.5)
Wells Fargo 2011		117.6		84.30
		(180.3)		(192.0)
Metlife 2011		110.2		91.50
		(107.6)		(118.6)
2010 Bank of Am. Share x 2011			-103.5	0.612
			(341.7)	(365.0)
2010 Wells Fargo Share x 2011				127.9
				(219.1)
2010 Metlife Share x 2011				136.1
				(334.1)
HECM Saver	Yes	Yes	Yes	Yes
Post Feb. 2011	Yes	Yes	Yes	Yes
Post Fee Change	Yes	Yes	Yes	Yes
Post Rate-Floor Change	Yes	Yes	Yes	Yes
Log House Value	Yes	Yes	Yes	Yes
Closing Month	Yes	Yes	Yes	Yes
Opening Month	Yes	Yes	Yes	Yes
Fee Change x Presence	Yes	Yes	Yes	Yes
Fee Change x Share	No	No	Yes	Yes
Adjusted R^2	0.011	0.011	0.011	0.011
Observations	96984	96984	96984	96984

Robust standard errors in parentheses, clustered at MSA level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11: Regression of Outcomes of Interest before Bank of America Enters Market, Jan. 2007 - Apr. 2007

	Pr(Rate Type=Fixed) (Retal Loans)	Borrower Age (Retal Loans)	Repair Funds (Funded Loans)
Bank of America	-0.0000655	0.0968	205.9*
	(0.000400)	(0.266)	(122.2)
Bank of America Market Share	0.00264		
	(0.00352)		
Closing Month FE	Yes	Yes	Yes
Ln(House Price)	Yes	Yes	Yes
Adjusted R^2	0.001	0.001	0.001
Observations	27508	27508	27508

Robust standard errors in parentheses, clustered at MSA level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12: Regression of Outcomes on Bank of America Presence, 1/10 - 3/11

	Pr(Rate=Fixed) (Retail Loans)	Borrower Age (Retail Loans)	Repair Funds (Funded Loans)
Bank of America	0.0865**	1.346***	-11.65
Bank of America Market Share	-0.439***		
Closing Month x Bank of America Indicator			
01/10	-0.0425	-0.847	266.5
02/10	-0.0967*	0.767	-455.9
03/10	0.0220	-0.704	304.8
04/10	-0.0394	0.0557	-409.5
05/10	-0.0460	-0.813	220.6
06/10	-0.0305	-0.284	2.081
07/10	-0.0343	-0.508	10.17
08/10	-0.0258	-0.277	-162.8
09/10	-0.0528	-0.726	166.1
10/10	-0.0578	0.0540	153.3
11/10	-0.0468	-0.858	298.9
12/10	-0.0309	-0.703	97.72
01/11	-0.00860	-0.276	86.09
02/11	-0.0185	-0.920*	214.9
Closing Month x Bank of America Market Share			
01/10	0.334		
02/10	0.166		
03/10	0.224		
04/10	-0.0484		
05/10	0.457***		
06/10	0.252*		
07/10	0.303**		
08/10	0.303**		
09/10	0.188		
10/10	0.0167		
11/10	0.0150		
12/10	-0.0965		
01/11	-0.0775		
02/11	-0.134		
Closing Month FE	Yes	Yes	Yes
ln(House Price)	Yes	Yes	Yes
Adjusted R^2	0.042	0.002	0.001
Observations	70154	70154	70154

Note: Baseline Month is March 2011. Significance calculated using robust standard errors, clustered at MSA level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

Full Ballots, Empty Pews? An Analysis of the Relationship between Elections and Volunteering

Abstract

Elections in the US regularly affect demand for political volunteering while also increasing the visibility of charitable organizations devoted to politically sensitive issues. Using 9 years of data from the Volunteer Supplement of the Current Population Survey (CPS) I analyze how elections and their intensity (as measured by deviation from historical voter turnout) affect uptake and intensity of a variety of different volunteering types. Preliminary results indicate that elections with higher turnout are positively related with increases in both community and political volunteering among the general population as well as full-time workers. Ballot measures related to same-sex marriage are associated with an increase in the probability of volunteering with a religious organization, after controlling for state and demographic characteristics.

3.1 Introduction

Almost all of the existing literature on the volunteer labor supply focuses on either examining the tradeoff between time and money or on changes in the effective wage (via changes in the marginal tax rate). Menchik and Weisbrod (1987) focus on the latter and find a negative relationship between wages and volunteering, while Andreoni et al. (1996), Duncan (2004), and Freeman (1997) all consider the former, with the general consensus that volunteering time and charitable contributions are gross complements, but compensated substitutes. In looking at motivations for volunteering and giving, Freeman (1997) found that being asked to volunteer was the most important factor in deciding to do so, and Duncan (2004) found that people most wanted to give when they felt it would make a difference ("impact philanthropy").

Outside events and factors, including elections, impact individuals' beliefs regarding their ability to make a difference, as well as their overall tastes for how they might do so. Klein (1996) shows a statistically significant relationship between elections and real business cycles, with an impact that goes beyond direct election spending and allows for elections to change expectations about the economy. Charles and Stephens (2011) see evidence that individuals with longer working hours and higher likelihood of full-time employment are less likely to vote in non-Presidential and Congressional elections; however, as their political awareness regarding issues and the election in general increases, this effect weakens. This demonstrates that before people feel elections are an opportunity to make a difference, they must follow political news enough to know about how their relevant issues and organizations of interest might be impacted by the election. Butler and O (2011), using election data from Switzerland and the linguistic fragmentation in that country, show that people hearing more in the media about elections taking place in their area of residence makes them more interested in the campaigns and aware of issues. This increased awareness of issues can also change their allocation of leisure time, including volunteering, through either increased salience or real changes in preferences.

