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Should I Stay or Should I Go? Bank CEOs and the Choice to Opt-out of the Temporary Liquidity Guarantee Program

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Abstract

Finance research shows that the personal and professional characteristics of Chief Executive Officers (CEOs) influence decision-making, yet there is a lack of research on the decisions of bank holding companies' (BHCs) CEOs during crises. The Temporary Liquidity Guarantee Program passed by the Federal Deposit Insurance Corporation in 2008 had two optional programs: the Transaction Account Guarantee Program and the Debt Guarantee Program. This study finds no evidence that any traditional CEO characteristics were significant in a BHC's decision to participate in either program. These results may be of use to policymakers in better understanding participation in optional crisis programs.

JEL Classification: G20, G38
Keywords: Behavioral Finance, Financial Crisis, CEO, Temporary Liquidity Guarantee Program

Introduction

On October 14, 2008, the Federal Deposit Insurance Corporation (FDIC) established two programs within the Temporary Liquidity Guarantee Program (TLGP). First, the Transaction Account Guarantee Program (TAGP) provided unlimited deposit insurance on noninterest-bearing transaction accounts for participating institutions until December 31, 2010. Second, the Debt Guarantee Program (DGP) allowed institutions the opportunity to issue FDIC guaranteed debt until October 31, 2009. Given that the U.S. Government was attempting to stabilize a shuttering banking system, it was crucial that institutions participated in these programs. Both programs were designed with a no-action default structure, meaning institutions were automatically included but were given the choice to opt out.

Surprisingly, there exists little research on the factors that influenced the choice of a financial firm to participate in these government programs. Moreover, a growing body of research points to the importance of understanding the personal and professional characteristics of Chief Executive Officers (CEOs) and how they may influence firm decision making. As Malmendier (2018, p. 87) notes, behavioral biases in managerial decisions can have "far-reaching consequences." While some research has examined bank CEOs' characteristics and decision-making (e.g. Delgado-García et al., 2010; Skala and Weill, 2018), there is a scarcity of research examining the intersection of government programs and bank CEO decision-making.

In this paper, breadth is added to the literature by exploring whether CEO personal and professional characteristics influence participation in optional government programs for bank holding companies (BHCs). This study examines approximately one hundred BHCs across the two separate decisions of the TLGP: whether to opt-out of the TAGP and whether to opt-out of the DGP. Interestingly, no evidence is found that CEO characteristics are significant in determining participation in either program, underscoring the importance of continued CEO decision-making research, as not all corporate decisions are affected by CEO personal or professional characteristics.

This research provides multiple contributions to both academic researchers and policymakers. First, this study adds to the behavioral finance literature about the behavior and corporate decision-making of BHC CEOs, who are often excluded from this line of research due to the regulatory environment in which they operate. Second, this research provides insights for policymakers, which they may consider when implementing future government intervention programs. Lastly, this is the first paper to examine the decision to participate in the two programs of the TLGP based on CEO personal and professional characteristics, and more generally, optional government program participation during a crisis.

The remainder of the paper is structured as follows. The following section explains the TLGP, the relevant literature and the hypotheses. The subsequent section provides the explanation of the data used in the analyses and the empirical models employed. Next, results are presented for the TAGP and the DGP. The last section concludes and provides thoughts on future analysis.

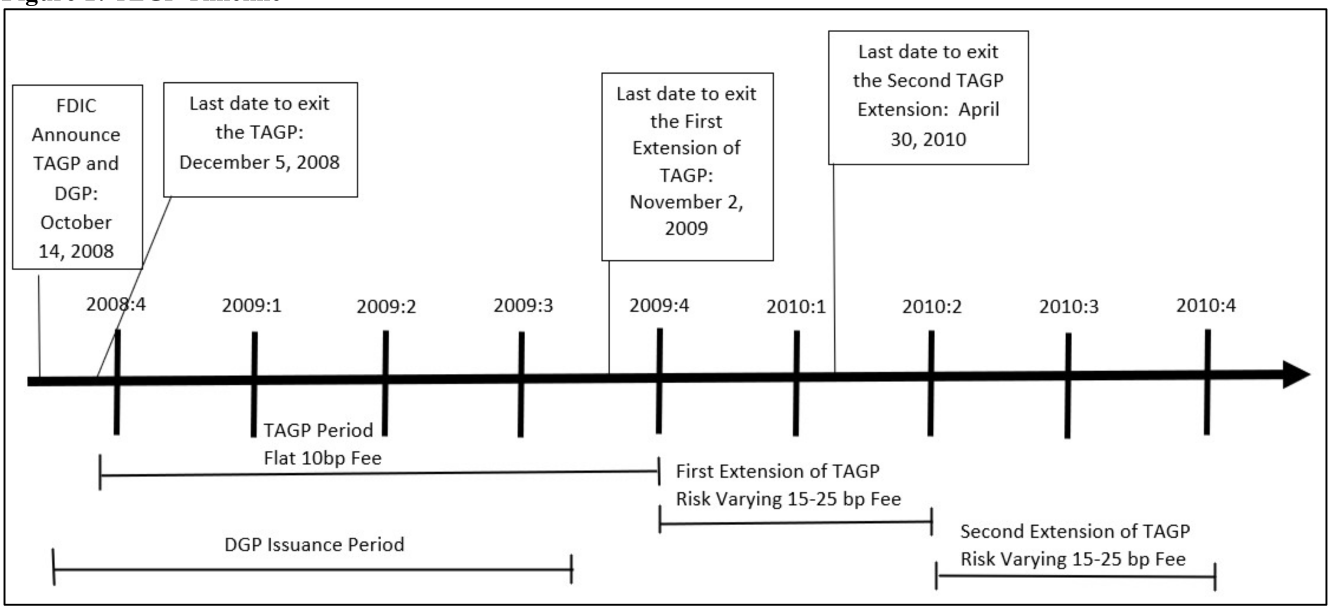
Program Overview, Literature, and Hypothesis Development

Temporary Liquidity Guarantee Program

The TLGP was passed by the FDIC on October 14, 2008 to both reassure the public that institutions were safe and to provide additional funding opportunities for banks. The TLGP achieved this through the TAGP and the DGP. Both programs were structured so that banks were automatically included, but were given the ability to opt-out, known as a no-action default. However, there are several differences between the two programs which are summarized below.

The TAGP provided unlimited FDIC insurance on noninterest-bearing transaction accounts (NIBTAs) from October 14, 2008 until December 31, 2009. Initially, all banks were insured free of charge until December 5, 2008. Institutions could opt-out of the TAGP, while remaining banks paid a 10-basis point insurance premium on deposits exceeding $250,000. The program was extended twice for six-month intervals, ending on December 31, 2010. At each extension, banks were given an additional opportunity to exit the program as insurance premiums increased. Figure 1 provides a timeline of the TLGP.

Figure 1: TLGP Timeline



The DGP provided an FDIC guarantee on new, senior, unsecured debt issued between October 14, 2008 and October 31, 2009. The debt was guaranteed through maturity or December 31, 2012, whichever was sooner. If a bank stayed in the program, it was not assessed any fees. Fees were only charged upon issuing guaranteed debt.

Once a bank opted out of either the TAGP or DGP, it was excluded from rejoining. BHCs were only allowed to exit the TAGP at designated times: 2008Q4, 2010Q1 and 2010Q3. In the sample, ninety-eight BHCs used the no-action default option to remain in the TAGP in 2008Q4, while only three BHCs opted-out. In 2010Q1 and 2010Q3, twelve and twenty-four BHCs exited, respectively. Under the DGP, banks were only able to exit during the initial quarter, 2008Q4, during which twelve BHCs in the sample exited. The low number of BHCs that exited demonstrates that the no-action default might have encouraged a high amount of participation. However, since there is no possibility of a counterfactual where banks were included by default, it would be impossible to test this empirically. After the deadlines, the FDIC published a list of nonparticipants and required banks to post signs in lobbies and on websites. With regards to the disclosure practices for participation in the program, some say that the FDIC indirectly punished banks that opted-out of the program by releasing their names (Black et al., 2014).

The limited attention given to the TLGP in finance literature is unfortunate given its potential in shaping future liquidity programs. Schich (2008) and Hoskins (2012) discuss the impact of the TAGP expiration and implications for its extension. Shapiro and Dowson (2012) concluded that a TAGP extension would have sent a negative signal to the market regarding bank stability. The research on the DGP is more extensive but is focused on its effects on liquidity and credit spreads (e.g. Amborse et al., 2013; Black et al., 2014; Black et al., 2016). Wilson and Wu (2018) reported that CEOs at firms that sought out FDIC debt guarantees earned higher compensation and systemically important banks were more likely to issue guaranteed debt.

CEO Factors

There are a growing number of studies examining how the professional and personal characteristics of CEOs alter corporate policies. This project explores five of these characteristics, as they tend to be the most used in prior research due to both the theoretical rationale and availability of data. Provided are a list of hypotheses based on the prior literature for CEO compensation structure, CEOs on the board of directors, CEO MBA education, CEO tenure, and CEO age.

First, CEO compensation structure is one professional attribute that alters corporate (Dittmar and Duchin, 2016) and bank (Saunders et al., 1990) risk-taking incentives. Specifically, CEOs with higher equity compensation will be more likely to increase risk-taking (Gande and Kalpathy 2017) and given that the general compensation structure for bank CEOs includes higher equity incentives, this induces risk-taking incentives (Chen et al., 2006). Additionally, the Troubled Asset Relief Program (TARP) set limits to executive compensation; therefore, higher executive compensation led to earlier repayment of bailout funds, insinuating there may be lower interest in participating in government programs (Cadman, 2012; Wilson and Wu, 2012).

H1: CEOs with more equity compensation will be more likely to opt out of the programs.

CEOs sitting on the firm's corporate board of directors traditionally follow two theoretical arguments. First, sitting on the board increases the CEO's power and reduces the independence that is needed for the monitoring role of the board (Jensen and Meckling, 1979). Having a CEO on the board is also associated with managerial entrenchment and weaker firm performance (Duru et al., 2016). Alternatively, researchers claim that CEO roles on the board of directors promote focused and flexible leadership, which facilitates organizational effectiveness (Finkelstein and D'Aveni, 1994; Dahya et al., 1996) and have argued that having a CEO on the board would be beneficial under conditions of high environmental uncertainty by providing a unity of command and speed of decision making that is necessary to manage uncertainty (Boyd, 1995).

H2: CEOs on the board of directors could be more or less likely to opt out.

Education and financial literacy have been shown to alter firm decisions. MBA classrooms put a strong focus on financial outcomes (Bennis and O'Toole, 2005; Ferraro at al. 2005) and MBA degrees have been used as a measure of financial literacy, which may lead managers to rely on external financing to internal cash savings (Dittmar and Duchin, 2016). Additionally, Bertrand and Schoar (2003) find MBA executives tend to run more levered firms. Alternatively, MBA programs attract conservative, risk-averse students, and teach analytical skills to avoid big mistakes or losses (Finkelstein and Hambrick, 1996; Hambrick and Mason, 1984). Furthermore, MBA CEOs take on less risk by spending less on R&D and are not as risk prone as more "self-made" executives (Barker III and Mueller, 2002; Collins and Moore, 1970).

H3: CEOs with MBAs could be more or less likely to opt out.

CEO tenure has been associated with more risk-taking (Chen and Zheng, 2014). This relationship may be due to an increase in managerial power with more tenure (Hermalin and Weisbach, 1998) or declining career concerns as the tenure increases (Gibbons and Murphy, 1992). However, as tenure increases, there is more invested and undiversified human capital (Chen and Zheng, 2014) and CEOs with longer tenure show more risk-aversion (Carter et al., 2007).

H4: CEOs with longer tenure could be more or less likely to opt out.

Conventional wisdom and empirical evidence suggest that age is inversely related to risk-taking. In investments, there exists a negative effect on age and equity investment participation (Campbell, 2006). CEO age has been shown to influence risk-taking choices and corporate decisions (Bertrand and Schoar, 2003). Specifically, older CEOs are found to be more risk-averse (Vroom and Pahl, 1971; Serfling, 2014) and survey results on executives suggest that older executives take on less risk (MacCrimmon and Wehrung, 1990).

H5: Younger CEOs will be more likely to opt out.

However, each of these hypotheses are not without contention. While these factors are commonly shown to influence decisions in *non-bank* corporations and for *non-stimulus* decisions such as cash holdings, R&D, payout policy, etc. it could be that BHC CEOs exhibit fewer behavioral biases than general corporate CEOs. There are assertions that would help explain CEO characteristics' lack of influence in government stimulus participation. The decision to participate in government stimulus might be different from traditional corporate decision-making, the feeling of being forced to take the stimulus, the higher regulatory environment in which they operate, or that bank CEOs are just different than other industry CEOs.

First, the TLGP was structured so that banks were automatically included in the programs, known as a "no-action default." Thus, the decision for management was one of whether they wanted to exit the program. This no-action default structure has been examined related to insurance choice (Johnson et al., 1993) and organ donation (Johnson and Goldstein, 2003) and found that structuring programs so that individuals must opt-out rather than opt-in increases participation. These cross-discipline findings are one factor plausibly diminishing the behavioral characteristics' influence on the TLGP and increasing policy makers successful implementation.

Second, there exists anecdotal evidence of banks feeling forced to take the stimulus, which could lead to a moderated influence of behavioral biases in the decision. It could be that management felt that the structure was a method of encouragement to participate in the TAGP and DGP. This may have also been reinforced by the fact that the FDIC immediately published a list of nonparticipants on its website and required banks to post signs in their lobbies and on their websites if they opted out. With regards to the disclosure practices for participation in the program, some say that the FDIC indirectly punished banks that opted-out of the program by releasing their names (Black et al., 2014).

Third, banks operate in a higher regulatory environment compared to the typical corporation. The higher regulatory environment may lead CEOs to exhibit fewer behavioral biases than those in other corporate settings. Lastly, it is possible that those persons who become CEOs in a highly regulated industry are inherently less likely to exhibit behavioral biases in their corporate decisions, whether due to their career progression in a higher regulatory environment or genetic traits and learned behaviors outside of a corporate setting.

Therefore, the general null hypothesis is that CEO factors do not influence the choice to participate in government stimulus programs. Given the lack of research in understanding bank CEOs, as many behavioral CEO decision-making projects drop financial institutions, and the limited research around the corporate decision on government stimulus, this project is an empirical investigation.

H6: CEO personal and professional characteristics do not influence participation in government stimulus.

Data and Empirical Model

BHC Sample Selection

The data on CEOs for publicly traded BHCs comes from Compustat's Execucomp and Boardex databases. Few independent banks are public companies, but approximately 80% of US banks are held in BHCs, which tend to be public companies. Under a BHC structure, each affiliated bank will have their own management that runs the day-to-day operations. However, the management of the BHC oversees the bank's operations, can hire and fire managers, and puts forth directives for the underlying banks to follow. In addition, all banks within a BHC were required to make uniform opt-out decisions across the TLGP. Therefore, this project provides a sample that allows for a proper investigation on decisions made by BHC CEOs on the impact of participation in the TLGP. Quarterly bank-level data is obtained from the Federal Financial Institutions Examination Council (FFIEC) and aggregated to the BHC level by using the unique regulatory identification number (RSSD ID).

In December 2008, the FFIEC reported that there were approximately 150 BHCs with assets greater than three billion dollars. The sample, which starts in December 2008, covers approximately 100 BHCs. Across the sample, the average number of FDIC insured banks held within a BHC is 2.14 and approximately 65% of the observations are considered single bank holding companies, meaning they have only one FDIC insured bank within the holding company. Thus, while the sample appears small, it captures a large percentage of BHCs.

Empirical Model

To examine the relationship between CEO characteristics and participation in the TLGP, a discrete, piece-wise constant, complementary log-log (proportional hazard) model is used. A hazard model is necessary as banks that chose to opt-out of either the TAGP or DGP were prohibited from rejoining the programs later. The discrete, piece-wise setup is appropriate, since banks were only allowed to exit the program at certain dates. The baseline model is defined by Equation (1).

$$Opt - Out_{i,t} = a_0 + \beta \boldsymbol{CEO\ Characteristic_{i,t}} + \delta \mathbf{X}_{i,t} + \gamma \boldsymbol{\Psi_t} + \mu \boldsymbol{D_t} + \varepsilon_{i,t} \tag{1}$$

BHCs are indicated by the subscript i and calendar quarters are indicated by the subscript t. The dependent variable of interest, $Opt - Out_{i,t}$, is an indicator variable equal to one if the BHC opted-out of the respective program during that quarter, and zero otherwise.

$\boldsymbol{CEO\ Characteristic_{i,t}}$ is a vector of variables measuring CEO characteristics that include the percentage of equity compensation, a dummy for whether the CEO is on the board, a dummy for whether the CEO has an MBA, the CEO's tenure, and the CEO's age. Data on CEO characteristics comes from Compustat's Execucomp and Boardex databases. To match this data to the BHC level data, BHC RSSD ID identifiers are matched to the Permco identifier from the Center for Research in Security Prices, CRSP. All variables are defined in Appendix Table A.1. All continuous CEO variables are winsorized at the 1% and 99% levels.

$\mathbf{X}_{i,t}$ is a vector of BHC-specific accounting variables following prior literature (e.g. Stone and Faulkner, 2024). Quarterly bank-level data comes from FFIEC Call Reports and is aggregated to the BHC level each quarter. The variables are intended to control for bank characteristics, specifically CAMELS components and include the equity capital ratio, loan charge-offs, efficiency ratio, net income, liquidity ratio, and funding gap. Other variables are included to measure changes in BHC policies: the one-quarter change in loans, the natural log of total assets, the standard deviation of assets over the prior year, and a dummy variable indicating whether the BHC received TARP funds. All variables are defined in Appendix Table A.1.

$\boldsymbol{\Psi_t}$ is a vector of two macroeconomic variables: the one-quarter growth rates in real gross domestic product and aggregate non-performing loans. Standard errors are clustered at the BHC level.

Results

TAGP Results

The main model used is presented in Equation (1) to examine if CEO characteristics influenced the decision to opt-out of the TAGP. The dependent variable, $TAGP\ Opt - Out_{i,t}$, is an indicator variable equal to one if the BHC opted-out of the TAGP, and zero otherwise. All BHC-specific accounting variables and macroeconomic variables discussed in the preceding section are included in the model. To control for the piece-wise specification, $\boldsymbol{D_t}$, is a vector of dummy variables (DUR1 and DUR2) that represent the intervals of the initial TAGP from 2008Q4 until 2009Q4, and the first two-quarter extension of the program from 2010Q1 until 2010Q2. Over the period of the TAGP, 2008Q4 until 2010Q4, the sample has 806 BHC-quarter observations and covers approximately 100 BHCs. Table 1 Panel A provides descriptive statistics for the TAGP sample and Table A.2 and Table A.4 Panel A provide the correlation matrix.

Table 1: Summary Statistics

Panel A					
Variable	**Mean**	**St. Dev**	**Min**	**Max**	**Obs**
OPTOUT	0.049	0.217	0	1	806
EQUITYCOMP	0.424	0.267	0	1	806
CEOBRD	0.908	0.288	0	1	806
MBA	0.241	0.428	0	1	806
TENURE	1.872	0.911	0	3.465	806
CEOAGE	4.055	0.124	3.610	4.418	806
EQUITYCAPITAL	0.108	0.027	0.036	0.276	806
CHARGEOFF	0.435	0.561	-3.721	5.754	806
EFFICIENCY	0.571	1.260	-32.454	9.839	806
NETINCOME	-0.000	0.006	-0.063	0.060	806
LIQUIDITY	0.245	0.129	0.029	0.827	806
FUNDINGGAP	0.181	0.172	-0.542	0.738	806
NETLOANGROWTH	0.002	0.095	-0.477	1.305	806
SIZE	16.206	1.491	12.739	21.347	806
STDEV	5.502	30.418	0.009	412.032	806
TARP	0.500	0.500	0	1	806
RGDPG	0.011	1.038	-2.163	1.098	806
NPLG	0.133	0.112	-0.051	0.296	806
Panel B					
	Mean	**St. Dev**	**Min**	**Max**	**Obs**
OPTOUT	0.027	0.163	0	1	436
EQUITYCOMP	0.442	0.268	0.022	1	436
CEOBRD	0.896	0.304	0	1	436
MBA	0.247	0.432	0	1	436
TENURE	1.875	0.876	0	3.434	436
CEOAGE	4.056	0.115	3.610	4.418	436
EQUITYCAPITAL	0.106	0.027	0.038	0.276	436
CHARGEOFF	0.441	0.598	-1.531	5.754	436
EFFICIENCY	0.536	1.708	-32.454	9.839	436
NETINCOME	-0.001	0.008	-0.063	0.060	436
LIQUIDITY	0.239	0.139	0.029	1.052	436
FUNDINGGAP	0.180	0.173	-0.542	1.000	436
NETLOANGROWTH	0.003	0.121	-0.477	1.305	436
SIZE	16.425	1.645	12.739	21.347	436
STDEV	8.829	40.679	0.009	412.032	436
TARP	0.548	0.4982	0	1	436

This table displays summary statistics for the TAGP in Panel A and DGP in Panel B samples. Variable descriptions are provided in Appendix Table A.1.

The main results are provided in Table 2. In the first five columns, each CEO characteristic is analyzed separately and then included jointly in Column 6. There is no evidence that CEO characteristics significantly influence participation in the TAGP. Thus, support exists for H6 that CEO behavioral characteristics did not influence the decision to participate in the

TAGP. The control variables are as expected and consistent with prior research. In particular, the more loan charge offs a BHC had, the less likely they were to opt-out of the TAGP, suggesting that weaker institutions valued the additional insurance protection. More profitable BHCs, as measured by Net Income, were less likely to opt out of the TAGP. BHC size is positively related to the decision to leave the TAGP. This is consistent with the literature which finds that larger banks left the program during the extensions. In addition, BHCs that received TARP funding were less likely to opt-out of the program which demonstrates consistency across crisis program participation during this time. Lastly, the decision is also significantly related to the growth rate of GDP suggesting that as the economy improved, BHCs did not need the additional insurance to retain deposits.

Table 2: TAGP Participation Results

	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	0.375					0.415
	(0.55)					(0.60)
CEOBRD		-0.588				-0.561
		(-0.78)				(-0.68)
MBA			-0.441			-0.462
			(-1.06)			(-1.05)
TENURE				0.189		0.215
				(0.88)		(0.85)
CEOAGE					0.799	-0.408
					(0.42)	(-0.19)
EQUITYCAPITAL	2.227	2.927	1.944	2.12	2.505	1.653
	(0.32)	(0.42)	(0.28)	(0.30)	(0.37)	(0.22)
CHARGEOFF	-0.715***	-0.724***	-0.773***	-0.729***	-0.716***	-0.786***
	(-3.19)	(-3.36)	(-3.20)	(-3.29)	(-3.29)	(-3.30)
EFFICIENCY	-0.0131	-0.00995	-0.00568	-0.0184	-0.0056	-0.0243
	(-0.21)	(-0.16)	(-0.09)	(-0.32)	(-0.09)	(-0.39)
NETINCOME	-87.10***	-87.89***	-87.10***	-86.77***	-87.71***	-88.43***
	(-3.09)	(-3.17)	(-3.05)	(-3.19)	(-3.17)	(-3.08)
LIQUIDITY	0.701	0.854	0.882	1.201	0.933	1.44
	(0.55)	(0.67)	(0.69)	(0.89)	(0.73)	(1.04)
FUNDINGGAP	1.754*	1.829*	1.859*	1.713	1.703*	1.909*
	(1.68)	(1.73)	(1.75)	(1.59)	(1.65)	(1.79)
NETLOANGROWTH	-0.249	-0.284	-0.0727	-0.464	-0.343	-0.276
	(-0.24)	(-0.27)	(-0.06)	(-0.44)	(-0.33)	(-0.24)
SIZE	0.911***	0.973***	0.977***	0.977***	0.950***	0.983***
	(4.71)	(4.73)	(4.78)	(4.82)	(4.86)	(4.64)
STDEV	-0.00836	-0.0101	-0.0107	-0.00983	-0.00955	-0.00946
	(-1.38)	(-1.46)	(-1.39)	(-1.42)	(-1.46)	(-1.44)
TARP	-0.982**	-1.043**	-1.070**	-1.081**	-1.079**	-0.919**
	(-2.23)	(-2.38)	(-2.53)	(-2.53)	(-2.55)	(-2.03)
RGDPG	-1.409***	-1.442***	-1.433***	-1.459***	-1.446***	-1.441***
	(-4.09)	(-4.28)	(-4.24)	(-4.41)	(-4.29)	(-4.27)
NPLG	0.308	-0.102	-0.121	-0.096	-0.0279	0.149
	(0.11)	(-0.04)	(-0.04)	(-0.03)	(-0.01)	(0.06)
DUR1	-7.330***	-7.271***	-7.289***	-7.273***	-7.267***	-7.466***
	(-7.63)	(-7.43)	(-7.33)	(-7.27)	(-7.39)	(-7.33)
DUR2	-1.886***	-1.849***	-1.836***	-1.803***	-1.849***	-1.838***
	(-4.05)	(-4.07)	(-4.07)	(-4.17)	(-4.08)	(-4.19)
CONSTANT	-15.79***	-16.22***	-16.57***	-17.16***	-19.56**	-15.28
	(-4.67)	(-4.72)	(-4.76)	(-4.74)	(-2.05)	(-1.56)
Number of Observations	806	806	806	806	806	806
Log Likelihood Ratio	-89.1	-88.84	-88.59	-88.81	-89.1	-87.68

This table presents the results from Equation (1). The dependent variable is TAGP OPT OUT, which is equal to one if the BHC opted out of the TAGP, and zero otherwise. Variables are defined in Appendix Table A.1. T-statistics in parentheses. * is p<.10, ** is p<.05, and *** is p<.01.

The findings hold up to several robustness tests, confirming support for H6. First, since the TAGP insured noninterest-bearing transaction accounts (NIBTAs) to an unlimited amount, the amount of deposits that banks had in these funds might have affected the decision to participate in the TAGP. However, the FDIC does not report the amount of NIBTAs over the limit except for banks that participated in the TAGP. This study proxies for NIBTAs by controlling for both the proportion of total noninterest-bearing deposits (NIBDs) to total deposits and total uninsured deposits to total deposits in the prior quarter. These results are provided in Panels A and B of Table 3 but do not affect the conclusions on any CEO characteristics and the variables themselves are not statistically significant from zero.

Table 3: TAGP Robustness -Deposit Variables

Panel A: Including Uninsured Deposits the Quarter Before the Decisions a Control Variable						
	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	0.323					0.355
	(0.48)					(0.49)
CEOBRD		-0.569				-0.587
		(-0.76)				(-0.70)
MBA			-0.355			-0.36
			(-0.82)			(-0.76)
TENURE				0.205		0.237
				(0.95)		(0.89)
CEOAGE					0.536	-0.628
					(0.28)	(-0.28)
UNINSURED	0.972	1.001	0.684	1.093	0.95	0.777
	(0.98)	(1.01)	(0.66)	(1.14)	(0.96)	(0.66)
Number of Observations	806	806	806	806	806	806
Log Likelihood Ratio	-88.69	-88.43	-88.42	-88.31	-88.73	-87.49
Panel B: Including NIBTAs to Total Deposits the Quarter Before the Decision as a Control Variable						
	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	0.385					0.419
	(0.57)					(0.60)
CEOBRD		-0.6				-0.569
		(-0.80)				(-0.67)
MBA			-0.409			-0.443
			(-0.90)			(-0.90)
TENURE				0.175		0.212
				(0.80)		(0.82)
CEOAGE					0.643	-0.442
					(0.34)	(-0.20)
NIBTAs TO TOTAL	0.564	0.593	0.275	0.429	0.49	0.168
	-0.65	-0.66	-0.23	-0.48	-0.54	-0.13
Number of Observations	806	806	806	806	806	806
Log Likelihood Ratio	-88.94	-88.68	-88.56	-88.73	-88.99	-87.67

This table presents several robustness results of Equation (1). The dependent variable is TAGP OPT OUT, which is equal to one if the BHC opted out of the TAGP, and zero otherwise. All controls are included but not shown for brevity, full results are available upon request. Variables are defined in Appendix Table A.1. T-statistics in parentheses. * is p<.10, ** is p<.05, and *** is p<.01.

Second, the results are examined across different samples to ensure robustness. Since BHCs were covered free of charge in the program until December 5, 2008, which covers most of 2008Q4, this quarter is removed from the sample. The results are provided in Panel A of Table 4; however, the results are not different from those presented in Table 3. In addition, since the BHCs could only opt-out at three specific quarters, one could argue that these are the only quarters that should be included in the analysis. Panel B of Table 4 shows results from restricting the sample to the three quarters where the opt-out decision was made. Again, the results support H6 that CEO personal and professional characteristics do not influence the decision to opt out.

Table 4: TAGP Robustness -Different Samples

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Removing 2008Q4						
EQUITYCOMP	0.616					0.647
	(0.78)					(0.77)
CEOBRD		-0.571				-0.611
		(-0.77)				(-0.76)
MBA			-0.33			-0.323
			(-0.79)			(-0.74)
TENURE				0.113		0.167
				(0.46)		(0.57)
CEOAGE					0.277	-1.036
					(0.14)	(-0.43)
Number of Observations	806	806	806	806	806	806
Log Likelihood Ratio	-88.69	-88.43	-88.42	-88.31	-88.73	-87.49
Panel B: Only Examining Three Quarters Where Opt-out Decision is Made						
	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	-0.0342					-0.0426
	(-0.05)					(-0.06)
CEOBRD		-0.545				-0.549
		(-0.78)				(-0.71)
MBA			-0.431			-0.401
			(-1.11)			(-1.00)
TENURE				0.208		0.213
				(0.98)		(0.89)
CEOAGE					0.83	-0.15
					(0.47)	(-0.08)
Number of Observations	282	282	282	282	282	282
Log Likelihood Ratio	-70.03	-69.7	-69.45	-69.57	-69.91	-68.73

This table presents several robustness results of Equation (1). The dependent variable is TAGP OPT OUT, which is equal to one if the BHC opted out of the TAGP, and zero otherwise. All controls are included but not shown for brevity, full results are available upon request. Variables are defined in Appendix Table A.1. T-statistics in parentheses. * is p<.10, ** is p<.05, and *** is p<.01.

The final robustness check explores the timing of the decision by leading the dependent variable by one quarter. BHCs making decisions regarding participation would not have had that quarter's final values but instead might have been making the decision based on previous quarters' information. Results for the full sample are provided in Table 5 Panel A and results when examining only opt out quarters are provided in Panel B. Regardless of sample, both results confirm H6.

Table 5: TAGP Robustness -Basing Opt-Out on Previous Quarters Characteristic

Panel A: Full Sample						
	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	0.604					0.722
	(0.95)					(1.13)
CEOBRD		-0.37				-0.381
		(-0.55)				(-0.52)
MBA			-0.319			-0.363
			(-0.86)			(-0.91)
TENURE				0.114		0.149
				(0.58)		(0.65)
CEOAGE					0.307	-0.66
					(0.19)	(-0.34)
Number of Observations	745	745	745	745	745	745
Log Likelihood Ratio	-136	-136.4	-136.1	-136.4	-136.7	-134.6
Panel B: Just Opt-out Quarters						
	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	0.339					0.525
	(0.51)					(0.74)
CEOBRD		-0.175				-0.144
		(-0.26)				(-0.19)
MBA			-0.494			-0.528
			(-1.26)			(-1.23)
TENURE				0.0311		0.0857
				(0.16)		(0.38)
CEOAGE					-0.11	-0.494
					(-0.07)	(-0.27)
Number of Observations	281	281	281	281	281	281
Log Likelihood Ratio	-68.98	-69.04	-68.41	-69.07	-69.08	-68.14

This table presents several robustness results of Equation (1). The dependent variable is TAGP OPT OUT, which is equal to one if the BHC opted out of the TAGP, and zero otherwise. All controls are included but not shown for brevity, full results are available upon request. Variables are defined in Appendix Table A.1. T-statistics in parentheses. * is p<.10, ** is p<.05, and *** is p<.01.

DGP Results

Next, participation in the DGP is examined by adjusting Equation (1). The dependent variable, $DGP\ Opt-Out_{i,t}$, is equal to one if the BHC opted-out of the DGP, and zero otherwise. All BHC control variables discussed in the empirical model section are included. However, no macroeconomic variables or interval periods are included since the DGP only had one opportunity for BHCs to make a participation decision. The new sample covers the period of the DGP, 2008Q4 through 2009Q4. This sample has 436 BHC-quarter observations, covering approximately 100 BHCs. Table 1 Panel B displays the descriptive statistics for the sample and Table A.3 and Table A.4 Panel B provide the correlation matrix.

The results from the DGP are presented in Table 6. The findings show that none of the CEO characteristics significantly influence a BHC's participation in the DGP. Banks were not charged fees for staying in the DGP, thus most stayed in, which eliminated any influence of behavioral characteristics. The results support H6 for the DGP. However, there are several significant BHC-level determinants in the decision to participate in the DGP. BHCs with higher ratios of charge-offs were more likely to participate in the DGP suggesting that weaker BHCs wanted the option to be able to issue FDIC guaranteed debt. BHCs that were more liquid were more likely to exit the DGP suggesting that these BHCs did not need access to additional short-term funding. BHCs with larger funding gaps were also more likely to participate in the DGP suggesting that BHCs needing short term funds maintained the ability to issue FDIC guaranteed debt. These findings suggest that the financial condition of the bank was more likely to impact the participation decision than characteristics of CEOs, which may be of specific interest to future policymakers and academics.