Although the papers listed above evaluated the volunteer labor supply and effects of elections on individuals' knowledge and preferences, only Segal and Weisbrod (2002) looks at sorting across volunteering categories, and none attempt to look at how the distribution of volunteering and total hours changes due to a non-monetary shock or event. This paper uses the periodic nature of US congressional and presidential elections, as well as the differences in turnout across states and elections, to examine how demand for a particular volunteer activity, as well as volunteering overall, shifts with the changes in civic awareness created by elections. I measure these changes both in terms of the binary decision of whether or not to volunteer as well as in terms of hours volunteered. I then break down volunteering by sector for similar analysis, and conclude by looking at the role of public spending in the relationship between elections and volunteering. After examination of the data, I find that on average elections correlate with a small, though statistically significant decrease in overall volunteering, though this decrease shrinks as turnout increases. Religious volunteering makes up a large portion of the decline; however, a recent trend in elections toward issue-specific ballot initiatives has resulted in features associated with changes in the decision to religiously volunteer. For sectors sensitive to public spending, little relationship exists between that portion of spending associated with election years and the decision to volunteer.

3.2 Theory/Intuition

The following model, developed by Andreoni et al. (1996), provides the basic theory needed to understand the potential impacts of elections on volunteering time. The model assumes utility is represented by the function

$$U = U(x, m, w_j^* h_j, l) \tag{3.1}$$

with a consumption good x; charitable donations m; w_j^*, the imputed wage of volunteer activity j (that is, what the organization would pay someone to perform a similar task); the hours volunteered h, and leisure. Assume the utility function is continuous, differentiable, quasi-concave, and with cross derivatives of zero. Since the value of the above items must equal what the worker could have earned working the full day under wage w, an individual maximizes the above utility subject to the budget constraint

$$x + m + (\sum_{j \epsilon J} h + l)w = wH \tag{3.2}$$

In the context of this paper, we wonder how elections might directly impact the above system. In particular, they can do so in three ways:

- *Elections will increase* w_p^*

Since the final output of political volunteering, vote percentage and its eventual policy consequences, takes place in election years, political organizations' value marginal product is higher during this time, and so the equilibrium wage they would be willing to offer a paid worker increases as well. The increase in imputed wages creates a substitution effect where volunteers will trade hours devoted to other activities, work, and leisure to political volunteering and its increased marginal return. At the same time, since volunteers can now generate just as much utility from political volunteering as before while contributing fewer hours, an income effect for those who were volunteering during the non-election year might result in contributing fewer (though likely still nonzero) hours than before. In total, this factor would likely contribute to an overall increase in the number of individuals who volunteer and mixed (though likely positive) results in terms of changes in hours volunteered by pre-existing contributors.

- *Elections will increase* U_{h_p}

In addition to the increase in demand for political volunteering driving the imputed wage increase listed earlier, the political (and frequently patriotic) advertising and campaigning that make up essential elements of the electoral cycle may also make individuals value participation in the activity more than before and increase the utility they receive from it. This phenomenon would unambiguously increase both the number of volunteers and the number of hours volunteered relative to non-election years.

- *Elections will increase* U_{h_j}

During political campaigns, key issues and policies for discussion frequently center around activities and initiatives that receive large numbers of volunteer hours, even if those other interests are not explicitly political. The publicity from the campaign may draw new individuals toward those activities, and also spur existing volunteers to put in even more hours. For example, the presence of a ballot initiative on school funding may draw attention to the need for more volunteers in a child's school, spurring a parent to devote time to educational volunteering they may not consider otherwise. Again, this should both increase the number of volunteers as well as the number of hours volunteered in these areas relative to non-election years.

While simply using elections as a reasonably exogenous event allows us to examine its relationship with volunteering, it cannot disaggregate the separate explanations provided above. In order to do this I would need some other variable directly related to only one of the above explanations, and use elections as an instrument on that variable in order to look at how they affect overall volunteering via their role in changes the new variable. Levitt (1997) found that public spending for police forces moves cyclically with elections. In the context of this paper, if politicians increase spending on public goods associated with a particular volunteering activity in a manner correlated with elections, this could also impact the decision to volunteer and/or the number of hours one decides to volunteer to that activity almost entirely through changes in the effective wage at which organizations value volunteer time.

3.3 Data

The main data used in this analysis comes from the September Current Population Survey and its Volunteer Supplement, covering the period 2002 - 2010. The main portion of the survey gathers general geographic and demographic information and asks questions regarding household income, schooling, employment, and home ownership status. The Volunteer Supplement then asks whether individuals volunteered at any point over the previous 12 months, and if so then gathers information about number of activities volunteered, organization type, frequency of volunteering, and total number of hours volunteered. Under the survey design households answer questions for four consecutive months, then rotate out of the survey for eight months before returning for a final four months in the sample. As a consequence the survey contains up to two waves of data from the Volunteer Supplement for each household interviewed in September. The US Census Bureau selects households using state-stratified geographic sampling based on information from the most recent decennial census. Due to this design the sample includes observations from all 50 states, with the bulk of the population weighted toward more populous states. The full unweighted sample used here includes 265,889 individuals, with 2 observations per individual, for a total of 531,778 observations. Additionally, as noted earlier Charles and Stephens found full-time employees face different tradeoffs of work and leisure over time than other individuals; as a consequence they might react to elections differently than the rest of the sample. As a consequence I perform my analysis both for the full set of individuals responding to the CPS as well as the subset of those with full-time employment around the time of the survey. Table 3.1 provides summary statistics for these individuals across both years. Approximately one third of respondents report volunteering in some activity over the previous year, with a very small percentage (.5 percent of all individuals, 1.5 percent of those who volunteer) reporting political volunteering. The full-time employed population is slightly more male-skewed, with a slightly higher household income. Much of the difference likely comes from the high proportion of retired individuals, 18 percent, in the full sample. Table 3.2 provides a breakdown of the frequency of volunteering across different activity types for the full sample. In order to record this information properly, the survey design for the Volunteer Supplement makes interviewers record the name of any volunteer organization the interviewee describes, and then recodes the organization into one of the 17 different types listed in Table 3.2. Besides political volunteering, I analyze the relationship between elections and six other types of volunteering, with these types generally falling into two separate categories. The first group, consisting of religious, youth education, and community service volunteering, are selected due to their relative popularity compared to the other activities; combined more than half of volunteers participated in one of these three activity types. The other three groups, environmental, labor/business, and hobby groups, consist of activities with heavy political associations with both representative elections and ballot initiatives. Although the hobby groups category initially appears unrelated, it should include individuals volunteering with groups associated with hunting and gun ownership, two politically divisive issues.

Election data comes from the United States Election Project (USEP), based at George Mason University. The data includes state-level turnout information for national elections between 1980 and 2010; under this analysis I use the Highest Office Turnout Rate for the Voting Eligible Population. The Voting Eligible Population includes all individuals over age 18 excluding non-citizens and those ineligible to vote, such as felons in some states. The CPS includes voting information in its own biannual surveys; however, these surveys use unmonitored, self-reported information on voting, leaving them susceptible to over-reporting bias. The USEP, meanwhile, uses actual voter turnout data to arrive at its estimates. A comparison of the difference in turnout rates from 1966 through 2004 reported from the USEP vs. the CPS and another survey, the American National Election Study, is available at the USEP website. Information on state-level ballot initiatives comes from the National Institute for Money in State Politics, an independently evaluated nonprofit that bills itself as "...the only nonpartisan, nonprofit organization revealing the influence of campaign money on state-level elections and public policy in all 50 states". For some volunteering sectors, determining the relevance of some initiatives to that sector became difficult; the results shown here are robust to the inclusion and exclusion of what could be considered marginal initiatives, e.g. bond issues, financial amendments, etc. A full listing of initiatives for this period, as well as a listing of those initiatives included in the analysis, are available on request from the author. Initiatives frequently relate to issues associated with religious, educational, environmental, labor/business, and hobby-based volunteering. Additionally, religious-associated initiatives can be further broken down into two separate subgroups, initiatives associated with abortion/conception/personhood, and initiatives associated with same-sex relationships and marriage. Analysis of these two issues separately is of particular relevance given the anecdotal evidence of political parties using same-sex marriage initiatives in tightly contested elections in order to increase turnout among sympathetic subpopulations. If the presence of these initiatives can induce otherwise non-voting citizens to head to the ballot box, it might also convince them to volunteer in related areas out of a similar concern, as well A breakdown of state-election year combinations for each initiative used in this analysis appears as Table 3.3.

Lastly, information on state and local outlays comes from the US Census Bureau Annual Survey of State and Local Government Finances, which contains data on state and local government outlays by sector from 2002-2009, excluding 2003. Although much state and local spending goes to organizations and functions that use little volunteer labor, the survey breaks down total spending into subcategories that do relate more closely to volunteer-dependent activities. The survey also breaks down spending within each category into operational spending and capital spending; as capital spending may involve long-term construction or minor infrastructure changes that do not impact volunteering within a year, instead this paper will focus on per-capita operational spending, which includes expenditures for staffing and day-to-day operations that are more likely to directly involve volunteers. Spending types associated with volunteer-heavy activities include K-12 education, welfare/community service, and parks/environment.

3.4 Estimation Strategy

Although the framework provided by Andreoni et al. provides an intuitive framework from which to consider the impacts of elections on volunteering, this paper will pursue a reduced-form strategy that seeks to describe the relationship between elections and different volunteering types. To test participation in volunteering I first estimate linear probability and probit regressions on the uptake of community (v_{it}) and political (p_{it}) volunteering in the form

$$v_{it} = \beta_1 E_t + \beta_2 VEP_{st} + \beta_3 Z_{ist} + u_v \tag{3.3}$$

$$p_{it} = \beta_1 E_t + \beta_2 VEP_{st} + \beta_3 Z_{ist} + u_p \tag{3.4}$$

where E_t indicates an election in year t, VEP_{st} represents the state level deviation in voter eligible turnout from the state mean over the period of the survey (implicitly, this variable includes an interaction with the election indicator), and Z_{ist} represents demographic covariates and state and time fixed effects. I initially assume zero correlation between u_v and u_p, then use a bivariate probit specification to allow for and test the level of correlation in the error terms. Additionally, I run the same bivariate probit model, but replace the general community volunteering indicator with a separate indicator for each category of volunteering listed earlier, and run the model separately for each. To examine volunteering intensity, I will use a similar format; however, given that most individuals in the sample do not volunteer, predicting the number of hours volunteered using OLS will result in biased, inconsistent estimates. Instead I estimate hours volunteered in a similar manner to uptake, using a tobit model with the specification

$$H_{v,it} = \begin{cases} \beta_1 E_t + \beta_2 VEP_{st} + \beta_3 Z_{ist} + u_v & H_{v,it} > 0 \\ 0 & H_{v,it} \leq 0 \end{cases} \tag{3.5}$$

$$H_{p,it} = \begin{cases} \beta_1 E_t + \beta_2 VEP_{st} + \beta_3 Z_{ist} + u_p & H_{p,it} > 0 \\ 0 & H_{p,it} \leq 0 \end{cases} \tag{3.6}$$

After examining overall volunteering trends, I then consider the relationship between sector-specific electoral activity and volunteering trends using the data on ballot initiatives by including an indicator for whether a state ballot included an initiative related to a given activity. Finally, to examine the link between public spending per capita on relevant areas and volunteering, I will use a two stage linear probability model with uptake in the volunteering area of interest as the dependent variable and per capita spending instrumented with elections and turnout, along with other covariates, as the right hand side variable.

3.5 Results

3.5.1 Volunteering Uptake

Overall Uptake

Table 3.4 presents the results for equation (3.3), using the OLS specification. Results are shown using both the general population, as well as the subpopulation of full-time employed individuals. After accounting for demographic controls, state fixed effects, and a polynomial time trend, election years with average turnout show a statistically significant -.8 percent decrease in the likelihood of volunteering in a non-political capacity. Given an unconditional probability of roughly one third, this represents a 2.7 percent relative decrease in the probability of an individual volunteering. An increase in turnout appears to mitigate this effect somewhat; however, a test of the joint hypothesis that an election with turnout 10 percent above normal sees no change in volunteering is rejected at the 1 percent level. Volunteering in political activities during the previous year is positively associated with volunteering in the current year; however, the presence of a congressional or presidential election decreases the magnitude of the coefficient, though the net impact remains negative. The second half of Table 3.4, with results for the full-time employed population, show similar relationships between variables as those listed above, with loss of significance on the coefficient associated with turnout and the additional significant result that previous volunteers become more likely to volunteer in the current period during high-turnout elections. Since full-time employees make up are more likely to be time-constrained than other individuals, this suggests a model where increased salience of election and volunteering-related issues, represented by increased turnout, brings the value of volunteering over the threshold required to participate.