Table 6: DGP Participation Results

	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	-2.5910					-2.5190
	(-1.12)					(-0.87)
CEOBRD		0.2580				-0.4270
		(0.21)				(-0.28)
MBA			-1.2600			-0.9950
			(-0.66)			(-0.51)
TENURE				-0.3220		-0.4890
				(-0.60)		(-0.95)
CEOAGE					-0.9050	0.2670
					(-0.42)	(0.13)
EQUITYCAPITAL	1.6710	1.7690	-0.8410	2.5740	1.2870	1.3580
	(0.11)	(0.12)	(-0.06)	(0.18)	(0.09)	(0.09)
CHARGEOFF	-2.985**	-2.444**	-2.617***	-2.408**	-2.427**	-3.020***
	(-2.17)	(-2.14)	(-2.60)	(-2.39)	(-2.06)	(-2.83)
EFFICIENCY	1.414*	1.2770	1.497*	1.537**	1.2640	1.943***
	(1.66)	(1.38)	(1.87)	(2.37)	(1.30)	(3.45)
NETINCOME	9.7940	17.1300	12.3000	24.9500	17.1900	19.4100
	(0.19)	(0.36)	(0.28)	(0.58)	(0.36)	(0.47)
LIQUIDITY	10.94***	10.99***	11.13***	11.47***	10.85**	11.88***
	(3.12)	(2.81)	(2.96)	(3.06)	(2.57)	(3.72)
FUNDINGGAP	-8.887***	-8.872***	-8.083***	-8.712***	-8.933***	-8.088***
	(-3.04)	(-2.85)	(-2.80)	(-2.59)	(-2.80)	(-3.00)
NETLOANGROWTH	1.0480	0.5140	-0.2160	-0.0055	0.7060	-0.4390
	(0.33)	(0.20)	(-0.08)	(-0.00)	(0.23)	(-0.17)
SIZE	-0.6190	-0.776*	-0.5790	-0.835*	-0.797*	-0.5580
	(-1.44)	(-1.68)	(-0.99)	(-1.89)	(-1.90)	(-0.82)
STDEV	-2.317**	-2.443**	-2.776*	-2.516**	-2.473**	-2.6490
	(-2.24)	(-2.11)	(-1.80)	(-2.27)	(-2.33)	(-1.58)
TARP	0.5320	0.6520	0.5330	0.6380	0.6650	0.4470
	(0.68)	(0.82)	(0.73)	(0.80)	(0.84)	(0.60)
CONSTANT	5.9020	7.0720	4.6370	8.3630	11.3600	4.7040
	(0.74)	(0.78)	(0.46)	(1.02)	(0.93)	(0.28)
Number of Observations	436	436	436	436	436	436
Log Likelihood Ratio	-34.33	-35.24	-34.7	-35.02	-35.18	-33.57

This table presents regressions on the decision to participate in the DGP. The dependent variable is DGP OPT OUT, which is equal to one if the BHC opted out of the DGP, and zero otherwise. Variables are defined in Appendix Table A.1. Standard errors clustered at the BHC level. T-statistics in parentheses. * is p<.10, ** is p<.05, and *** is p<.01.

The results hold up to several robustness tests. First, it could be argued that since the BHCs could only optout during one quarter, that this is the only quarter that should be included in the analysis. The results are provided in Panel A of Table 7; however, they are not different from those presented in Table 6. Next, this study explores the timing of the decision by leading the dependent variable by one quarter. The thought here is that BHCs might have been using previous quarters information when deciding to opt-out. The results are shown for the full sample (Panel B), just the initial quarter (Panel C) and the results do not change from those provided in Table 6, confirming support for H6 within the DGP.

Table 7: DGP Robustness

Panel A: Only Examining One Quarter Where Opt-out Decision is Made						
	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	-1.89					-1.383
	(-0.88)					(-0.64)
CEOBRD		0.293				-0.261
		(0.29)				(-0.22)
MBA			-1.222			-1.237
			(-0.65)			(-0.68)
TENURE				-0.383		-0.404
				(-0.96)		(-1.04)
CEOAGE					-0.59	0.663
					(-0.29)	(0.25)
Number of Observations	100	100	100	100	100	100
Log Likelihood Ratio	-20.05	-20.48	-20.06	-20.19	-20.49	-19.43
Panel B: Opt-Out Based on Previous Quarters Characteristics						
	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	-2.607					-2.528
	(-1.12)					(-0.88)
CEOBRD		0.358				-0.279
		(0.28)				(-0.18)
MBA			-1.03			-0.762
			(-0.56)			(-0.38)
TENURE				-0.359		-0.447
				(-0.75)		(-0.92)
CEOAGE					-1.354	-0.233
					(-0.71)	(-0.13)
Number of Observations	349	349	349	349	349	349
Log Likelihood Ratio	-31.76	-32.64	-32.33	-32.38	-32.51	-31.1
Panel C: Opt-Out Based on Previous Quarters Characteristics- Only Initial Quarter						
	(1)	(2)	(3)	(4)	(5)	(6)
EQUITYCOMP	-1.89					-1.383
	(-0.88)					(-0.64)
CEOBRD		0.293				-0.261
		(0.29)				(-0.22)
MBA			-1.222			-1.237
			(-0.65)			(-0.68)
TENURE				-0.383		-0.404
				(-0.96)		(-1.04)
CEOAGE					-0.59	0.663
					(-0.29)	(0.25)
Number of Observations	100	100	100	100	100	100
Log Likelihood Ratio	-20.05	-20.48	-20.06	-20.19	-20.49	-19.43

This table presents several robustness results of Equation (1). The dependent variable is DGP OPT OUT, which is equal to one if the BHC opted out of the TAGP, and zero otherwise. All controls are included but not shown for brevity, full results are available upon request. Variables are defined in Appendix Table A.1. T-statistics in parentheses. * is p<.10, ** is p<.05, and *** is p<.01.

Conclusion

This project examines the influence of BHCs CEO personal and professional characteristics on government program participation. The literature on CEO corporate decision-making typically removes banks due to the regulatory environment and the literature on stimulus program participation decisions is sparse. This unique setting allows an opportunity for analysis of BHC CEO decision-making by exploiting the choice of participation in the TLGP, which included both the TAGP and the DGP. Interestingly, CEO characteristics did not affect participation in the TAGP or DGP.

There may be several explanations for why CEO characteristics show little influence on bank decisions on government stimulus including the structure of the programs, the peer pressure to take the stimulus, the higher regulatory environment in which BHCs operate, and that BHC CEOs are just different. These are provided as inspiration for future research. Regardless of these future inquiries, the general lack of influence of CEO characteristics is an interesting addition to the extant finance literature on CEO decision making.

This research can provide insight to policymakers who will look to programs from the Great Recession when formulating future policy. Since 2008 there have been opportunities for additional programs similar to the TAGP and DGP. However, limited research has examined these programs. Policymakers can see that this program and its structure were not influenced by the CEO characteristics examined in this study. Additional research may explore whether the TLGP and DGP structure was an effective implementation to achieve participation by BHCs in times of financial crisis.

The most notable outcome for this study is an increased understanding about whether bank CEO personal and professional characteristics influence corporate stimulus decision-making during crises. Overall, there are opportunities for extended research in understanding bank CEO decision-making, as well as, cross-disciplinary research on the intersection of psychology, finance and management; including CEOs and corporate decision-making, government sponsored programs, and the implementation of these programs.

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Appendix

Table A.1: Variable Descriptions

Variables	Definition
TAGP OPT OUT	Indicator variable equal to one if the BHC opted out of the TAGP, and zero otherwise
DGP OPT OUT	Indicator variable equal to one if the BHC opted out of the DGP, and zero otherwise
EQUITYCOMP	The fraction of the manager's total compensation paid in stock and options grants
CEOBRD	Indicator variable equal to one if CEO sits on the board, and zero otherwise
MBA	Indicator variable equal to one if CEO has an MBA degree, and zero otherwise
LOGTENURE	Natural log of one plus the number of years as CEO
LOGCEOAGE	Natural log of one plus the current age of the CEO
EQUITYCAPITAL	Total equity capital divided by the previous quarter's total assets
CHARGEOFF	Total amount of charged-off loans and lease financing receivables to the previous quarter's total loans
EFFICIENCY	Noninterest expense less amortization of intangible assets as a percentage of net interest income plus noninterest income. A lower value indicates greater efficiency.
NET INCOME	Net income divided by the previous quarter's total assets
LIQUIDITY	The sum of average noninterest-bearing balances due from depository institutions, average currency and coin, and average federal funds sold and securities purchased under agreements to resell and available for sale securities divided by the previous quarter's total assets
FUNDINGGAP	Short term liabilities minus short term assets divided by the previous quarter's total assets
NETLOANGROWTH	One-quarter growth rate in net loans and leases
SIZE	Natural log of total assets in 2009 dollars
STDEV	Standard deviation of total assets across the previous year
TARP	Indicator variable equal to one if a bank within the BHC received TARP funds
RGDPG	One-quarter change in Real Gross Domestic Product
NPLG	One-quarter change in aggregate non-performing loans

Table A.2: TAGP Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1) TAGP OPTOUT	1.00																
2) EQUITYCOMPENSATION	0.13*	1.00															
3) CEOBRD	0.01	-0.12*	1.00														
4) MBA	0.02	0.19*	0.00	1.00													
5) TENURE	-0.01	-0.09*	-0.06	0.01	1.00												
6) CEOAGE	-0.01	0.03	-0.15*	0.06	0.32*	1.00											
7) EQUITYCAPITAL	0.07	0.11*	-0.02	-0.04	0.03	-0.02	1.00										
8) CHARGEOFF	-0.11*	-0.22*	0.06	-0.10*	-0.01	0.08*	-0.15*	1.00									
9) EFFICIENCY	0.00	-0.02	-0.01	0.01	0.06	-0.02	-0.06	0.12*	1.00								
10) NETINCOME	0.02	0.0983*	-0.05	0.00	0.03	-0.06	0.14*	-0.57*	-0.10*	1.00							
11) LIQUIDITY	0.10*	0.11*	0.12*	0.10*	-0.02	-0.10*	-0.14*	-0.06	-0.01	0.10*	1.00						
12) FUNDINGGAP	0.00	-0.18*	0.12*	-0.03	0.17*	0.02	0.00	-0.03	0.00	0.06	0.26*	1.00					
13) NETLOANGROWTH	0.02	0.05	0.00	0.06	0.01	-0.04	0.23*	-0.08*	-0.14*	0.23*	0.13*	0.06	1.00				
14) SIZE	0.18*	0.43*	0.04	0.19*	-0.09*	0.03	0.09*	-0.13*	-0.07*	0.04	0.12*	-0.26*	0.05	1.00			
15) STDEV	0.02	0.13*	0.05	0.13*	-0.08*	-0.01	0.03	-0.07*	-0.11*	0.03	0.07*	-0.14*	0.19*	0.49*	1.00		
16) TARP	-0.13*	-0.16*	0.01	-0.02	-0.01	0.10*	0.00	0.23*	0.04	-0.16*	-0.21*	-0.16*	-0.04	0.10*	0.08*	1.00	
17) RGDPG	0.087*	-0.08*	0.00	-0.01	-0.01	0.03	0.05	0.03	0.06	0.12*	0.05	0.04	-0.07*	-0.03	-0.09*	-0.10*	1.00
18) NPLG	-0.23*	0.05	-0.02	-0.02	0.02	-0.01	-0.10*	-0.04	-0.02	-0.06	-0.04	0.01	-0.02	0.10*	0.11*	0.14*	-0.56*

This table presents correlation matrix of dependent and control variables for the TAGP. Variables are defined in Appendix Table A.1. * is p<0.10

Table A.3: DGP Correlation Matrix

	1	2	3	4	5	6	7	8	9	0	11	12	13	14	15
1) DGP OPTOUT	1.00														
2) EQUITYCOMPENSATION	-0.08	1.00													
3) CEOBRD	0.01	-0.13*	1.00												
4) MBA	-0.06	0.21*	-0.01	1.00											
5) TENURE	-0.02	-0.09	-0.01	0.09	1.00										
6) CEOAGE	-0.10*	0.16*	-0.18*	0.13*	0.23*	1.00									
7) EQUITYCAPITAL	0.04	0.04	-0.06	-0.04	0.08	-0.05	1.00								
8) CHARGEOFF	-0.06	-0.23*	0.06	-0.09*	0.09	0.09	-0.13*	1.00							
9) EFFICIENCY	0.01	-0.01	-0.01	0.01	0.07	-0.03	-0.05	0.14*	1.00						
10) NETINCOME	-0.06	0.12*	-0.06	-0.02	-0.03	-0.10*	0.09	-0.57*	-0.10*	1.00					
11) LIQUIDITY	0.14*	0.10*	0.09*	0.14*	0.01	-0.11*	-0.10*	-0.03	-0.02	0.08	1.00				
12) FUNDINGGAP	0.00	-0.24*	0.14*	-0.06	0.24*	-0.01	0.10*	0.05	0.00	0.05	0.29*	1.00			
13) NETLOANGROWTH	0.03	0.01	0.05	0.04	-0.01	-0.07	0.28*	-0.06	-0.15*	0.23*	0.20*	0.11*	1.00		
14) SIZE	-0.15*	0.47*	0.02	0.20*	-0.13*	0.106*	0.01	-0.16*	-0.08	0.08	0.08	-0.35*	0.03	1.00	
15) STDEV	-0.04	0.15*	0.06	0.17*	-0.11*	0.00	0.03	-0.09	-0.11*	0.05	0.09	-0.16*	0.19*	0.53*	1.00
16) TARP	-0.04	-0.07	0.01	0.01	0.01	0.120*	0.03	0.17*	0.04	-0.08	-0.19*	-0.22*	-0.04	0.16*	0.10*

This table presents correlation matrix of dependent and control variables for the DGP. Variables are defined in Appendix Table A.1. * is p<0.10.

Table A.4: Correlation Matrix

Panel A: TAGP CEO Correlation Matrix

	1	2	3	4	5	6
1) TAGP OPTOUT	1					
2) EQUITYCOMPENSATION	0.133***	1				
3) CEOBRD	0.013	-0.117***	1			
4) MBA	0.018	0.185***	-0.001	1		
5) TENURE	-0.012	-0.094**	-0.063	0.007	1	
6) CEOAGE	-0.006	0.033	-0.149***	0.062	0.322***	1

Panel B: DGP CEO Correlation Matrix

	1	2	3	4	5	6
1) DGP OPTOUT	1					
2) EQUITYCOMPENSATION	-0.082	1				
3) CEOBRD	0.011	-0.125**	1			
4) MBA	-0.064	0.214***	-0.015	1		
5) TENURE	-0.022	-0.091	-0.011	0.089	1	
6) CEOAGE	-0.097*	0.161***	-0.183***	0.133**	0.231***	1

This table presents correlation matrix of dependent and CEO variables for TAGP (Panel A) and the DGP (Panel B). Variables are defined in Appendix Table A.1. * is p<.10, ** is p<.05, and *** is p<.01.

US Elections and Stock Market Returns: Revisiting the Relationship

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Abstract

Extending by 20 years the interval studied by Jones and Banning (2009), this paper examines the period between the elections of 1896 and 2020 for relationships between U.S. stock market returns and several variables related to elections. The most striking finding is that scenarios that display above-average levels of volatility are not rewarded by above-average returns, and if anything the opposite occurs. In particular, the market has both higher average returns, and lower variance in returns, under a divided government consisting of a Democratic president and Republican Congress, than under a divided government with a Republican president and Democratic Congress.

Introduction and Literature Review

The impact of political happenings on U.S. stock market returns has been the subject of much study. Johnson et al. (1999) note that while there is a widespread perception among the public that the market performs better under Republican presidents, various empirical findings refute this notion. Indeed, the opposite result has been found by Huang (1985), Siegel (2002), Santa Clara and Valkanov (2003), and, to a lesser extent, Johnson et al. (1999). Sy and Al Zaman (2011) likewise find higher average returns during Democratic presidencies but also find that these higher average returns can largely be attributed to compensation for greater risk. However, Beyer et al. (2004) find that long term returns are far more responsive to changes in monetary policy than to political changes. Jones and Banning (2009) find no significant relationship between market returns and partisan control of the presidency. Powell et al. (2006) criticize the statistical tests applied by Santa Clara and Valkanov (2003) and argue that under proper statistical testing returns do not differ noticeably based on control of the presidency.

Additional studies deal with the market's immediate reaction to the election of a president. Niederhoffer, Gibbs, and Bullock (1970), Riley and Luksetich (1980), Homaifar, Randolph, Helms, and Haddad (1988), and Siegel (2002) all produce results that tend to support the view that the stock market has a better reaction to the election of a Republican president than to the election of a Democrat. However, in a study by Chien et al. (2014), results are mixed in terms of the market's ability, in the immediate aftermath of a presidential election, to forecast the economic performance of the incoming administration.

Also, several studies examine the "second half" effect, which is the notion that the stock market tends to perform better during the second half a given presidential term. Studies that are mostly supportive of this idea include Allvine and O'Neill (1980), Huang (1985), Stovall (1992), Johnson et al. (1999), and Siegel (2002). However, Jones and Banning (2009) find that the second half effect is mixed. While average market performance is significantly stronger during the second half of the first term that a given political party has controlled the presidency, for the sample as a whole the second half effect is not found to be statistically significant. This continues to be the case in the later sample period of Ding et al. (2019), who find that there is very little evidence for a second half effect during the early part of the 21st century.

In addition to the issues described above, Jones and Banning (2009) view other issues such as majority control of both the U.S. Senate and the U.S. House of Representatives, combinations of control (e.g., a united government under Democratic leadership compared to a divided government with a Democratic president and a Republican Congress), and the number of consecutive terms that the same party has held the presidency. The paper finds that on the whole, these variables display little relationship to market returns.

This paper extends many of the same tests performed by Jones and Banning (2009) to include the presidencies of George W. Bush and Barack Obama and the first presidency of Donald Trump. It should be noted that each of these three presidencies included both periods of united government (meaning that the same party that controlled the presidency had majority control of both houses of Congress) and periods of divided government (meaning that the party not controlling the presidency had majority control of at least one house of Congress). So, this 20-year extension of the test period allows for more extensive examinations of each of the major comparisons performed by Jones and Banning (2009): control of each of the aforementioned political entities separately, various combinations of partisan control, the second half effect, and the number of consecutive terms that the same political party has controlled the presidency.

Perhaps most importantly, based on the suggestion of an anonymous referee this paper examines relative levels of volatility under various scenarios, in addition to comparing mean returns under those scenarios. This leads to some surprising findings. First, there are multiple instances in which significant differences are found between the variances of returns under contrasting scenarios. Second, in no instance is the significantly higher volatility of one scenario as compared to another rewarded with higher mean returns. In fact, in each of the only two instances in which mean returns differ significantly across scenarios, the scenario producing a significantly higher mean return also features significantly lower variance of returns. Third, in the majority of cases significantly higher volatility is not rewarded even with insignificantly higher mean returns; more often than not, when the difference in variance is significant the sign on the difference in mean returns is in the opposite direction.

It is important to acknowledge that not all statistically significant findings – whether regarding differences in means or differences in variances – can be assumed to be the result of causation. Market returns often will be impacted by exogenous factors, so any argument along the lines of "Party X is better for the stock market" or "changing political control of the White House frequently is good for the stock market" should be viewed with caution.

Data and Test Variables

The Yahoo! Finance website currently provides daily data on the Dow Jones Industrial Average dating back to January 2, 1992. In addition, however, many years ago Dow Jones directly supplied data from May 26, 1896 through August 23, 2002. These two sets of data have been combined for purposes of calculating monthly returns. In the few instances during the overlap of the two data sets where there are slight differences (mostly due to rounding), the more recently listed data is used.

Using data going back to 1896 is helpful, because that year there was a presidential election in which partisan control of the presidency changed from the Democratic Party (Grover Cleveland's second presidency) to the Republican Party (William McKinley). So, monthly returns have been calculated from the date of the presidential election of 1896 through the date of the presidential election of 2020. The monthly returns are based on daily closing prices, spaced as closely to one month apart as possible. For instance, the first month after President Obama's election runs from November 4 to December 4 of 2008. The second monthly return is based on the closing number for Friday, January 2, 2005, the last trading day prior to January 4.

Party control designations for each date in the dataset are based on election dates rather than swearing-in dates. Jones and Banning (2009) describe at length the logic for this decision, but the crux of the argument is as follows. First, if an administration that is presiding over a poor economy is defeated for re-election, it would seem illogical to credit any positive market reaction to the president whose defeat generated that positive reaction. Second, throughout much of our sample period a significant amount of time often passed between Congressional elections and the date that the new Congress was seated. While one party might not yet have assumed formal control of a chamber of Congress, the information regarding which party would be controlling that chamber would long since have been known.

An exception to the "election day" cutoff is that the one-zero variable for control of the Senate is changed as of the date that Senator James M. Jeffords left the Republican Party and became an independent who caucused with the Senate Democrats. Due to the uncertainty surrounding the 2000 presidential election, which was not resolved until slightly over one month past election day, the two-month period following that election is treated as a single month. Also treated as a single month is a four-month period during 2014, due to missing data. Finally, since the sample period ends with election day of 2020, no decision is required regarding the date on which the result of that election became known.

Each date is also classified based on whether it falls before or after a midterm election. Further, each date is assigned a value equal to the number of consecutive presidential elections won by the same political party as of that date.

Results

Initial Results for Primary Test Variables

The study begins by examining the five primary test variables identified above, using three forms of the following multiple regression model:

$$R = \alpha + \beta_1 Term + \beta_2 2ndHalf + \beta_3 Pres + \beta_4 Sen + \beta_5 House$$

where:

R = monthly return;
Term = the number of consecutive terms that the same party has been elected to the presidency;
2^{nd}Half = 1 for dates falling within the second half of a presidential term, 0 otherwise;
Pres = 1 if the Republican Party was elected to control of the presidency in the most recent election, 0 otherwise;
Sen = 1 if the Republican Party was elected to majority control of the Senate in the most recent election, 0 otherwise; and,
House = 1 if the Republican Party was elected to majority control of the U.S. House in the most recent election, 0 otherwise

Table 1 displays the results of three specific models. In the first of these, the two variables of interest are the two that relate to timing, as opposed to whether a specific political party is in power. The coefficient for the term number is negative, implying lower returns the longer the same political party has controlled the presidency. The coefficient for the second half variable is positive, implying higher returns during the second half of a presidential term. However, neither variable is statistically significant, or even particularly close to significant.

The second model tests the three one-zero variables that relate to political control. The regression coefficients are negative for both Republican control of the presidency and a Republican majority in the United States Senate and are positive for a Republican majority in the United States House of Representatives. Here, too, none of the results are remotely significant.

The third model tests all five variables at the same time. The results for each variable are virtually indistinguishable from those shown in the first two models. It also is worth noting the intercept term is positive and, to varying degrees, statistically significant in all three models, consistent with the general expectation that average market returns will be positive over time.

In sum, the initial examination of the five basic test variables reveals no statistically significant relationship between average market returns and the election cycle, and no statistically significant relationship between average market returns and which political party is in power. In addition, the overall explanatory power of the regression equation is very weak.

Table 1: Regressions of Monthly Returns on Issues Related to Election Cycles and Political Control

Test Variable	Model 1	Model 2	Model 3
Intercept	0.0065 (1.9761) [0.0484]**	0.0043 (1.9051) [0.0570]*	0.0065 (1.6657) [0.0960]*
Term number	-0.0017 (-1.2816) [0.2002]		-0.0017 (-1.2503) [0.2114]
1/0 variable for “second half” of term	0.0024 (0.8532) [0.3937]		0.0026 (0.9173) [0.3592]
1/0 variable for Republican president		-0.0025 (-0.7906) [0.4294]	-0.0028 (-0.8522) [0.3943]
1/0 variable for Republican Senate majority		-0.0010 (-0.2278) [0.8199]	-0.0010 (-0.2142) [0.8305]
1/0 variable for Republican House majority		0.0047 (1.1242) [0.2612]	0.0047 (1.0979) [0.2725]
R^2	0.0016	0.0016	0.0033

Monthly stock returns are regressed on the test variables identified above. In each case, the first number shown is the regression coefficient. The corresponding t-statistic is shown immediately below, in parentheses. Lastly, the corresponding significance level is shown in brackets. Significant findings are designated with * (10% level), ** (5% level), and *** (1% level).

Are Riskier Scenarios More Rewarding?

As noted by an anonymous referee, the Sy and Al Zaman (2011) paper cited above provides a critical reminder of an issue largely overlooked in most studies on this topic. If a given scenario is associated with significantly above-average returns but also is associated with significantly above-average risk, then one needs to find some method (such as calculating risk-adjusted returns) to evaluate whether the additional returns truly represent a superior investment environment. Taking this logic further, if a given scenario is associated with significantly above-average risk, but not with significantly above-average returns, one can make a strong argument that the added risk is not being compensated sufficiently. Finally, if a given scenario is associated with significantly above-average risk, and there is no advantage at all (not even a statistically insignificant advantage) in terms of average returns, then clearly there is no reward for the added risk. Thus, rather than running a series of simple regressions on the various one-zero variables tested in the multiple regressions in Table 1 above, a more complete analysis can be provided by instead comparing means and variances of various subsets of the sample.

Investigation of the Second Half Effect

Table 2 displays the results of this type of analysis for the second half effect. First, the sample as a whole is divided into dates that fall into the first half of a term and dates that fall into the second half of a term. Then, the same comparison is provided for the first versus second halves of the first term that a given party has controlled the presidency, the second term that a given party has controlled the presidency, and so on.

Table 2: Tests of the second half effect

Comparison	Mean return	Variance of returns
Total sample: 2nd half term (N = 744)	0.0056	0.0032
Total sample: 1st half term (N = 740)	0.0032	0.0028
2nd half term minus 1st half term	0.0024	0.0004
Test statistic	0.8563	1.1718
P-value	0.3920	0.0650*
First terms: 2nd half term (N = 312)	0.0106	0.0020
First terms: 1st half term (N = 308)	0.0033	0.0029
2nd half term minus 1st half term	0.0073	(0.0009)
Test statistic	1.8512	1.4437
P-value	0.0647*	0.0007***
Second terms: 2nd half term (N = 264)	0.0045	0.0032
Second terms: 1st half term (N = 264)	0.0036	0.0024
2nd half term minus 1st half term	0.0009	0.0008
Test statistic	0.1874	1.3517
P-value	0.8514	0.0075***
Third terms: 2nd half term (N = 96)	(0.0069)	0.0082
Third terms: 1st half term (N = 96)	0.0002	0.0047
2nd half term minus 1st half term	(0.0071)	0.0035
Test statistic	(0.6140)	1.7415
P-value	0.5401	0.0037***
Fourth terms: 2nd half term (N = 48)	0.0028	0.0011
Fourth terms: 1st half term (N = 48)	0.0041	0.0021
2nd half term minus 1st half term	(0.0013)	(0.0010)
Test statistic	(0.1567)	1.8219
P-value	0.8759	0.0212**
Fifth terms: 2nd half term (N = 24)	0.0081	0.0010
Fifth terms: 1st half term (N = 24)	0.0066	0.0014
2nd half term minus 1st half term	0.0015	(0.0004)
Test statistic	0.1486	1.4272
P-value	0.8826	0.4965

For each comparison, the relevant number (mean or variance) is provided both for dates that fall in the second half of a term and dates that fall in the first half. The difference is then shown, followed by the t-statistic (for comparisons of means) or F-statistic (for comparisons of variances). Negative numbers are shown in parentheses. The final number displayed for each comparison is the significance level associated with the test statistic. Significant findings are designated with * (10% level), ** (5% level), and *** (1% level). Slight differences in sample sizes for the first half and the second half, both for the overall sample and for the first-term subsample, are due to the missing data points for 1914 and 2000 described earlier in the paper.

Several results stand out. For the sample as a whole, there is both greater volatility and a higher average return during the second half of a term than during the first half; however, while the difference in volatility is easily significant at the 10% level, the difference in the mean return is not remotely significant. This appears to confirm the Ding et al. (2019) findings questioning the second half effect.

When the sample is broken down into subsamples based on the term number, the results become even more interesting. The single most striking result is that for first terms, the second half effect is indeed on full display, with both significantly higher average returns and significantly lower variance. In none of the other instances featuring significant differences in volatility are there significant rewards in terms of higher average returns. In fact, in the case of third terms the period that involves greater volatility (in this case the second half rather than the first) does not show even an insignificantly higher average return.

Does the Market Have Partisan Preferences?

In addition to investigating the political party variables tested in the multiple regression equations in Table 1, based on the reviewer's suggestion the next step is to look at each of these variables – control of the presidency, control of the Senate, and control of the House – by comparing both the means and the variances of returns under Republican versus Democratic leadership. Table 3 displays the results of these comparisons.

In each instance, there is a highly significant difference in the volatility of returns depending on partisan control. In contrast to the Sy and Al Zaman (2011) finding of greater risk under Democratic administrations, this study finds that Republican control of the presidency is associated with a greater variance of returns than is Democratic control of the presidency. Republican majority control of the Senate is likewise associated with a higher variance of returns. However, Democratic majority control of the House of Representatives is associated with a greater variance of returns than is Republican control.

In no instance is greater volatility rewarded with significantly greater average returns, and in only in instance – Republican control of the Senate – is greater volatility rewarded even with insignificantly greater average returns. (Recall that in the multiple regression results in Table 1, the regression coefficient on a one-zero variable for Republican control of the Senate was negative, albeit not significant. However, when not controlling for the other variables, it turns out that the average returns are higher, although again not to a significant extent, under a Republican Senate majority than under a Democratic Senate majority.)

In the case of both greater volatility under Republican presidents and greater volatility under a Democratic majority in the House, the higher variance is not rewarded even with an insignificantly higher average return. Instead, to the extent that there is any difference at all, the higher variance scenario produces lower average returns.

Table 3: Political party control

Comparison	Mean return	Variance of returns
Republican control of presidency (N = 815)	0.0035	0.0034
Democratic control of presidency (N = 669)	0.0055	0.0025
Republican control minus Democratic control	(0.0020)	0.0009
Test statistic	(0.7066)	1.3346
P-value	0.4800	0.0001***
Republican majority control of Senate (N = 677)	0.0050	0.0034
Democratic majority control of Senate (N = 807)	0.0038	0.0027
Republican majority minus Democratic majority	0.0012	0.0007
Test statistic	0.4188	1.2750
P-value	0.6755	0.0005***
Republican majority control of House (N = 599)	0.0064	0.0026
Democratic majority control of House (N = 885)	0.0030	0.0033
Republican majority minus Democratic majority	0.0034	(0.0007)
Test statistic	0.1874	1.2583
P-value	0.8514	0.0012***

For each comparison, the relevant number (mean or variance) is provided both for periods of Republican control and for periods of Democratic control. The difference is then shown, followed by the t-statistic (for comparisons of means) or F-statistic (for comparisons of variances). Negative numbers are shown in parentheses. The final number displayed for each comparison is the significance level associated with the test statistic. Significant findings are designated with * (10% level), ** (5% level), and *** (1% level).

Combinations of Partisan Control

The last set of tests in Jones and Banning (2009) involved testing for differences in mean returns among different sub-samples, which were created by breaking down the sample based on control of both the presidency and the Congress.

The authors had expected to find higher average returns under the combination of a Democratic President and a Congress in which the Republicans controlled at least one chamber, than under the combination of a Republican President and a Congress in which the Democrats controlled at least one chamber. This expectation was no doubt a result of (relatively) recent experience – the last six years of the Clinton presidency featured far stronger market returns than did the eight years of the Nixon and Ford presidencies.

The study did find that the difference between the mean returns of these two combinations of control came closer to attaining statistical significance than did the difference found in any other pairwise comparison of combinations of political control. However, the test statistic on this difference was not statistically significant (p-value = 0.1822).

Adding the presidencies of George W. Bush, Barack Obama, and Donald Trump to the sample significantly strengthens this finding. Average monthly returns are ranked as follows. The highest average monthly returns (0.0085) occur when there is a Democratic president with divided government. Next comes a situation in which there is a Republican president with united government (0.0063). Third is a situation in which there is a Democratic president with united government (0.0043). The lowest average monthly returns occur when there is a Republican president with divided government (0.0009).

Table 4: Comparisons of Mean Returns Across Different Combinations of Partisan Control

Form of partisan control	Mean return	Variance of returns
Democratic president with unified government (N = 477)	0.0043	0.0028
Democratic president with divided government (N = 192)	0.0085	0.0018
Republican president with divided government (N = 426)	0.0009	0.0038
Republican president with united government (N = 389)	0.0063	0.0029
Dem president /unified minus Dem president / divided	(0.0042)	0.0010
Test statistic	(-1.0738)	1.5682
P-value	0.2836	0.0002**
Dem president /unified minus Rep president / divided	0.0034	(0.0010)
Test statistic	0.8702	1.3570
P-value	0.3845	0.0006***
Dem president /unified minus Rep president / unified	(0.0020)	(0.0001)
Test statistic	(0.5586)	1.0175
P-value	0.5766	0.4277
Dem president / divided minus Rep president / divided	0.0076	(0.0020)
Test statistic	1.7638	2.1280
P-value	0.0784*	0.0001***
Dem president / divided minus Rep president / unified	0.0022	(0.0011)
Test statistic	0.5281	1.5956
P-value	0.5977	0.0002***
Rep president / divided minus Rep president / unified	(0.0054)	(0.0009)
Test statistic	(1.3338)	1.3337
P-value	0.1827	0.0020***

Both the mean and variance are displayed for each of the four combinations of partisan control of government, along with the number of observations for each of the four possible scenarios. Below that, each of the six pairwise comparisons among these four scenarios is examined. This comparison includes the difference between the two scenarios being compared, followed by the t-statistic (for comparisons of means) or F-statistic (for comparisons of variances). Negative numbers are shown in parentheses. The final number displayed for each comparison is the significance level associated with the test statistic. Significant findings are designated with * (10% level), ** (5% level), and *** 1% level).

Table 4 displays the results of a series of statistical comparisons of these average monthly returns, along with comparisons of variances. After lengthening the test period by 20 years, the excess of average monthly returns under a Democratic President/Republican Congress over a Republican President/Democratic Congress is easily significant at the 10% level, with a p-value of 0.0784. None of the other differences in mean returns are statistically significant.

That having been said, there are several instances in which there is a significant difference in the variance of returns. Of particular note is that the single largest such difference is likewise between the combination of a Democratic president with a Republican Congress and a Republican president with a Democratic Congress. However, the difference is precisely the opposite of what the risk-return tradeoff would ordinarily predict. The single highest-variance scenario among the four is the combination of a Republican president and a Democratic Congress – the very scenario that produces the lowest average returns. The single lowest-variance scenario is the combination of a Democratic president and a Republican Congress.

Four of the remaining five pairwise comparisons display a statistically significant difference in the variance of returns. In none of these comparisons is the greater volatility of the higher-variance scenario rewarded with significantly greater mean returns. In fact, in only one of these instances of significantly differing variances is there even an insignificant reward for volatility; in all the rest, the higher-variance scenario is the one in which average returns are lower.

Conclusions

This study constitutes, to the best of the author's knowledge, the lengthiest sample period of any analysis of the relationship between political occurrences and stock market returns in the United States. It extends by 20 years the time frame of Jones and Banning (2009) which examined not only the classic questions of how the market performs under Democratic vs. Republican presidents and the strength of the second half effect, but also political party control of each of the two houses of Congress, divided vs. united party control of Congress and the White House, and the length of time that the same political party has controlled the presidency.

The study also follows Sy and Al Zaman (2011) in examining relative levels of risk across different scenarios and it is here that the most noticeable findings emerge. The results show that there are numerous instances in which a comparison of two scenarios shows that return volatility is significantly greater under one scenario than another. These include greater variance: during the second half of a presidential term as compared to the first half of a presidential term (for the sample as a whole); during the second half of either the second or third term that the same party has held the presidency; during the first half of either the first or fourth term that the same party has held the presidency; when the Republican Party has been elected to control of the presidency; when the Republican Party has been elected to majority control of the Senate; and when the Democratic party has been elected to majority control of the House of Representatives. They also include greater variance under five of the six possible pairwise comparisons regarding different possible combinations of control of the presidency and Congress.

In none of these instances of significantly different variances is the greater variance accompanied by a significantly greater average return. In fact, in fewer than half of these instances is the greater variance accompanied even by an insignificantly greater return, meaning that as often as not there is apparently no reward at all for the additional risk faced by an investor.