Table 3.5 provides results for equation (3.4) under an OLS specification. Given the low overall uptake of political volunteering among the population, even small changes in magnitude can represent dramatic shifts in the likelihood of volunteering relative to the null. Although the average election does not appear to change political volunteering, a ten percent increase in the turnout from the state mean is associated with a .07 percent increase in political volunteering. When compared to the overall unconditional likelihood of .57 percent, this represents a 14 percent increase in the relative probability of volunteering for the average individuals. While I cannot test for how much of this increase comes from an increase in volunteer demand coming from the higher value of political volunteering in a big election, vs. an increase in supply coming from heightened awareness of the importance of elections, I can get some idea of the role of the latter using the data on ballot initiatives and state and local spending, shown later. Although results show an increase in political volunteering during election years from those who volunteered in a political activity the year before, I cannot attribute this directly to increased volunteer demand, as the result could come from selection arising from having a higher proportion of repeat, committed volunteers during non-election years. The second half of Table 3.5 provides evidence of positive, larger, and statistically significant relationships between covariates for the full-time employed population. Tables 3.6 and 3.7 provide similar results to the previous two tables, but under the probit specification.

While the probit specification used in Tables 3.6 and 3.7 does not allow for easy interpretation of coefficients, a simple modification to the error structure allows for examination of the level of correlation in the unexplained variation in the two types of volunteering by estimating a bivariate probit of the two equations and allowing for correlation ρ between u_v and u_p. Given many individuals appear to volunteer across multiple activities, such a correlation most likely exists. Table 3.8 shows results for both populations mentioned earlier. Although allowing for this specification does not meaningfully change the coefficient magnitudes or significance, it does show positive and highly statistically significant correlation between error terms across political and community volunteering, with a value of .09 for all individuals and .11 for full-time employed individuals. For comparison, Feldman (2010)'s similar comparison of the relationship between overall giving and volunteering found a correlation of .41.

Uptake by Activity Type

If elections impact volunteering through salience and information, some volunteering types may relate and respond to some election-sensitive issues differently than others. Table 3.9 takes the previous table one step further by breaking volunteering uptake down for the six main activity types listed earlier in the data section of the paper across the full sample and full-time employees. Among the overall population, four of the six activity types analyzed show at least a weakly significant positive relationship between turnout and uptake, with a highly significant negative relationship between religious volunteering and turnout for those who have not volunteered previously. Restricting analysis to the most likely time-constrained individuals, full-time employees, eliminates the significant coefficient values for all activities except religious volunteering, where the coefficients negatively associating turnout and volunteering remain significant and increase in magnitude. Results across both groups show no net change associated with turnout, however, for individuals who previously volunteered in religious activities.

To further examine the role of salience in the relationship between elections and volunteering, I now incorporate the information on ballot initiatives, using an OLS specification to provide more easily translatable coefficients. Results appear as Table 3.10. Here, again, I see little impact from the presence of elections or initiatives on non-religious activities, both among the general population as well as the subset of full-time employees. Results for religious volunteering, though, show a different story. In this sector both populations' volunteering uptake decreases with turnout, and the probability of volunteering increases under the presence of a same-sex marriage initiative by 1.3% - 1.5%, representing a relative increase of 10% from the unconditional mean for religious volunteering. The coefficient for other religious-related initiatives (e.g., abortion, etc.) is negative across both specifications, with increased significance among the full-time employed. This relationship between same-sex marriage initiatives and increased non-political volunteering parallels the impact these ballot measures had on electoral outcomes as described in Smith et al. (2006) and Dyck and Seabrook (2010). If these initiatives actively mobilize voters to participate in the election, they should also mobilize voters into participating in related nonpolitical activities through changing preferences. Similarly, the relationship between other religion-related initiatives and volunteering suggests some negative relationship, including the potential for voter fatigue, exists between awareness and mobilization regarding these issues and religious volunteering participation.

3.5.2 Volunteering Hours

Though the previous tables demonstrate the relationship between electoral activities and the overall decision to volunteer, I can also attempt to quantify the change in number of hours volunteered in those activities. Table 3.11 presents results for estimates of annual hours volunteered in community and political activities. For election years, community volunteering hours decrease slightly among both samples, with the decline equal to approximately the length of one typical workday, 8.5 hours, among the full-time employed population. Within the overall population an increase in turnout is related to mitigation of this effect. In both populations for individuals above or near the threshold to decide to politically volunteer, without having done so in the previous year, a ten percent increase in turnout over the state-level mean is associated with an increase of 30 hours of political volunteering time. Finally, while earlier results showed an increase in repeat political volunteering in election years and a decrease in the same individuals' rate of community volunteering, analysis of hours shows no change in the number of hours these individuals devote to political activities, while they do show a statistically significant drop of 72 to 80 hours of community volunteering for full-time employees and all individuals, respectively.

In a sector-level analysis, only religious volunteering showed any impacts from elections on hours volunteered. Table 3.12 shows that religious volunteering intensity decreased slightly for previous sector non-volunteers as election turnout increased, with a 10 percent turnout increase associated with a decrease of 4.5-6.5 hours volunteered for individuals above the zero hours threshold. Results here parallel those in Table 3.10, with elections containing initiatives related to same-sex marriage issues associated with an increase of 20-24 hours among those not volunteering in the previous year depending on the population of interest, while the net hours volunteered by returnees remains unchanged statistically. This provides further evidence that same-sex marriage initiatives might benefit religious institutions in terms of bringing in new volunteers at a fairly sizeable level of intensity.

3.5.3 Volunteering and Spending

Finally, Table 3.13 presents first stage and IV results for the relationship between changes in public spending per capital related to elections and popular volunteering activities. Here we see that although elections do have a statistically significant positive relationship with per capita spending in all three areas of interest, the variation in that election-related spending has little bearing on the decision to volunteer in any sector. Since this analysis found no significant relationship between education or environmental volunteering in elections overall, these results are not surprising; however, even though community service volunteering changed with elections I find no evidence that these changes came from elections' relationship with per capita spending on social services.