Finally, there are two instances in the study in which one scenario offers significantly greater average returns than does the other, and in each of those instances the higher-return scenario also displays significantly lower volatility in returns. The first of these comparisons involves returns during the first term that a given party has held the presidency: the second half of a first term is characterized both by significantly lower volatility and by significantly higher average returns.

The second relates to partisan control of government. Both the highest average returns, and the lowest volatility, are associated with situations in which the Democratic Party has been elected to the presidency, but in which the Republican Party has been elected to majority control in at least one chamber of Congress. Both the lowest average returns, and the greatest volatility, are associated with situations in which the opposite holds true: the Republican Party has been elected to the presidency, but the Democratic Party has been elected to majority control in at least one chamber of Congress. The former scenario displays both significantly higher average returns, and significantly lower variance of returns, than does the latter scenario.

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Green Stamps: Infrastructure Investment and Jobs Act and the Transportation Industry

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Abstract

This study analyzes the effects of the Infrastructure Investment and Jobs Act (IIJA) on the transportation sector using event study analysis. The IIJA focuses on sustainable infrastructure and reducing climate pollution. However, as the transportation industry heavily relies on crude oil, there may be potential negative consequences due to the need for decarbonization. The study examines market reactions of the S&P 500 and selected energy stocks following significant IIJA-related announcements. By employing an event study approach, the results capture short-term market responses and shed light on investor sentiment regarding the transportation industry's future.

JEL classification: G14, G18
Keywords: infrastructure investment and jobs act; transportation; investor sentiment; macroeconomic uncertainty

Introduction

The urgent need for climate action to achieve the United Nations Sustainable Development Goals (SDGs) has made it imperative for governments and businesses to implement sustainable practices and reduce carbon emissions. One such initiative is the Infrastructure Investment and Jobs Act (IIJA), which seeks to reduce climate pollution and develop sustainable infrastructure. However, the passage of legislation may have significant implications for industries, particularly the transportation sector, which relies heavily on fossil fuels. To understand the market's response towards the IIJA, this study uses an event study approach to analyze the market performance of the transportation industry and a sub-sample of energy stocks surrounding the important announcement dates associated with the Act. The study's findings can provide insights into the potential impact of climate policies on industries and inform investment decisions that align with the SDGs. Furthermore, the urgency of climate action calls for increased climate finance to support the transition towards a sustainable future. As such, this study serves as a call to action for stakeholders to prioritize climate finance and invest in sustainable solutions that align with the SDGs.

The United Nations' Sustainable Development Goals (SDGs) call for the transformation of the global economy towards more sustainable and inclusive practices. One of the key challenges to achieving these goals is the need for climate finance, which is essential to financing the transition to a low-carbon economy. Climate finance serves as a collaborative framework of funds for programs and projects that contribute to the transition to a low carbon economy, reduction of greenhouse gas emission levels, and building resilience to climate change (Karolyi and Scheinkman, 2020). The financial sector, including capital markets, plays a crucial role in mobilizing climate finance to support sustainable development.

Legislation and regulations can have a significant impact on the financial markets, as they shape the incentives and behaviors of market participants. There has been a growing recognition of the importance of aligning financial regulations with climate and sustainability goals in recent years. For example, the European Union has developed a comprehensive framework for sustainable finance which includes regulations on disclosure, taxonomy, and benchmarks for green investments (European Commission, 2019a; European Commission, 2019b; European Commission, 2019c; European Commission, 2020). Similarly, the United States has taken steps to integrate environmental, social, and governance (ESG) factors into financial regulations, including the Dodd-Frank Wall Street Reform and Consumer Protection Act which includes provisions for climate risk disclosure (Dodd-Frank, 2010).

Research has shown that legislation and regulations can have both positive and negative effects on financial markets. For instance, Brown et al. (2020) found that the announcement of the Paris Agreement on climate change led to an increase in the valuation of renewable energy companies, but a decrease in the valuation of coal and oil companies. In contrast, Tang et al. (2022) found that regulations on carbon emissions in the Chinese electricity sector led to a decrease in the market value of electricity firms. These findings highlight the complex interactions between policy and market dynamics, and the need to carefully design and implement climate and sustainability policies.

In conclusion, the Infrastructure Investment and Jobs Act (IIJA) is poised to have a significant impact on the transportation industry and financial markets. The legislation represents a significant shift in the government's approach to sustainability and carbon emissions reduction, placing increased pressure on the transportation industry to reduce its carbon footprint. As such, investors and policymakers must understand the potential implications of the IIJA for financial markets and the transportation industry.

Overall, the IIJA will have significant implications for the transportation industry and financial markets. By understanding the potential impact of this legislation, policymakers and investors can better position themselves to navigate the changing landscape of sustainability and climate finance to achieve fiduciary duties. The remainder of the paper is as follows: Section II presents a discussion of the related literature and develops hypotheses accordingly. Section III describes the sample and the research design. Section IV presents the main test results. Section V concludes the paper.

Literature Review and Hypotheses Development

The Infrastructure Investment and Jobs Act (IIJA) is a significant legislative effort aimed at investing in sustainable infrastructure and promoting job creation. This comprehensive piece of legislation encompasses various aspects of infrastructure development, including the transportation sector. While specific details of the IIJA may vary, its primary objective is to foster sustainability, facilitate decarbonization, and support economic growth United States Congress. (2021). The IIJA acknowledges the pressing need to reduce climate pollution and address the challenges posed by climate change. IIJA allocates more than $1 trillion in substantial funding and resources to projects that promote sustainable practices and contribute to the transition toward a low-carbon economy. This may involve investments in renewable energy infrastructure, the expansion of electric vehicle charging networks, and the modernization of transportation systems to enhance efficiency and reduce greenhouse gas emissions.

In terms of its impact on financial markets, the IIJA has the potential to create new investment opportunities and influence investor sentiment. The emphasis on sustainable infrastructure projects can generate increased interest and capital allocation towards sectors such as renewable energy, clean technology, and environmentally friendly infrastructure. This shift in investment patterns can shape market dynamics as investors assess the risks and returns associated with the ongoing transition toward a more sustainable and resilient economy. Specifically, the IIJA targets initiatives to transform the transportation sector and reduce its reliance on fossil fuels. This involves supporting mass adoption of electric vehicles, investing in public transportation systems, and improving the efficiency of transportation networks.

This literature review aims to examine the potential impact of the IIJA on the market performance of the transportation industry, particularly companies heavily dependent on crude oil. Additionally, it investigates the short-term market reactions associated with significant announcement dates related to the IIJA for both the S&P 500 and a sub-sample of energy stocks. Furthermore, it explores whether the market response to the IIJA announcement dates differs between the transportation industry and other sectors, such as renewable energy or technology.

H1: The passing of the Infrastructure Investment and Jobs Act will have a significant negative impact on the market performance of the transportation industry, particularly companies heavily dependent on crude oil.

Numerous studies have explored the relationship between government policies and the market performance of industries. A study by Apergis and Payne (2012) found that oil prices have a significant negative impact on transportation stock returns, suggesting that companies heavily dependent on crude oil may experience adverse market reactions. The authors suggest the importance of policy measures and investments to foster the transition towards renewable energy sources to achieve both environmental and economic goals. Similarly, Dechezleprêtre and Sato (2017) stated that environmental regulations can have short-term adverse effects on competitiveness. These findings support H1, suggesting that the implementation of the IIJA may have a significant negative impact on the market performance of the transportation industry, especially for companies heavily reliant on crude oil.

H2: Significant announcement dates related to the Infrastructure Investment and Jobs Act will lead to short-term market reactions for both the S&P 500 and a sub-sample of energy stocks.

Event study analysis is a widely employed methodology to assess short and long-term market reactions to significant events. By examining the market response to announcement dates related to IIJA, valuable insights into investor sentiment can be obtained. Antoniuk and Leirvik (2021) investigated the effect of the Paris Climate Agreement on the stock prices of energy firms and observed a significant negative reaction following the announcement. Castro et al. (2021) similarly found that investors have a favorable assessment of firms' environmental performance, ultimately impacting stock prices. These studies support H2, suggesting that significant announcement dates related to the IIJA are likely to result in short-term market reactions for both the S&P 500 and a sub-sample of energy stocks.

H3: The market response to the Infrastructure Investment and Jobs Act announcement dates will differ for the transportation industry compared to other industries, such as energy or the S&P 500.

The market response to government policies can vary across different industries. For example, Antoniuk and Leirvik (2021) demonstrated that the Paris Climate Agreement had a significant negative impact on energy sector stock prices. In contrast, Bernstein and Hoffman (2019) found that policies promoting renewable energy had a positive impact on the stock market value of firms in the clean energy sector. Therefore, H3 posits that the market response to the IIJA announcement dates will vary across sectors.

The literature reviewed supports the hypotheses related to the impact of the Infrastructure Investment and Jobs Act on the market performance of the transportation industry, short-term market reactions associated with the IIJA announcement dates, and the differential market response between the transportation industry and other sectors. The passing of the IIJA is expected to have a significant negative impact on the market performance of the transportation industry, particularly for companies heavily dependent on crude oil for transportation. Furthermore, significant announcement dates related to the IIJA are likely to result in short-term market reactions for both the S&P 500 and a sub-sample of energy stocks. The market response to the IIJA announcement dates may differ between the transportation industry and other sectors. These findings provide valuable insights into the potential market effects of the IIJA and underscore the importance of considering sector-specific dynamics in analyzing policy impacts on financial markets.

Sample and Empirical Methodology

Data Source and Sample Selection

The study examines the event study returns related to the passing of the Infrastructure Investment and Jobs Act and its impact on the transportation sector. The objective is to assess how investors value federal government actions aimed at decarbonization. Given that markets are forward-looking and legislation undergoes a traditional process before passage, the announcement period returns may also reflect the resolution of significant uncertainty in the transportation sector as the United States promotes the mass adoption of electrification for achieving a carbon-neutral environment.

The analysis utilizes the Dow Jones Transportation Average Index, a well-known weighted index comprising 20 major U.S. companies, to evaluate the transportation sector's performance. This selection enables the study to derive generalized conclusions despite the small sample size. To further investigate investor sentiment within the transportation sector, the analysis includes the Standard & Poor’s 500 index and a group of energy firms from the Standard & Poor’s 1500. Financial firms and utilities are excluded from the analysis due to regulatory factors, while energy and transportation firms are omitted to prevent overlapping results. As of December 2022, the sample comprises 20 U.S.-listed companies from the Dow Jones Transportation Average, 358 firms from the S&P 500, and 58 firms from the Standard & Poor’s 1500.

The Infrastructure Investment and Jobs Act was introduced to the House of Representatives by the Transportation and Infrastructure Committee on June 4, 2021, and progressed through the legislative process to become public law on November 15, 2021.

Empirical Model

The event study primarily examines abnormal changes in stock prices, also referred to as abnormal returns, following a specific event. First introduced by Ball and Brown (1968), event studies have become a widely utilized methodology in economic and finance literature for analyzing the impact of new information from specific events on stock prices. Binder (1998) provides a comprehensive review of this method. The event study methodology is based on testing the semi-strong form of the efficient market hypothesis (Fama, 1970; 1991), which asserts that stock prices incorporate all publicly available and relevant information. According to this hypothesis, stock prices should respond quickly to public information announcements. From this perspective, stock price movements can be interpreted as investors processing and responding to newly available information. In this article, the event study methodology is applied to analyze the impact of the Infrastructure Investment and Jobs Act on the transportation industry. A short window is utilized to minimize the influence of irrelevant information on stock prices.

The common approach to event studies begins with a regression of stock returns on market returns to estimate the parameters needed for calculating expected stock returns. There are three primary models for determining abnormal returns (He, Sun, Zhang, and Li, 2020): the average-adjusted return rate model, the market index-adjusted return rate model, and the market model. Each model presents its advantages and limitations. First, the average adjusted return rate model can result in significant deviations when a bull or bear market coincides with the event day (Klein and Rosenfeld, 1987). Second, the market index-adjusted return model often relies on strong assumptions about relationships, which complicates its application and renders it unsuitable in many cases (Huang and Li, 2018). Lastly, the market model is the most widely used in the literature due to its relatively strong predictive power. This model describes asset return behavior by using the value-weighted market portfolio derived from Center for Research in Security Prices (CRSP) files. For this study, the market model was selected due to its reliability and predictive capability. The model is defined as follows:

Calculate the normal rate of return:

$$R_{i,t} = \alpha_i + \beta_i R_{i,Mi,t} \tag{1}$$

Calculate the average abnormal rate of return:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{i,Mi,t}) \tag{2}$$

Calculate the cumulative abnormal rate of return:

$$CAR_{i(t1,t2)} = \Sigma_{t=2}^{t=1}(AR_{i,t}) \tag{3}$$

Where, $R_{i,t}$ is the return rate of stock i on the trading day t. $R_{i,Mi,t}$ is the market return rate of the trading market, α_i and β_i are the regression coefficients of the daily return rate of the stock i and the market return rate. The expected normal of individual stock i can be calculated if α_i and β_i remain stable during the estimation period. $AR_{i,t}$ is the average abnormal return rate of stock i on the trading day t. This is acquired by subtracting the expected return from the actual return. If $AR_{i,t}$ significantly differs from zero, it implies that market value deviates from fair value. The fair value's proxy is based on the CRSP value-weighted market portfolio. The portfolio is composed of NYSE, AMEX, and NASDAQ stocks. $CAR_{i(t1,t2)}$is an accumulated abnormal return of stock i during periods t_1 and t_2. The investigation of whether the market value deviates from the fair value involves testing if $CAR_{i(t1,t2)}$is significantly different from zero. Depending on whether $CAR_{i(t1,t2)}$ is negative or positive, conclusions can be drawn about whether stock prices deviate from their fair value during the examined period as investors and the market react to new information.

To perform the event study of the impact of the Infrastructure Investment and Jobs Act on the transport sector, it is necessary to identify the dates of the legislative process, referred to as announcement dates (AD). Attention is focused on two specific dates: the date the act was introduced to the House of Representatives (June 4, 2021) and the date it became public law (November 15, 2021). An event window of five days before and five days after the event (-5, +5) is utilized. The (-5, +5) event window is selected to reflect the efficiency of stock markets and aligns with prior literature in transportation and logistics research, which recommends an event window no longer than 10 days (Maneenop and Kotcharin, 2020; Gong et al., 2008; Gong et al., 2006; Park, 2004). Additionally, a short event window is employed to minimize the effects of additional announcements and prevent the overlapping of event periods. The objective is to examine whether abnormal returns exist surrounding the specified event period. The results suggest time-varying behaviors among participants in the stock markets within the transportation industry.

The literature has criticized the use of the event study methodology due to potential bias arising from the non-normality of the distribution of abnormal returns. To address this issue, Cowan's (1992) Generalized Sign Z test is adopted as a robustness check. Nonparametric tests do not require a distribution to meet specific assumptions to be applied. A rank test, while available, may be sensitive to the length of the event window or return variance, and is therefore avoided in this study. Instead, the generalized sign Z test is utilized due to its ability to account for a possible asymmetric return distribution under the null hypothesis.

Empirical Analysis

The Infrastructure Investment and Jobs Act represents the largest investment in U.S. infrastructure history, totaling $1.2 trillion. Following the methodology of previous researchers (Pham et al., 2019; Antoniuk and Leirvik, 2021), this study investigates how climate policy and decarbonization initiatives influence the business environment by examining the correlation between policy announcements and stock prices. Given that the transport sector is one of the largest contributors to greenhouse gas emissions, attention is focused on this sector by analyzing the market value of stocks before and after the announcement dates detailed in the legislative process.

Figure 1 depicts the averages of the cumulative abnormal returns for the Dow Jones Transportation Average during the introduction date of the Act. As seen from the figure, the introduction of the law had a negative impact on the Dow Jones Transportation Average's stock prices. Closely observing, each sample continued to follow a negative trend post introduction date. The energy sector experienced positive significant returns during [-5,0], before following a negative trend. There could be multiple interpretations surrounding the energy sector during this period. In an annual report released by S&P Global, energy demand outpaced supply leading to increased prices due to supply constraints, this could be in accordance with the volatility (S&P Global Inc., 2022). Investor sentiment shifted in favor of energy markets despite the introduction of the Infrastructure Investment and Jobs Act.