3.6 Conclusion

This paper argues that given evidence of individuals' sensitivity to media and leisure time influencing the decision to vote in elections, we might also reasonably expect that these same factors could lead to the decision to volunteer not only in political activities, but in other, more generally popular activities related to civic engagement. Reasons for the change could be due to an increase in the value of volunteer time, an increase in the utility received from volunteering, or both. Even though political volunteering itself makes up a very small portion of the sample, little research exists that looks at large-scale volunteering responses to cyclical events of any type. Use of the CPS data set finds individuals volunteer less frequently in average election years than non-election years, but that the gap shrinks as turnout - a variable highly correlated with electoral interest, visibility, and mobilization - increases. The activity most directly impacted by the elections, political volunteering, sees a 14 percent relative increase in volunteer numbers for a 10 percent change in turnout. While overall results only show a 2.7 percent relative decrease in community volunteering during an average election year, further analysis shows that only one activity type, religious volunteering, maintains a statistically significant decrease at the activity level. This activity also responds significantly to the presence of ballot initiatives in the state. Although I cannot determine the direction of causality, the positive relationship between gay marriage initiatives and religious volunteering, even after controlling for demographics, provides compelling reasons for non-political religious figures to follow and engage with ballot initiatives more closely. In general these results, combined with the lack of relationship between election-based public spending and volunteering, provide further evidence that political and media phenomena can impact non-political economic choices indirectly.

Table 3.1: Summary Statistics - Individuals in Year 2 of Survey

	FT Empl. (N=127,026)	Total (N=265,889)
Election	0.501	0.503
	(0.5)	(0.5)
Volunteer	0.326	0.316
	(0.46)	(0.465)
Pol. Volunteer	0.00577	0.00548
	(0.0715)	(0.0738)
VEP Rate - Highest Office	0.512	0.515
(Election=1)	(0.117)	(0.117)
Employed	0.949	0.625
	(0.434)	(0.484)
Married	0.644	0.588
	(0.499)	(0.492)
Age	43.63	47.69
	(21.65)	(17.76)
Top Code - Age	0.00107	0.0427
	(0.287)	(0.202)
Income $\leq$ \$5,000	0.00963	0.018
	(0.164)	(0.133)
HH Income	\$67,747.50	\$58,574.50
	(\$40,297.40)	(\$42,115.90)
Income $\geq$ \$150,000	0.0776	0.0637
	(0.213)	(0.244)
Years Ed.	13.87	13.28
	(2.801)	(2.792)
Top Code - Ed.	0.0177	0.0132
	(0.0894)	(0.114)
# of Own Children	0.439	0.21
	(1.143)	(1.256)
No Children in HH	0.27	0.335
	(0.492)	(0.472)
Male	0.562	0.472
	(0.483)	(0.499)
NILF		0.342
		(0.474)
Retired		0.18
		(0.384)
NILF - Other		0.113
		(0.317)

Table 3.2: Frequency of Volunteering by Activity Type

Activity	Count	Pct. of All Indiv.
Non-Political Volunteering	80,344	30.2
Political Volunteering	1,370	0.5
Non-Political Volunteering Type:		
Religious Org.	34,390	12.9
Child Education	19,927	7.5
Comm. Svc.	15,574	5.9
Civic Org.	5,151	1.9
Health Research	4,991	1.9
Other Ed	4,899	1.8
Hospital	4,837	1.8
Youth Svcs.	2,889	1.1
Arts	2,587	1.0
Environ.	2,408	0.9
Sports or Hobby	2,285	0.9
Public Safety	1,612	0.6
Labor	1,194	0.4
Int'l. Org.	752	0.3
Imm. Assist.	276	0.1
Other	2,887	1.1
N	265,889	100.0

Note: Individual Activities do not sum to total number of individuals who volunteer as people can participate in multiple activities

Table 3.3: Count of State-Year Ballot Initiatives by Related Volunteer Activity Type

Activity	Count
Environ.	56
Religious Org.	47
-*Same-Sex Marriage*	*32*
Business or Labor	33
Child Education	29
Hospital	23
Other Ed	15
Immigration	11
Sports or Hobby	1

Table 3.4: LPM Estimates of Community Volunteering

	(1)	(2)	(3)	(4)
All Individuals				
Vol_{t-1}	0.524***	0.523***	0.471***	0.470***
	(0.00182)	(0.00182)	(0.00295)	(0.00295)
Pol_{t-1}				0.177***
				(0.0183)
E_t	-0.0108***	-0.0108***	-0.00929***	-0.00883***
	(0.00151)	(0.00151)	(0.00191)	(0.00191)
VEP_{st}		0.102***	0.0292**	0.0300**
		(0.00919)	(0.0128)	(0.0128)
V_{t-1} * E_t			-0.00659*	-0.00615
			(0.00394)	(0.00395)
P_{t-1} * E_t				-0.0758***
				(0.0265)
V_{t-1}*VEP_{st}			0.0441	0.0476*
			(0.0273)	(0.0273)
P_{t-1}*VEP_{st}				-0.275
				(0.198)
Adj. R^2	0.282	0.282	0.313	0.314
N	265,889	265,889	211,943	211,943
Full Time Employees				
Vol_{t-1}	0.501***	0.500***	0.448***	0.447***
	(0.00251)	(0.00252)	(0.00402)	(0.00403)
Pol_{t-1}				0.171***
				(0.0226)
E_t	-0.0110***	-0.0111***	-0.00957***	-0.00904***
	(0.00215)	(0.00215)	(0.00271)	(0.00271)
VEP_{st}		0.0879***	0.0184	0.0185
		(0.013)	(0.018)	(0.018)
V_{t-1} * E_t			-0.0104*	-0.00972*
			(0.0054)	(0.00541)
P_{t-1} * E_t				-0.0766**
				(0.0354)
V_{t-1}*VEP_{st}			0.0792**	0.0809**
			(0.0372)	(0.0372)
P_{t-1}*VEP_{st}				-0.051
				(0.265)
Adj. R^2	0.257	0.258	0.291	0.292
N	138,863	138,863	113,352	113,352

Eqns. (3) and (4) include demographic terms, state fixed effects, and intercept. Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.5: LPM Estimates of Political Volunteering

	(1)	(2)	(3)	(4)
All Individuals				
Vol_{t-1}				0.00514***
				(0.000567)
Pol_{t-1}	0.236***	0.236***	0.192***	0.191***
	(0.0112)	(0.0112)	(0.0154)	(0.0154)
E_t	0.000561**	0.000561**	0.000259	0.000175
	(0.00027)	(0.00027)	(0.000293)	(0.000276)
VEP_{st}		0.0108***	0.00877***	0.00797***
		(0.00174)	(0.00211)	(0.00201)
V_{t-1} * E_t				0.000175
				(0.000794)
P_{t-1} * E_t			0.0835***	0.0833***
			(0.0248)	(0.0249)
V_{t-1}*VEP_{st}				0.00308
				(0.00565)
P_{t-1}*VEP_{st}			0.313	0.314
			(0.196)	(0.196)
Adj. R^2	0.059	0.0591	0.0596	0.0606
N	265,889	265,889	211,943	211,943
Full Time Employees				
Vol_{t-1}				0.00430***
				(0.000749)
Pol_{t-1}	0.232***	0.232***	0.166***	0.165***
	(0.0143)	(0.0143)	(0.0183)	(0.0183)
E_t	0.00134***	0.00132***	0.00117***	0.000762*
	(0.000388)	(0.000387)	(0.000412)	(0.000393)
VEP_{st}		0.0145***	0.0127***	0.0124***
		(0.00258)	(0.00302)	(0.00294)
V_{t-1} * E_t				0.00115
				(0.00108)
P_{t-1} * E_t			0.115***	0.114***
			(0.0318)	(0.0318)
V_{t-1}*VEP_{st}				0.00151
				(0.00795)
P_{t-1}*VEP_{st}			0.378	0.38
			(0.254)	(0.255)
N	138,863	138,863	113,352	113,352
Adj. R^2	0.0613	0.0616	0.0586	0.0594

Eqns. (3) and (4) include demographic terms, state fixed effects, and intercept. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Probit Estimates of Community Volunteering

	(1)	(2)	(3)	(4)	Margins
All Individuals					
Vol_{t-1}	1.510***	1.510***	1.342***	1.341***	0.448***
	(0.00578)	(0.00578)	(0.00938)	(0.00939)	(0.00252)
Pol_{t-1}				0.574***	0.149***
				(0.0609)	(0.0147)
E_t	-0.0412***	-0.0419***	-0.0457***	-0.0435***	-0.0145***
	(0.00568)	(0.00569)	(0.00875)	(0.00876)	(0.00231)
VEP_{st}		0.386***	0.171***	0.175***	0.0585***
		(0.0349)	(0.0605)	(0.0605)	(0.0159)
V_{t-1} * E_t			0.00366	0.00396	
			(0.0131)	(0.0131)	
P_{t-1} * E_t				-0.247***	
				(0.0879)	
V_{t-1}*VEP_{st}			0.00681	0.0143	
			(0.0907)	(0.0908)	
P_{t-1}*VEP_{st}				-0.849	
				(0.638)	
Adj. R^2	0.225	0.225	0.26	0.261	
N	265,889	265,889	211,943	211,943	
Full Time Employees					
Vol_{t-1}	1.425***	1.425***	1.268***	1.266***	0.431***
	(0.00784)	(0.00784)	(0.0126)	(0.0126)	(0.00337)
Pol_{t-1}				0.554***	0.147***
				(0.0744)	(0.0195)
E_t	-0.0397***	-0.0406***	-0.0434***	-0.0409***	-0.0158***
	(0.00772)	(0.00773)	(0.0118)	(0.0118)	(0.00317)
VEP_{st}		0.315***	0.0935	0.0942	0.0526**
		(0.0473)	(0.081)	(0.081)	(0.0217)
V_{t-1} * E_t			-0.0116	-0.011	
			(0.0176)	(0.0176)	
P_{t-1} * E_t				-0.244**	
				(0.114)	
V_{t-1}*VEP_{st}			0.172	0.177	
			(0.121)	(0.121)	
P_{t-1}*VEP_{st}				-0.131	
				(0.821)	
Adj. R^2	0.204	0.204	0.241	0.241	
N	138,863	138,863	113,352	113,352	113,352

Eqns. (3) and (4) include demographic terms, state fixed effects, and intercept
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Probit Estimates of Political Volunteering

	(1)	(2)	(3)	(4)	Margins
All Individuals					
Vol_{t-1}				0.368***	0.00304***
				(0.034)	(0.000241)
Pol_{t-1}	1.958***	1.963***	1.719***	1.695***	0.0148***
	(0.0376)	(0.0377)	(0.0594)	(0.0605)	(0.000878)
E_t	0.0318	0.0203	0.0111	0.00839	8.40E-05
	(0.0202)	(0.0205)	(0.0245)	(0.0359)	(0.000223)
VEP_{st}		0.823***	0.733***	0.971***	0.00704***
		(0.129)	(0.163)	(0.233)	(0.00143)
$V_{t-1} * E_t$				0.00218	
				(0.0465)	
$P_{t-1} * E_t$			0.195**	0.187**	
			0.0855	(0.0872)	
$V_{t-1} * VEP_{st}$				-0.373	
				(0.304)	
$P_{t-1} * VEP_{st}$			0.354	0.483	
			0.602	(0.612)	
Adj. R^2	0.127	0.129	0.161	0.177	
N	265,889	265,889	211,943	211,943	
Full Time Employees					
Vol_{t-1}				0.333***	0.00270***
				(0.0462)	(0.000301)
Pol_{t-1}	1.934***	1.937***	1.659***	1.639***	0.0137***
	(0.0488)	(0.0489)	(0.0774)	(0.0787)	(0.00111)
E_t	0.0829***	0.0655**	0.0788**	0.0551	0.000535*
	(0.0274)	(0.028)	(0.0341)	(0.0486)	(0.000288)
$VEP_{st} * E_t$		0.964***	0.999***	1.422***	0.00927***
		(0.174)	(0.22)	(0.314)	(0.0018)
$V_{t-1} * E_t$				0.0358	
				(0.0626)	
$P_{t-1} * E_t$			0.260**	0.252**	
			0.113	(0.116)	
$V_{t-1} * VEP_{st}$				-0.672*	
				(0.404)	
$P_{t-1} * VEP_{st}$			0.357	0.503	
			0.771	(0.788)	
Adj. R^2	0.133	0.137	0.164	0.178	
N	138,863	138,863	113,352	113,352	113,352