Figure 1: The Dow Jones Transportation Average cumulative abnormal returns on the introduction date

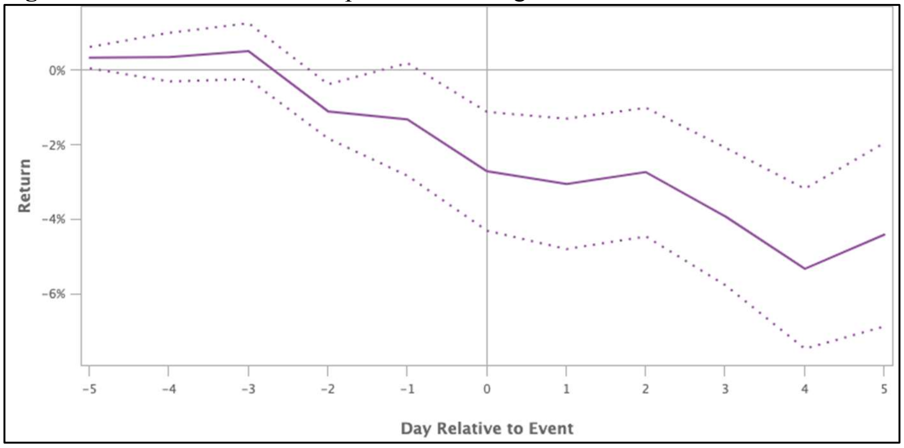


Figure 2 S&P 500's cumulative abnormal returns on the introduction date

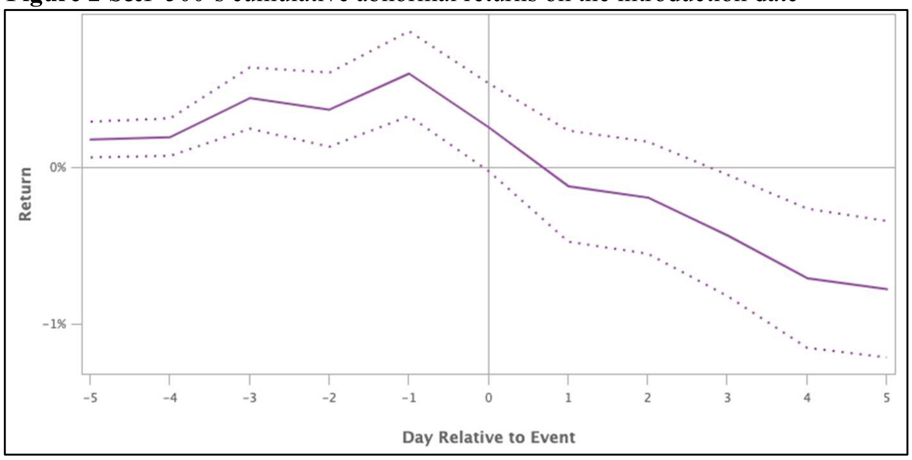
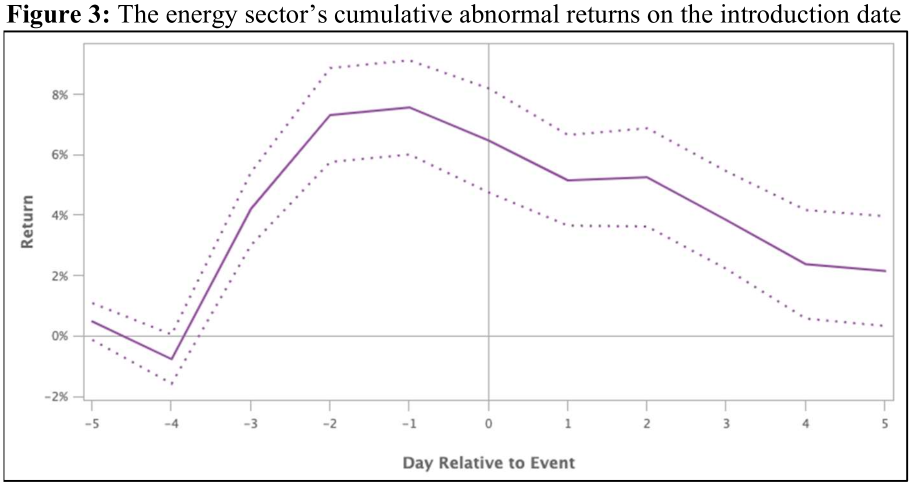


Figure 3: The energy sector's cumulative abnormal returns on the introduction date



Consequently, when the Infrastructure Investment and Jobs Act became public law (event 2), markets reacted differently compared to its introduction. The transportation sector and the S&P 500 experienced minimal positive impacts, whereas the energy markets faced a negative impact on stock prices. However, it is possible that the market had already priced in the public law announcement date due to the act being presented by the president on November 8th, 2021. This argument is further elaborated in Table 1, which is discussed in more detail next.

Table 1 presents the cumulative abnormal returns of the Dow Jones Transportation Average, the S&P 500 with the exclusion of energy, transportation, financials, and utilities, and the energy sector derived from the Standard & Poor's 1500 during two different event windows. Initially, observing Event 1, the Dow Jones Transportation Average experienced significant negative reactions by investors throughout all three windows observed. Investors interpreted the introduction of the Infrastructure Investment and Jobs Act negatively for the Dow Jones Transportation Average compared to its counterparts. The Dow Jones Transportation Average on the day of the introduction to the House of Representatives experienced nearly double the decline of energy stocks. In other words, 80 basis points.

Table 1 presents the cumulative abnormal returns for the Dow Jones Transportation Average, the S&P 500 (excluding energy, transportation, financials, and utilities), and the energy sector derived from the Standard & Poor's 1500 over two distinct event windows. During Event 1, significant negative investor reactions were observed for the Dow Jones Transportation Average across all three event windows. Furthermore, during this event, investor sentiment towards the Dow Jones Transportation Average was more pessimistic compared to its counterparts. Notably, on the day the Act was introduced to the House of Representatives, the Dow Jones Transportation Average experienced a decline twice as large as that of energy stocks, amounting to 80 basis points. This indicates that investors perceived the Act unfavorably in the context of the Dow Jones Transportation Average. Additionally, the generalized z nonparametric test corroborates the stock price reaction to the introduction date of Event 1. A potential explanation for the significant stock price declines in the transportation sector is that investors may view the current state of transportation as an unattractive investment amid the U.S. transition toward electrification.

Table 1: Cumulative abnormal returns in markets during different event window periods

Market	Window	Event 1 (Jun. 4, 2021) Mean	Event 1 (Jun. 4, 2021) Generalized Sign Z	Event 2 (Nov. 15, 2021) Mean	Event 2 (Nov. 15, 2021) Generalized Sign Z
Pre-event					
Transportation	[-5,0]	-2.84%	6.441*	-0.80%	-0.354
S&P 500	[-5,0]	-0.19%	-0.646	0.46%	3.237*
Energy	[-5,0]	8.53%	6.609*	-3.00%	-2.949*
On-event					
Transportation	[0,0]	-1.60%	-3.892*	0.33%	1.435***
S&P 500	[0,0]	-0.23%	-4.140*	0.05%	0.488
Energy	[0,0]	-0.80%	-3.047*	0.09%	1.490***
Post-event					
Transportation	[0,+5]	-3.26%	-2.997*	-0.32%	-0.802
S&P 500	[0,+5]	-0.74%	-4.458*	-0.19%	-0.780
Energy	[0,+5]	-2.92%	-2.783*	-6.37%	-5.821*

* Significant at the 1% level, ** significant at the 5% level, *** significant at the 10% level

Consequently, Event 2 lacks significance in the nonparametric test relative to Event 1. Within Event 2, the observed samples rarely moved during the event [0,0], with the Dow Jones Transportation Average gaining 33 basis points, significant at the 10 percent level. However, though it is not significant the Dow Jones Transportation Average lost its gains post-event [0,+5]. The energy sector generated significantly negative returns post-event [0,+5] with a mean cumulative abnormal return of -6.55 percent. As mentioned earlier, the energy sector became extremely volatile during the COVID-19 pandemic followed by geopolitical tensions (Aslam et al. 2023). Overall, we find that the Dow Jones Transportation Average reacted negatively towards introducing the Infrastructure Investment and Jobs Act rather than when the Act became public.

Conclusion

The transportation sector is a pivotal element in advancing the U.S. economy's sustainability and growth. Therefore, it is crucial to dissect the repercussions of the Infrastructure Investment and Jobs Act on this vital sector. By employing an event study methodology, stock price fluctuations of the Dow Jones Transportation Average, the S&P 500, and the specialized energy cohort from the S&P 1500 were observed pre and post-enactment. The data reveals a negative correlation on the introduction date: the Act's initiatives toward electrification efforts have, in the short-term, adversely affected the returns of companies listed in the Dow Jones Transportation Average. However, the Act offers a silver lining – companies can redirect funds from the Act towards strategic diversification and innovation, seeding potential for long-term resilience and a competitive edge. Future inquiries, bolstered by a broader dataset, promise to deepen understanding of these dynamics and supply chain interactions.

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All Small Credit Unions Are Not the Same: Evidence of Submarket Heterogeneity in Assets and Strategies

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Abstract

While much attention has been given to large credit union member growth and asset diversification, the market for small credit unions has also evolved since the turn of the century. This paper provides an empirical analysis of the small credit union market by dividing the data into three subsets, delineated by total asset size. Results show that the small credit union market continues to segment by loan composition and revenue strategy. U.S. small credit unions are following increasingly diverse loan and revenue strategies indicative of increasing complexity and diversity in this segment of the credit union market.

JEL Classification: G21
Keywords: credit unions, loans, income sources, credit and earnings risk

Introduction

The Federal Credit Union Act of 1934 (FCUA) provided regulatory guidelines for U.S. credit unions, a new type of not-for-profit financial institution designed to provide savings and lending opportunities for small individual consumers. Credit unions were designed to operate as cooperatives, owned by the participating members, to provide a low-cost source of credit and promote thrift for low net worth individuals associated through a common bond, such as a specific employer or a regional affiliation. Over the years, the original FCUA has been amended numerous times, and augmented with more federal legislation, resulting in an expansion of both the scope and mission of credit unions.

Recent research on credit union risk has primarily focused on the growth of large, federally chartered institutions (Esho et al., 2005; Goddard et al., 2016; Gomez-Biscarri et al. 2021) and specifically how larger credit unions have pursued growth strategies and increased revenues through increased lending in riskier types of loans and enhancement of non-loan sources of revenues (Goddard et al., 2008; Pleshko, 2006). This paper extends the literature by focusing on changes in the market for small credit unions, defined as under $50 million in total assets. The research shows that this segment of the market is fragmenting over time, with different sized smaller credit unions pursuing alternative asset strategies. The empirical results illustrate how the loan portfolio asset composition has evolved, resulting in different revenue streams in recent years.

This paper compares large versus small credit union changes in loan portfolios and income sources over the sample period to determine whether small credit unions are employing different strategies from large credit unions. Using univariate and matching estimation, the results show there are significant differences in loan portfolio composition and income sources between large and small credit unions. In addition, large credit unions have a more diverse loan portfolio and derive more income from non-loan interest sources. The analysis examines how these different types of loans and incomes sources affect forward-looking credit and earnings risk. The results show unsecured, used vehicle, and business loans add to forward-looking credit risk while nontraditional interest and operating income add to forward-looking earnings risk.

The small credit union sample is then divided into three subsets, delineated by total asset size, to examine whether the small credit union market is further segmented by loan composition and revenue strategy. Even across the smaller credit unions, as the size of the institution increased, the strategy changed to reflect greater lending in real estate-related loans and less emphasis on unsecured member debt. In terms of income sources, the smaller the institution, the greater the percentage of total income derived from loan interest. The results provide support for the continued fragmentation of the overall credit union market, with implications for the systemic risk exposure and regulation requirements based on the size and strategies employed by individual institutions.

Evolution of Credit Union Assets and Risk Exposure

Originally, credit unions pooled the savings deposits (known as shares) of members and used the deposits to make small, short-term personal or home improvement loans of two years or less to members. Multiple legislative amendments have expanded permitted types of loans as well as the maximum allowable term. By 1968, credit unions were allowed to help members by making up to 5-year unsecured loans, up to 10-year secured loans, as well as longer-term residential mortgage loans. By 1977, regulations were amended to allow up to 30-year residential loans, as well as home improvement and mobile home loans greater than 15-years in length.

Over the years, the breadth of acceptable loans that credit unions can make has expanded greatly (Getter, 2021). Today, credit unions may lend through credit cards and other forms of open-ended credit lines, make second mortgages, and offer home equity lines of credit, offer loans secured by mobile homes, boats, income producing properties, and on raw or improved acreage. Member business loans include loans for working capital needs, for term business needs to acquire capital assets, for agricultural purposes, and floor plan loans for dealer inventories. Credit unions are allowed to initiate loans guaranteed by the Small Business Administration (SBA), guaranteed student loans (part of the Federal Family Education loan program), and mortgages guaranteed by the Federal Housing Administration and Veterans Administration. Getter (2021) provides an excellent summary of the historical legislation that has changed the industry in terms of common bond restrictions, permitted loan types, and non-loan growth opportunities.

As financial intermediaries, credit unions face risks similar to that of other lenders. Repricing risk occurs due to the mismatched maturities associated with short-term liabilities (checking and savings deposits) and long-term assets (loans and investments). Since most loans are fixed rate, the ability to adjust to an increased cost of funds due to rising market interest rates is limited. Likewise, the market value of longer-term assets is much more price sensitive to shifts in the yield curve. Additionally, credit unions also have regulated interest rate caps on member loans. Disintermediation from member deposit withdrawals is also a concern.

The combination of restrictions on member base due to common bond requirements and new product development due to risk-based regulatory standards and examinations affects credit union growth prospects. Pleshko (2006) shows that, especially for established credit unions that have previously achieved significant penetration in existing markets, opportunities for growth derive primarily from current (rather than new) services offered. Wheelock and Wilson (2011) find that despite consolidation trends within the industry, most credit unions were still too small to take full advantage of scale economies. Goddard et al. (2016) show that large credit unions are more likely to survive a significant economic shock than small credit unions, and that younger credit unions are more likely to survive than older institutions.

The issue of risk diversification by credit unions is mixed. Neil et al. (2005) note that while the conventional view is that greater diversification of revenue sources results in lower risk of earnings volatility, credit unions expanding into revenue activities beyond traditional lending may result in higher risk due to moral hazard and agency problems. In a study of Australian credit unions, they find that increased reliance on fee income sources of revenue resulted in increased credit union risk.

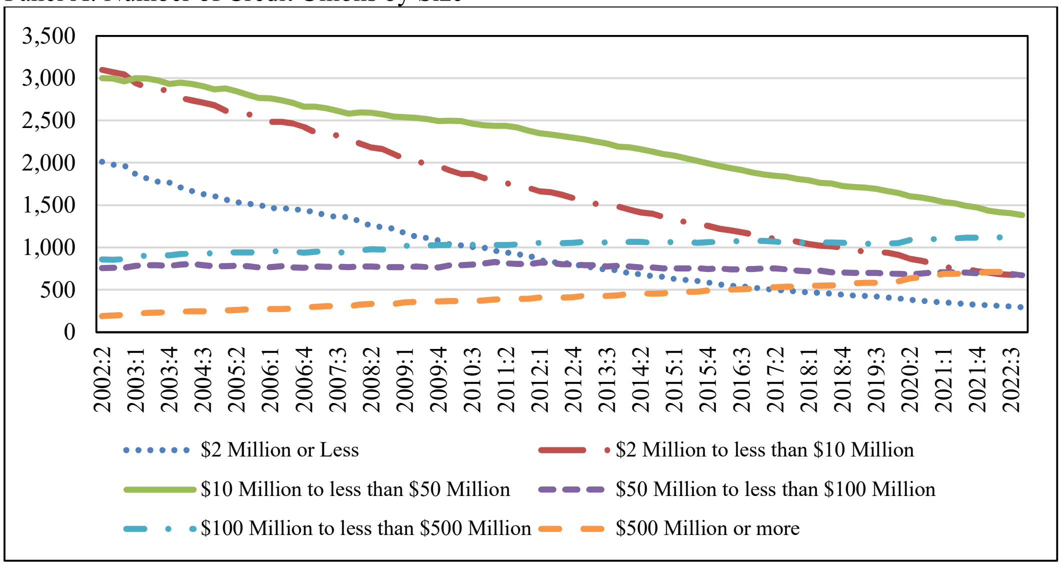
Literature and Hypothesis Development

Historically, the mission of providing small, unsecured loans to members meant that the average size, in both number of members and total assets, for credit unions was small relative to commercial banks. The common bond restriction on membership effectively enforced this ceiling on growth. However, Walter (2006) identifies five factors that diminished the influence on common bond membership and lending restrictions. One important factor was the emergence of national credit rating services that reduced the information advantage associated with member knowledge of personal trust and credit worthiness. As home ownership nationwide expanded dramatically in the second half of the twentieth century, the ability to obtain loans secured by home equity provided an alternative source of household debt. Additionally, the availability of credit cards as a preapproved unsecured line of credit decreased the need for local knowledge and presence for unsecured lending sources. Finally, the passage in 1970 of the National Credit Union Share Insurance Fund (NCUSIF) provided deposit insurance protection for federally chartered credit unions. Thus, the need for membership to monitor borrowers to protect their own interests was eliminated. The combination of these factors moved credit unions away from the historical model of small, member-organized and managed local institutions. The 1998 Credit Union Membership Act recognized these industry trends by revising the historical common bond restrictions to allow credit unions to expand service to multiple groups of members. Van Rijn (2024) shows that credit unions which converted to community charters (> 1000 institutions) experienced enhanced growth in membership, loan generation, and net income without suffering from reduced asset quality. Panel A of Figure 1 demonstrates that the number of small credit unions, classified as total assets less than $50 million, fell dramatically since 2002 while the number of large credit unions steadily rose. However, Panel B of Figure 1 shows the majority of member growth since 2002 occurred within the very largest segment of the market, credit unions with over $500 million in total assets. In fact, all other sized credit unions aggregately have witnessed declines in the number of members.