Eqns (3) and (4) include demographic terms, state fixed effects, and intercept
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Bivariate Probit Estimates of Volunteering Patterns

	All Individuals		Full-Time Employees	
	(1)	(2)	(3)	(4)
Community Volunteering				
Vol_{t-1}	1.341***	1.341***	1.266***	1.266***
	(0.00939)	(0.00939)	(0.0126)	(0.0126)
Pol_{t-1}	0.574***	0.573***	0.554***	0.551***
	(0.0609)	(0.0604)	(0.0744)	(0.0737)
E_t	-0.0435***	-0.0435***	-0.0409***	-0.0411***
	(0.00876)	(0.00876)	(0.0118)	(0.0118)
VEP_{st}	0.175***	0.175***	0.0942	0.0939
	(0.0605)	(0.0605)	(0.081)	(0.081)
$V_{t-1} * E_t$	0.00396	0.00401	-0.011	-0.0109
	(0.0131)	(0.0131)	(0.0176)	(0.0176)
$P_{t-1} * E_t$	-0.247***	-0.245***	-0.244**	-0.239**
	(0.0879)	(0.0873)	(0.114)	(0.113)
$V_{t-1}*VEP_{st}$	0.0143	0.0141	0.177	0.177
	(0.0908)	(0.0908)	(0.121)	(0.121)
$P_{t-1}*VEP_{st}$	-0.849	-0.853	-0.131	-0.128
	(0.638)	(0.634)	(0.821)	(0.814)
Political Volunteering				
Vol_{t-1}	0.368***	0.371***	0.333***	0.337***
	(0.034)	(0.0339)	(0.0462)	(0.0461)
Pol_{t-1}	1.695***	1.701***	1.639***	1.645***
	(0.0605)	(0.0603)	(0.0787)	(0.0784)
E_t	0.00839	0.00912	0.0551	0.0545
	(0.0359)	(0.0359)	(0.0486)	(0.0487)
VEP_{st}	0.971***	0.971***	1.422***	1.422***
	(0.233)	(0.233)	(0.314)	(0.314)
$V_{t-1} * E_t$	0.00218	0.00148	0.0358	0.0368
	(0.0465)	(0.0465)	(0.0626)	(0.0626)
$P_{t-1} * E_t$	0.187**	0.183**	0.252**	0.248**
	(0.0872)	(0.087)	(0.116)	(0.115)
$V_{t-1}*VEP_{st}$	-0.373	-0.372	-0.672*	-0.672*
	(0.304)	(0.304)	(0.404)	(0.403)
$P_{t-1}*VEP_{st}$	0.483	0.473	0.503	0.496
	(0.612)	(0.612)	(0.788)	(0.788)
N	211,943	211,943	113,352	113,352
ρ		0.0922		0.108
$\chi^2(\rho > 0)$		31.13		24.48

All specifications include demographic terms, state fixed effects, and intercept. Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.9: Bivariate Probit Estimates of Volunteering Patterns by Activity Type

	(1) Religious	(2) Child Ed.	(3) Comm. Svc.	(4) Environ.	(5) Labor/Bus.	(6) Sport/Hobby
A. All Individuals						
E_t	0.0124	-0.0172	-0.0329***	-0.0171	0.0182	-0.0255
	(0.0101)	(0.0108)	(0.0107)	(0.0214)	(0.0267)	(0.0202)
VEP_{st}	-0.222***	0.0824	0.159**	0.268*	0.360**	0.271*
	(0.0689)	(0.0749)	(0.0746)	(0.149)	(0.174)	(0.145)
$Type_{t-1}$*(VEP_{st})	0.265**	0.0851	0.275	-0.0349	0.437	-0.185
	(0.124)	(0.155)	(0.17)	(0.428)	(0.665)	(0.495)
ρ	0.0695	0.0592	0.138	0.125	0.222	0.126
$\chi^2(\rho > 0)$	12.41	7.006	66.90	18.76	48.63	18.89
N	211,943	211,943	211,943	211,943	211,943	211,943
B. FT Employees						
E_t	0.0259*	-0.00169	-0.0551***	-0.0294	-0.00926	-0.0508**
	(0.0139)	(0.0139)	(0.0145)	(0.0275)	(0.031)	(0.0252)
VEP_{st}	-0.315***	0.0781	0.145	0.365*	0.196	0.156
	(0.0945)	(0.0958)	(0.1)	(0.19)	(0.207)	(0.185)
$Type_{t-1}$*(VEP_{st})	0.362**	0.0931	0.169	-0.679	-0.186	-0.160
	(0.173)	(0.199)	(0.235)	(0.568)	(0.77)	(0.605)
ρ	0.0835	0.0696	0.0727	0.139	0.118	0.0887
$\chi^2(\rho > 0)$	10.013	6.253	7.261	10.01	5.926	3.903
N	113,352	113,352	113,352	113,352	113,352	113,352

All specifications include demographic terms, state fixed effects, and intercept
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.10: OLS Estimates of Electoral Activity on Volunteering Uptake by Activity Type