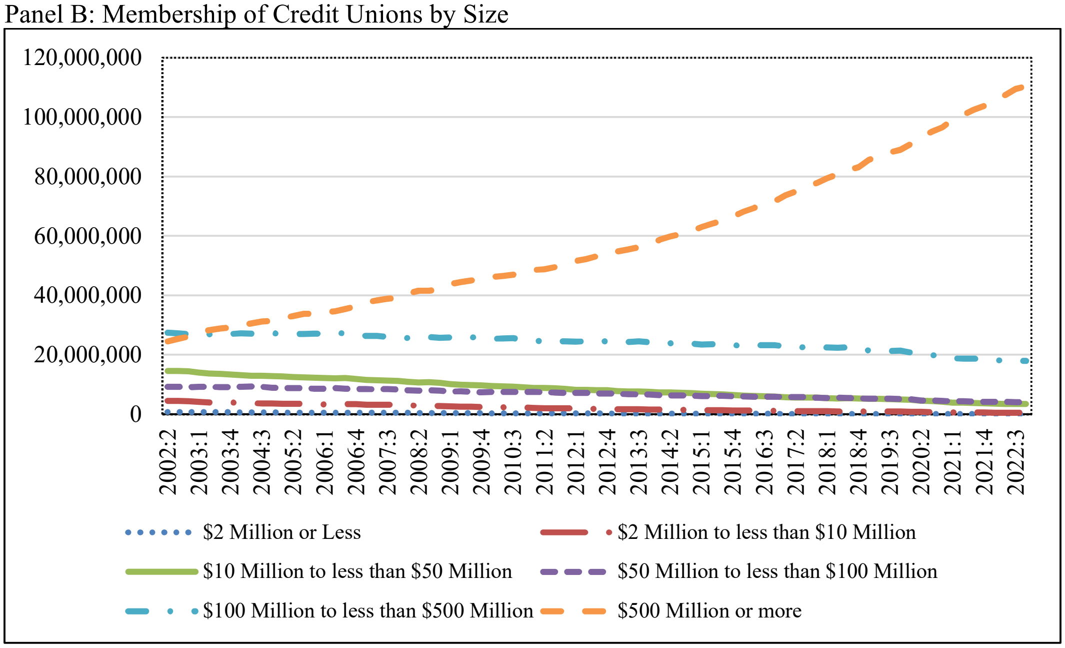
The literature on credit union performance and market influence indicates that size impacts both markets and institutions. Feinberg (2001) showed that in small metropolitan areas and rural counties where two banks held dominant market shares, the influence of "fringe" credit unions (i.e., price-takers) had a significant impact on the average lending rates for two distinct types of consumer loans. Despite the low market share, the presence of small credit unions had a strong direct effect on the rates offered on 24-month unsecured loans and 48-month new vehicle loans in these markets.

Wilcox (2006) studied the performance of large and small credit unions (less than $100 million in total assets) from 1980-2004. He reports significant economies of scale available to larger institutions, particularly in noninterest expenses associated with operations. The study shows this operating advantage increasing over time, with federal regulation enhancing the cost advantage of large credit unions. As the cost advantage grew during the sample period, the absolute number of small credit unions shrank from 17,132 to 7,859. Nevertheless, van Rijn (2022) found that despite changes in credit union size, membership requirements, and regulations, U.S. credit unions continue to reflect their cooperative identify and retain distinctive characteristics from other financial institutions.

Fig. 1. Number and membership by credit union size
Panel A: Number of Credit Unions by Size



Panel B: Membership of Credit Unions by Size



Notes: Data on total number of credit unions (Panel A) and total members (Panel B) was gathered from NCUA Call Reports from 2002Q2 until 2022Q4 and aggregated across credit unions each quarter based on six size groups.

As the regulations regarding credit union lending increasingly allowed for more diverse and risky loans, non-interest revenue sources rose, and membership bond restrictions relaxed, the credit union market has increasingly diverged between large and small institutions (Walter, 2006). Larger credit unions have pursued more aggressive lending and developed greater reliance on non-interest revenue sources, while taking advantage of economies of scale and scope (Esho et al. 2005). While previous studies indicated that many credit unions were overcapitalized (Jackson, 2007), Goodard et al. (2016) studied the factors affecting the capital to asset ratios of credit unions. Their findings indicate that large credit unions are more likely to survive than small credit unions, and younger credit unions are more likely to survive than older credit unions. In a previous study, these authors investigated the impact of revenue diversification strategies on credit union performance and found that small credit unions have more difficulty benefiting from diversification (Goodard et al., 2008).

The first hypothesis focuses on the differences in loan types between large and small credit unions, defining small credit unions as having total assets with less than $50 million. In addition, the paper also examines differences in sources of income, interest versus non-interest, between large and small credit unions.

Null Hypothesis (H$_0$): There is no difference between the loan portfolio composition of small and large credit unions.
Null Hypothesis (H$_0$): There is no difference between the sources of income for large and small credit unions.

The delineation of the credit union market into two subsets, small and large, follows much of the literature to date. This paper extends the literature by investigating whether the small credit union market underwent additional segmentation by subdividing the market for small credit unions into three groups, including institutions less than $2 million in total assets, $2 million to less than $10 million in total assets, and $10 million to $50 million in total assets. Each of the three peer groups of small credit unions are tested against each other to examine possible market segmentation.

Null Hypothesis (H$_0$): There is no difference between loan portfolio compositions of small credit unions of different sizes.
Null Hypothesis (H$_0$): There is no difference between sources of income for small credit unions of different sizes.

Do Loan and Income Sources Differ Based on Credit Union Size?

To examine changes in the loan strategies and sources of income for credit unions, National Credit Union Administration (NCUA) call report data for all natural person credit unions from 2002Q2 until 2022Q4 is used. The start of the data, 2002Q2, is selected because credit unions of all sizes were required to report balance sheet and income statement data quarterly to the NCUA. Prior to 2002Q2, only large credit unions defined as credit unions with assets greater than $50 million had to report quarterly and all others reported semiannually.

Univariate Analysis

Figure 2 provides a graphical depiction of the investment in different types of loans by large and small credit unions, respectively, over the sample period. SBA Loan data is not available from the NCUA until 2004Q1. While used and new vehicle loans are some of the more popular loans at credit unions regardless of size, first lien real estate loans are the majority of loans at large credit unions but only around ten percent of loans at small credit unions. Large credit unions also seem to be the dominant provider of business loans.

Fig. 2. Mean loan composition for credit unions based on size
Panel A: Credit Unions with Assets Greater than $50 Million

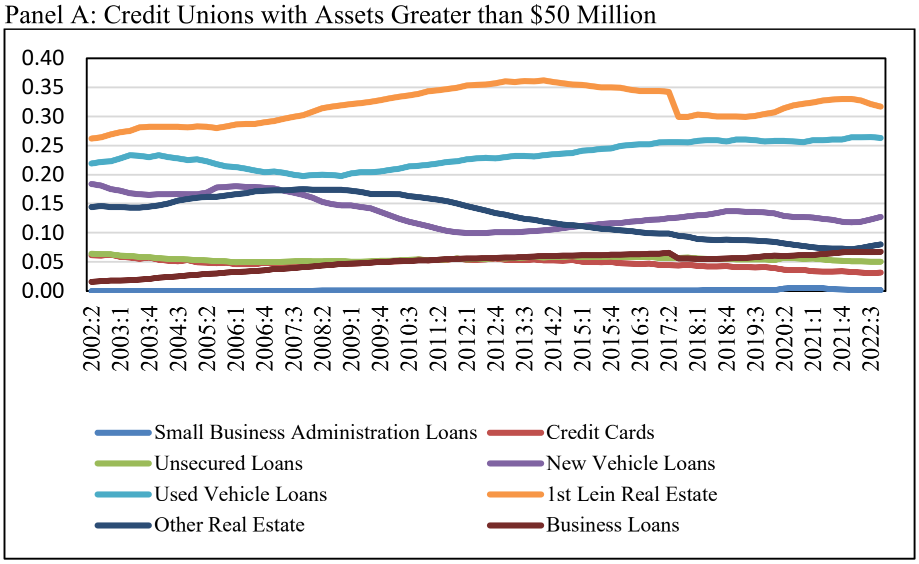
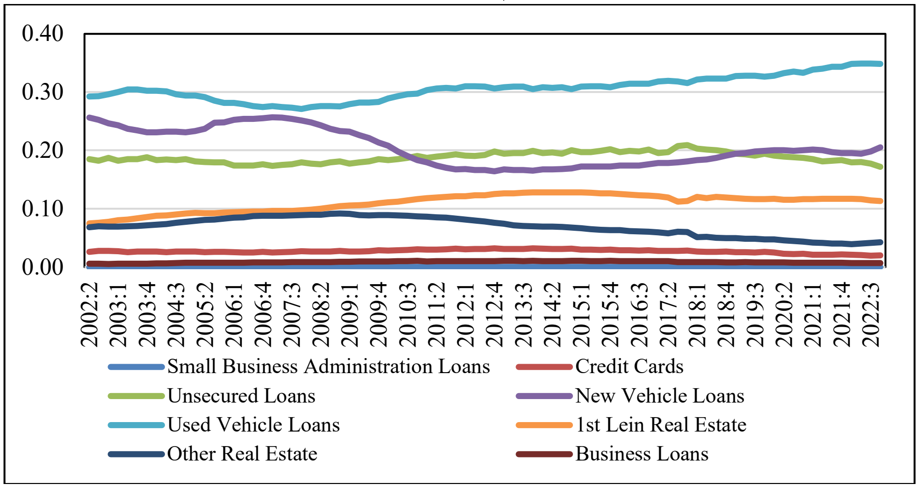
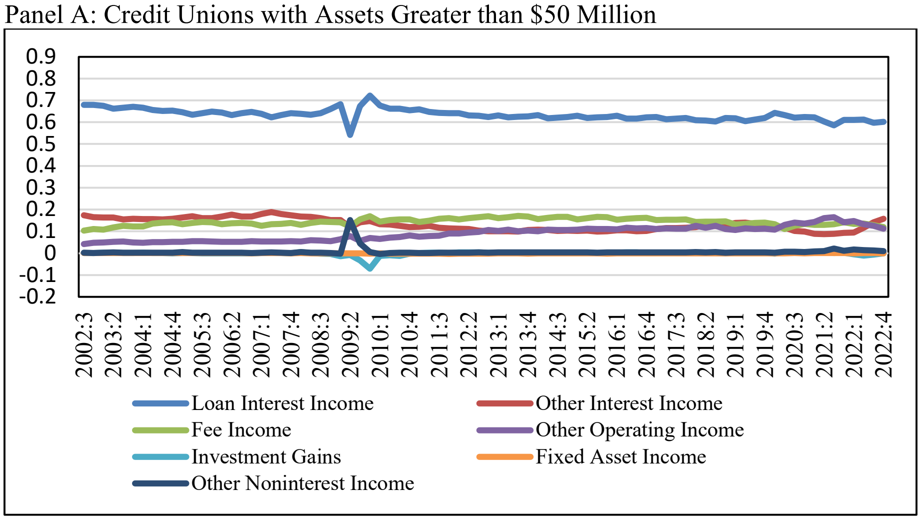


Fig. 2. Mean loan composition for credit unions based on size
Panel B: Credit Unions with Assets Less than $50 Million

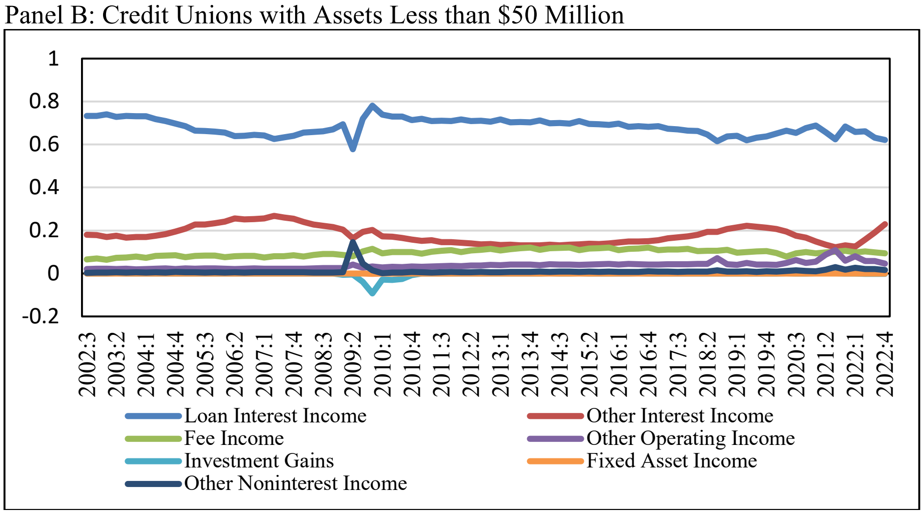


Notes: Data on loans was gathered from the NCUA Call Reports and aggregated across credit unions based on their size, measured by total assets, that quarter. Variables are defined in Appendix Table A.1.

Fig. 3. Mean income source comparisons for credit unions based on size
Panel A: Credit Unions with Assets Greater than $50 Million



Panel B: Credit Unions with Assets Less than $50 Million



Notes: Data on income was gathered from the NCUA Call Reports and aggregated across credit unions based on their size, measured by total assets, that quarter. Variables are defined in Appendix Table A.1.

Figure 3 provides a graphical depiction of the different income sources by large and small credit unions, respectively, over the sample period. Regardless of size, loan interest income is the largest source of income. Across both sizes of credit unions, fee income has increased across the sample period, although it has decreased recently. Large credit unions have seen a significant increase in other operating income and a decrease in other interest income across the sample period.

Table 1 Panel A contains t-tests for differences in means for the individual types of loans comprising the respective portfolios of small and large credit unions. The results indicate that there are significant differences in the mean values for each component of the average institution's loan portfolio. The null hypothesis of no significant difference in the loan portfolio components of small and large credit unions is rejected. Larger institutions had greater investments in SBA loans, credit cards, real estate, and business lending, while smaller credit unions had almost fifty percent of their total loans in new and used car loans, as well as nineteen percent in unsecured member lending.

Likewise, there are significant differences in the mean values for the respective sources of income. Table 1 Panel B reports the tests for differences in mean values. The null hypothesis of no difference in mean values of sources of income between small and large credit unions is rejected for each source of income. Larger institutions had greater income from fees, other

Table 1: T-tests of Differences in Means

	Assets > \$50 Million		Assets < \$50 Million			
	Number of Observations	Mean	Number of Observations	Mean	Difference	P-Value
Panel A: Loan Types						
SBA Loans	170268	0.0011	351975	0.0001	0.0010	0.0000
Credit Cards	183403	0.0470	406800	0.0270	0.0200	0.0000
Unsecured Loans	183403	0.0547	406800	0.1864	-0.1318	0.0000
New Vehicle Loans	183403	0.1344	406800	0.2120	-0.0776	0.0000
Used Vehicle Loans	183403	0.2342	406800	0.3003	-0.0661	0.0000
1st Lien Real Estate	183403	0.3199	406800	0.1057	0.2142	0.0000
Other Real Estate	183403	0.1260	406800	0.0733	0.0527	0.0000
Business Loans	183403	0.0504	406800	0.0081	0.0423	0.0000
Panel B: Income Sources						
Loan Interest Income	183068	0.6333	398618	0.6865	-0.0532	0.0000
Other Interest Income	183068	0.1293	398618	0.1840	-0.0547	0.0000
Fee Income	183068	0.1432	398618	0.0933	0.0499	0.0000
Other Operating Income	183068	0.0918	398618	0.0328	0.0590	0.0000
Investment Gains	183068	-0.0012	398618	-0.0035	0.0023	0.0000
Fixed Asset Income	183068	-0.0006	398618	-0.0002	-0.0004	0.0000
Other Noninterest Income	183068	0.0062	398618	0.0094	-0.0031	0.0000

Notes: T-tests between small and large credit unions from 2002Q2 until 2022Q4. Variables are defined in Appendix Table A.1.

operations, and investments while smaller credit unions had almost eighty-seven percent of their total income derived from interest, comprised of sixty-eight percent from loans and eighteen percent from other interest income.

The results support the prior research of Esho et al. (2005) and Goddard et al. (2008), who find that larger institutions pursue greater loan diversification strategies and derive higher percentages of total revenues from sources other than interest on loans. These results update the analysis through a more recent period. It is important to note that these results do not allow control for other credit union differences (beyond size as measured by total assets) that could be driving the differences in loan and income portfolios.

Matching Estimation

Next, matching estimation methodology is used to control for credit union variables that might be driving the differences in loan portfolio and income structure. Small and large credit unions are matched based on a \$50 million threshold on several financial ratios intended to proxy for CAMELS components as suggested by the Financial Performance Report User Guide provided by the NCUA. Following this list, matches are based on net worth for capital adequacy, delinquent loans for asset quality, membership growth for management quality, ROA for earnings, cash to assets for liquidity, and net long-term assets for sensitivity to market risk. To control for other credit union practices, the three-year volatility in ROA, the quarterly growth in the loan portfolio, a dummy variable to control for whether the credit union has a low-income designation, and a dummy variable to control for whether the credit union has a state or federal charter are included in the match. Appendix Table A.1 provides a detailed list of variable names and descriptions.

Since several of the credit union variables used to match on are continuous, exact matching cannot be done so Mahalanobis matching was employed. The Mahalanobis method matches based on the covariance-weighted distance between covariates so that each treated unit is matched to the nearest control observation. The standard errors for the Mahalanobis estimates are calculated using the robust standard errors developed by Abadie and Imbens (2011). In addition, the Mahalanobis estimates are adjusted for large-sample bias that can be introduced by matching on multiple continuous covariates, as recommended by Abadie and Imbens (2006).

In the baseline analysis, results are presented based on nearest neighbor, but for added robustness the results are also presented with the nearest two and three neighbors.

The results are provided in Table 2. Panel A provides results for the different loan types and Panel B for the income sources. Overall, the results largely support the conclusions reached with the univariate analysis. There are statistically significant differences across all eight types of loans examined. Small credit unions make fewer SBA loans, credit card loans, 1st mortgages, and business loans. While small credit unions make more unsecured loans and both new and used vehicle loans.

The only differences between these results and the univariate results are that other real estate loans are found to be larger for small credit unions in the matched results than large credit unions as in the t-tests. The results are similar when using nearest two and three neighbors.