	(1) Religious	(2) Child Ed.	(3) Environ.	(4) Labor/Bus.	(5) Sport/Hobby
A. All Individuals (N=211,943)					
E_t	0.00215*	-0.00162	-0.00049	0.000248	-0.000365
	(0.00122)	(0.00106)	(0.000384)	(0.000295)	(0.000396)
VEP_{st}	-0.0334***	0.00454	0.00460*	0.00358*	0.00502*
	(0.0081)	(0.00702)	(0.00247)	(0.00195)	(0.00262)
$Type_{t-1}$*VEP_{st}	-0.00306	0.0890*	0.0707	0.193	0.0446
	(0.00581)	(0.0501)	(0.141)	(0.163)	(0.116)
Relevant Initiative	-0.00503*	0.000839	0.00111*	5.86E-05	-0.00204
	(0.00296)	(0.0025)	(0.000664)	(0.000523)	(0.00393)
Same-Sex Marriage Initiative	0.0125***				
	(0.00346)				
Adj. R^2	0.324	0.178	0.117	0.029	0.031
B. FT Employees (N=113,352)					
E_t	0.00423***	-0.000437	-0.000586	-0.000151	-0.00107*
	(0.00163)	(0.00156)	(0.000564)	(0.000476)	(0.0006)
VEP_{st}	-0.0401***	0.00765	0.00706**	0.00261	0.00353
	(0.0107)	(0.0103)	(0.00357)	(0.0031)	(0.00392)
$Type_{t-1}$*VEP_{st}	-0.00785	0.0818	-0.159	0.0478	0.0154
	(0.0082)	(0.0649)	(0.185)	(0.188)	(0.142)
Relevant Initiative	-0.00984**	-0.0000652	0.000156	4.81E-04	-0.00647
	(0.00394)	(0.0036)	(0.000945)	(0.000879)	(0.0057)
Same-Sex Marriage Initiative	0.0156***				
	(0.00463)				
Adj. R^2	0.314	0.154	0.111	0.029	0.033

All specifications include demographic terms, state fixed effects, and intercept
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3.11: Tobit Estimates of Volunteer Hours

	(1) All Hrs.	(2) Non-Pol. Hrs.	(3) Pol. Hrs.
All Individuals			
Vol_{t-1}	324.0***	324.4***	138.1***
	(4.439)	(4.479)	(16.91)
Pol_{t-1}	221.3***	154.5***	621.4***
	(16.7)	(16.42)	(50.09)
E_t	-5.732**	-10.97***	4.68
	(2.513)	(2.534)	(13.56)
VEP_{st}	22.26	57.75***	313.5***
	(17.35)	(17.58)	(88.84)
$V_{t-1} * E_t$	1.767	3.675	0.879
	(3.472)	(3.488)	(17.68)
$P_{t-1} * E_t$	-62.97***	-82.17***	40.77
	(22.74)	(22.41)	(31.63)
$V_{t-1}*VEP_{st}$	-12.1	-21.47	-139.6
	(23.79)	(23.98)	(115)
$P_{t-1}*VEP_{st}$	293.5*	-71.14	307.3
	(164.4)	(162.9)	(213)
Adj. R^2	0.0483	0.0486	0.09
N	211,943	211,943	211,943
FT Employees			
Vol_{t-1}	261.2***	262.0***	96.68***
	(5.156)	(5.202)	(17.5)
Pol_{t-1}	190.9***	141.6***	448.9***
	(19.13)	(19.25)	(49.12)
E_t	-4.266	-8.499***	18.3
	(2.916)	(2.947)	(13.59)
VEP_{st}	-4.191	18.61	366.2***
	(20.34)	(20.61)	(93.94)
$V_{t-1} * E_t$	-3.466	-2.098	5.963
	(4.015)	(4.039)	(17.45)
$P_{t-1} * E_t$	-56.32**	-72.19***	30.7
	(25.26)	(25.85)	(30.54)
$V_{t-1}*VEP_{st}$	27.83	24.09	-176.8
	(27.66)	(27.9)	(111.2)
$P_{t-1}*VEP_{st}$	479.0***	160.3	261
	(172.9)	(171.1)	(197.4)
Adj. R^2	0.0448	0.0451	0.0929
N	113,352	113,352	113,352

All specifications includes demographic terms, state fixed effects, and intercept. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3.12: Tobit Estimates of Religious Volunteer Hours

Equation	(1) All Indiv.	(2) FT Emp.
Rel_{t-1}	409.7***	356.5***
	(8.407)	(10.33)
Pol_{t-1}	11.05	23.84
	(19.6)	(25.22)
E_t	0.853	3.695
	(2.898)	(3.43)
VEP_{st}	-45.56**	-65.92***
	(19.43)	(23.16)
Rel_{t-1} * E_t	-0.641	-7.461
	(4.493)	(5.46)
P_{t-1} * E_t	-40.72	-59.01*
	(25.74)	(32.63)
Rel_{t-1}*VEP_{st}	89.52***	114.8***
	(30.52)	(37.62)
P_{t-1}*VEP_{st}	-312.8*	-268.3
	(188.6)	(225.7)
Rel. Initiative	-5.482	-12.62*
	(5.554)	(6.44)
SSM Initiative	19.99***	23.82***
	(7.002)	(8.261)
SSM * Rel_{t-1}	-22.12***	-12.94
	(8.313)	(9.909)
SSM * Pol_{t-1}	31.5	26.98
	(44.03)	(53.89)
Adj. R^2	0.0849	0.0881
N	211,943	113,352

All specifications includes demographic terms, state fixed effects, and intercept
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.13: Public Spending and Volunteering

	Child Education		Community Service		Environment	
	1st Stage	IV	1st Stage	IV	1st Stage	IV
A. All Indiv.						
E_t	0.00987***		0.00139***		0.000989***	
	(9.81E-05)		(5.54E-05)		(2.43E-05)	
VEP_{st}	0.183***		0.0293***		0.0205***	
	8.72E-04		(6.20E-04)		(1.68E-04)	
Sector Spending		-0.0102		0.0161		0.0244
(Per Capita)		(0.0412)		(0.247)		(0.142)
N	154,139	154,139	154,139	154,139	154,139	154,139
Adj. R^2	0.958	0.18	0.861	0.0963	0.904	0.119
F	35583		15005		16347	
χ^2		13662		6106		1346
B. FT Indiv.						
E_t	0.00994***		0.00137***		0.000995***	
	(1.37E-04)		(7.97E-05)		(3.36E-05)	
VEP_{st}	0.183***		0.0307***		0.0206***	
	1.19E-03		(8.84E-04)		(2.32E-04)	
Sector Spending		0.0243		-0.134		-0.0574
(Per Capita)		(0.0595)		(0.324)		(0.204)
N	83,134	83,134	83,134	83,134	83,134	83,134
Adj. R^2	0.957	0.156	0.86	0.0813	0.903	0.111
F	19625		8300		9116	
χ^2		6602		3095		797.4

Note: All Results include state-level fixed effects, quadratic time trend, and intercept
Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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