In terms of income sources, the matching results also widely confirmed the findings in the univariate analysis. Small credit unions are found to have more income derived from interest, both loans and other sources, as well as fixed asset income, however they have less income from fees, other operations, and investment gains. Unlike the t-tests where large credit unions had statistically less other nonoperating income, there is no evidence that other nonoperating income is statistically different from zero. The results for two and three nearest neighbor matching are similar.

Analysis is provided for robustness of the results. First, two additional matching variables for periods of heightened risk such as 2008/2009 and 2020 are included in the analysis. The first is a dummy variable for the 2008/2009 recession and the second is a dummy variable for 2020 as these were both periods of heightened risk that might affect loan and income composition. The results are available in the first row of both Panels A and B of Table 3. Across both loans and income sources results remain similar to those in the baseline sample, suggesting that the 2008/2009 and 2020 heightened risk periods did not alter the results.

Second, credit unions are chartered based on a single common bond (such as a specific employer), a multiple common bond (such as service in one of the branches of the U.S. military), or a community-based bond (such as living in a specific geographic region). The historical requirement of common bond membership imposes limits on the potential market a credit union may serve. The common bond requirement implies that credit unions might have a higher default likelihood because of similarity among members than other types of financial institutions without common bond memberships. Thus, it might be necessary to control for this common bond. However, in 2002Q2 the NCUA stopped requiring state-chartered credit unions to report common bond data. To examine the impact that common bond requirements might have on risk, the sample is reduced to only examine federally chartered credit unions. Next, the matching is repeated with a few changes. First, because all state-chartered credit unions are dropped, the state-chartered dummy as a match is deleted. Second, additional dummies are added to match on: community, single, and multiple, which are equal to one if the credit union has a common bond membership for each type and zero otherwise. The results are found in the second rows of both panels A and B of Table 3. Again, the results are similar to those presented in the baseline results, except for investment income which is no longer statistically significant.

Do Different Loan and Income Types Affect Credit and Earning Risk?

Since previous results established that loan and income sources vary based on credit union size, it follows to examine if these differences contribute differently to risks that credit unions face, specifically credit and earnings risk.

Regression Model

Equation 1 provides the regression model used to examine the relationship between credit and earnings risk and the types of loans and income that credit unions employ.

$$Risk_{i,t} = \boldsymbol{\beta Sources_{i,t-1}} + \boldsymbol{\gamma Z_{i,t-1}} + \boldsymbol{\mu X_{i,t-1}} + \alpha_i + \varepsilon_{i,t} \quad (1)$$

Credit unions are indicated by subscript *i* and calendar quarters are indicated by subscript *t*. The dependent variable, *Risk*, is one of two measures of forward-looking risk, one, three, or five years ahead. The first is forward-looking credit risk calculated as the sum of the non-performing loans and charge-offs over the total amount of loans following Gomez-Biscarri et al. (2021). The second is forward-looking earnings risk calculated using return on assets (ROA) defined as net income over total assets. It might be argued that because credit unions are not-for-profit institutions, earnings risk does not matter as the goal of a credit union is not profit maximization. However, the contention here is that while profit might not be their primary motivation, they must maintain profitability to stay in operation and so earnings risk would be something management and stakeholders are monitoring. $Sources_{i,t-1}$ are the main variables of interest and represent either a vector of the eight different types of loans or a vector of the seven different income sources as used in the previous analysis and as defined in Appendix Table A1.

The vector $\boldsymbol{Z_{i,t-1}}$ includes several measures of credit union financial variables that were also used in the matching analysis. These include net worth, delinquent loans to total loans, membership growth, ROA, cash to assets, and net long-term assets. In models where the dependent variable is credit risk, the control for asset quality is excluded as credit risk is calculated using measures of asset quality. In models where the dependent variable is earnings risk, the control for earnings is excluded as earnings risk is calculated using ROA. To control for other credit union practices, the size of the credit union, the three-year volatility in ROA, the quarterly growth in the loan portfolio, a dummy variable to control for whether the credit union has a low-income designation, and a dummy variable to control for whether the credit union has a state charter versus a federal charter, are included.

The vector $\boldsymbol{X_{i,t-1}}$ includes several variables controlling for the macroeconomic market. First, the monthly unemployment rate at the state-level is gathered from the United States Bureau of Labor Statistics (BLS) and averaged to create quarterly observations. Second, quarterly census region-level Consumer Price Index (CPI) data is gathered from the BLS. Third, state-level quarterly personal income is gathered from the Bureau of Economic Analysis. Finally, the state-level quarterly housing price index is gathered from the Federal Housing Finance Agency. Data is matched to the credit union data on the state and census region where the credit union is headquartered. Appendix Table A.1 provides a detailed list of variable names and descriptions.

The term $\boldsymbol{\alpha_i}$ controls for credit union fixed effects. Standard errors are clustered at the credit union and quarter level and estimated using the *reghdfe* Stata command (Correia, 2016). The sample period is from 2002Q2 through 2022Q4 and covers 9,155 natural person credit unions. Table 4 provides the summary statistics for this sample.

The results from estimating Equation 1 when the dependent variable is credit risk can be found in Table 5. Columns 1 through 3 presents results using the one-year ahead risk variable for the full sample but also separating the sample into small and large credit unions based on the \$50 million cutoff, respectively. In Table 5, note that SBA loans statistically contribute to less credit risk. Other unsecured loans contribute to more credit risk, regardless of credit union size. While large credit unions made fewer used vehicle loans than small credit unions, the results indicated that these loans contribute to more credit risk at large credit unions. It is also shown that real estate loans and business loans contribute to the credit risk of large credit unions. So, while small credit unions seem to specialize in making vehicle loans, these do not seem to contribute significantly to credit risk for small credit unions. Columns 4 through 6 contain the results when examining the 3-year forward looking credit risk while columns 7 through 9 contain the results when the dependent variable is the 5-year forward looking credit risk. While the results remain similar to those presented with the 1-year credit risk, the significance does weaken for several of the variables with the exception of business loans which remain positive and statistically significant for large credit unions across all forward years.

Table 6 provides the results from estimating equation 1 when the dependent variable is earnings risk, and the variables of interest are the seven income sources. The table is laid out in a similar manner to Table 5. Regardless of credit union size, these results indicate that loan interest income contributes less to earnings risk. Other interest income contributes positively to earnings risk for small credit unions. Other operating income contributes positively to earnings risk for large credit unions. The finding that large credit unions have more income derived from these sources suggests they have more earnings risk. When looking at the results for the 3- and 5-year ahead earnings risk, similar results are found in those with one-year earnings risk. Interestingly, fee income and other operating income are positively related to 5-year forward earnings risk for all credit unions. In addition, other interest income is negatively related to the 5-year ahead earnings risk for small credit unions.

Robustness Tests

This section examines three robustness tests: removing heightened risk periods, controlling for common bond, and controlling for branch level macroeconomic indicators and bank competition. While results for the robustness tests are not provided for brevity, they are all available upon request from the authors upon request. First, to ensure that the 2008/2009 and 2020 periods of heightened credit risk are not driving the results, both the 2008/2009 period as well as the 2020 period are excluded jointly to recalculate the risk measures. Results are similar in direction of sign to those presented in Tables 5 and 6, although significance does vary. The results illustrate that while the sample period does cover several years of heightened risk, these periods are not driving the results.

To examine the impact that common bond might have on risk, the sample is reduced to only examine federally chartered credit unions. To examine the relationship, two new dummy variables are included. First, *community* is a dummy variable equal to one if the credit union has a community field of membership and zero otherwise. Second, *multiple* is a dummy variable equal to one if the credit union has a multiple common bond and zero otherwise. There is no control for a single common bond to avoid the model being exactly identified. Results are similar to those presented in Tables 5 and 6.

Finally, branch-weighted county macroeconomic indicators are included to control for macroeconomic characteristics of a credit unions operations, not just the headquarters. Additional controls for annual county-level measures of personal income, unemployment rate, GDP, and HPI are included. Credit union-level variables are created by weighing all measures by the percentage of a credit union's branches that are in that county and merging based on calendar year. In addition, to control for bank's presence in the county the methodology follows that used by Ely (2014) to control for the county-level measure of HHI of the total banking market and the percentage of the credit unions market that is small banks (banks less than $1 billion) as these are seen to be in direct competition of credit unions. However, branch level data is not reported by the NCUA until 2010 so this reduces the sample to be from 2010 until 2022. Results are similar to those presented in Table 5 and 6.

Table 2: Matching Results of Differences

Panel A: Loan Types	SBA Loans	Credit Cards	Unsecured Loans	New Vehicle Loans	Used Vehicle Loans	1st Lien Real Estate
Nearest Neighbor	0.0009***	0.0082***	-0.0383***	-0.0120***	-0.0189***	0.0647***
	(59.70)	(33.14)	(-69.77)	(-21.12)	(-27.95)	(58.10)
Nearest 2 Neighbors	0.0009***	0.0081***	-0.0384***	-0.0120***	-0.0191***	0.0647***
	(60.92)	(35.34)	(-75.11)	(-22.53)	(-30.11)	(62.04)
Nearest 3 Neighbors	0.0009***	0.0080***	-0.0385***	-0.0121***	-0.0193***	0.0647***
	(62.11)	(36.07)	(-77.73)	(-23.57)	(-31.43)	(64.24)
Panel B: Income Sources	Loan Interest Income	Other Interest Income	Fee Income	Other Operating Income	Investment Gains	Fixed Asset Income
Nearest Neighbor	-0.0263***	-0.0345***	0.0208***	0.0407***	0.0005***	-0.0003***
	(-33.71)	(-46.62)	(41.60)	(109.19)	(3.85)	(-7.88)
Nearest 2 Neighbors	-0.0258***	-0.0350***	0.0208***	0.0407***	0.0004***	-0.0003***
	(-35.67)	(-51.37)	(44.48)	(115.55)	(4.03)	(-8.45)
Nearest 3 Neighbors	-0.0256***	-0.0351***	0.0208***	0.0407***	0.0004***	-0.0003***
	(-36.61)	(-53.60)	(45.90)	(118.55)	(4.02)	(-9.01)

Notes: This table contains the results from Mahalanobis matching with one, two and three nearest neighbors for differences between small and large credit uni
Variables are defined in Appendix Table A.1. T-statistics are reported in parentheses where * is p<0.10, ** is p<0.05, and *** is p<0.01.

Table 3: Matching Results Robustness Tests

Panel A: Loan Types	SBA Loans	Credit Cards	Unsecured Loans	New Vehicle Loans	Used Vehicle Loans	1st Lien Real Estate
Controlling for Recession and Covid	0.0009***	0.0083***	-0.0382***	-0.0123***	-0.0192***	0.0635***
	(53.59)	(33.68)	(-67.76)	(-21.78)	(-28.58)	(58.09)
Only Federally Chartered	0.0009***	0.0075***	-0.0354***	-0.0113***	-0.0239***	0.0663***
	(48.88)	(22.13)	(-61.06)	(-15.88)	(-28.01)	(48.58)
Panel B: Income Sources	Loan Interest Income	Other Interest Income	Fee Income	Other Operating Income	Investment Gains	Fixed Asset Income
Controlling for Recession and Covid	-0.0264***	-0.0344***	0.0211***	0.0402***	0.0008***	-0.0003***
	(-33.99)	(-46.33)	(42.15)	(106.81)	(6.41)	(-8.54)
Only Federally Chartered	-0.0270***	-0.0253***	0.0172***	0.0368***	0.0001	-0.0002***
	(-28.36)	(-28.10)	(28.13)	(78.54)	(0.66)	(-3.71)

Notes: This table contains the robustness results from Mahalanobis matching with one, two and three nearest neighbors for differences between small and large
sources. Variables are defined in Appendix Table A.1. T-statistics are reported in parentheses where * is p<0.10, ** is p<0.05, and *** is p<0.01.

Table 4: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
Panel A: Loan Types					
SBA Loans	0.0004	0.0027	0	0.0292	491295
Credit Cards	0.0340	0.0444	0	0.2381	503399
Unsecured Loans	0.1375	0.1851	0	1	503399
New Vehicle Loans	0.1822	0.1375	0	0.6677	503399
Used Vehicle Loans	0.2792	0.1643	0	0.7910	503399
1st Lien Real Estate	0.1840	0.2072	0	0.8193	503399
Other Real Estate	0.0926	0.1192	0	0.6051	503399
Business Loans	0.0234	0.0646	0	0.5068	503399
Panel B: Income Sources					
Loan Interest Income	0.6636	0.1636	0.1062	1.1719	503327
Other Interest Income	0.1659	0.1544	-0.0003	0.8291	503327
Fee Income	0.1130	0.0960	-0.0305	0.4818	503327
Other Operating Income	0.0549	0.0704	-0.1212	0.3790	503327
Investment Gains	-0.0030	0.0321	-0.3209	0.0813	503327
Fixed Asset Income	-0.0004	0.0063	-0.0539	0.0400	503327
Other Noninterest Income	0.0086	0.0534	-0.1753	0.4532	503327
Panel C: Control Variables					
Net Worth	0.1345	0.0600	0.0471	0.4319	503399
Delinquent Loans	0.0184	0.0404	0	1	503399
Membership Growth	0.0001	0.0358	-0.2063	0.2727	503399
Return on Assets (ROA)	0.0009	0.0036	-0.0268	0.0133	503399
Cash	0.2668	0.1639	0.0259	0.8965	503399
Net-Long Term Assets	0.1844	0.1533	0.0037	0.6372	503399
Size	16.9501	2.0219	11.5368	22.0552	503399
ROA Volatility	0.0022	0.0030	0.0002	0.0267	503399
Loan Growth	0.0078	0.0543	-0.1985	0.3221	503399
Low Income	0.2578	0.4374	0	1	503399
State Charter	0.3935	0.4885	0	1	503399
Community	0.2682	0.4430	0	1	305311
Multiple	0.3370	0.4727	0	1	305311
Unemployment	0.0596	0.0221	0.019	0.2347	503399
CPI	5.4117	0.1185	5.1548	5.7555	503399
Personal Income	12.7454	0.9899	9.6707	14.9367	503399
HPI	5.8741	0.3456	5.0737	7.0140	503399
Panel D: Risk Measures					
1-Year Earnings Risk	0.0008	0.0025	-0.0144	0.0082	503399
3-Year Earnings Risk	0.0008	0.0019	-0.0083	0.0065	435480
5-Year Earnings Risk	0.0008	0.0016	-0.0062	0.0059	368490
1-Year Credit Risk	0.0200	0.0326	0	0.2807	503399
3-Year Credit Risk	0.0193	0.0284	0	0.2406	435480
5-Year Credit Risk	0.0189	0.0259	0.0001	0.2213	368490

Notes: This table presents summary statistics for the full sample of credit unions from 2002Q2 until 2022Q4. All data is gathered from NCUA call reports. A list of variable descriptions is available in Appendix Table A.1.

Table 5: Credit Risk Results

	(1) All 1-Year	(2) Small Only 1-Year	(3) Large Only 1-Year	(4) All 3-Year	(5) Small Only 3-Year	(6) Large Only 3-Year	(7) All 5-Year	(8) Small Only 5-Year	(9) Large Only 5-Year
SBA Loans	-0.0820**	-0.244*	-0.0383	-0.101**	-0.393**	-0.0408	-0.0538	-0.3110	0.0039
	(-2.36)	(-1.96)	(-1.32)	(-2.45)	(-2.50)	(-1.10)	(-0.88)	(-1.48)	(0.07)
Credit Cards	0.0135*	0.0230**	0.0040	0.0106	0.0209**	-0.0051	0.0002	0.0099	-0.0156***
	(1.97)	(2.14)	(0.84)	(1.55)	(2.00)	(-0.96)	(0.04)	(1.23)	(-2.90)
Unsecured Loans	0.0140***	0.0136***	0.0220***	0.0086***	0.0082***	0.0210***	0.0042*	0.0042*	0.0117**
	(5.48)	(5.04)	(5.13)	(3.83)	(3.47)	(4.29)	(1.92)	(1.82)	(2.10)
New Vehicle Loans	-0.0037	-0.0051	0.0000	-0.0004	-0.0013	0.0035	0.0020	0.0027	0.0023
	(-1.17)	(-1.28)	(-0.01)	(-0.13)	(-0.33)	(1.30)	(0.69)	(0.75)	(0.80)
Used Vehicle Loans	0.0056**	0.0055	0.0049**	0.0056*	0.0062	0.0029	0.0044	0.0060	-0.0001
	(2.01)	(1.52)	(2.22)	(1.95)	(1.66)	(1.31)	(1.54)	(1.65)	(-0.05)
1st Lien Real Estate	0.0024	-0.0006	0.0070***	0.0055**	0.0030	0.0089***	0.0032	0.0029	0.0029
	(0.97)	(-0.18)	(2.83)	(2.25)	(0.93)	(3.23)	(1.32)	(0.96)	(0.86)
Other Real Estate	0.0034	-0.0027	0.0135***	0.0091***	0.0030	0.0177***	0.0059**	0.0030	0.0082**
	(1.07)	(-0.68)	(4.66)	(3.05)	(0.82)	(5.18)	(2.15)	(0.92)	(2.30)
Business Loans	0.0167***	0.0122	0.0166***	0.0207***	0.0169**	0.0233***	0.0168***	0.0115*	0.0221***
	(4.82)	(1.61)	(4.64)	(5.15)	(2.35)	(4.79)	(4.20)	(1.88)	(4.17)
Net Worth	0.0553***	0.0739***	-0.0260**	0.0581***	0.0764***	0.0117	0.0493***	0.0662***	0.0234**
	(6.38)	(7.05)	(-2.09)	(7.04)	(7.41)	(1.16)	(6.30)	(6.57)	(2.57)
Membership Growth	0.0027***	0.0004	0.0101***	0.0044***	0.0033***	0.0096***	0.0043***	0.0043***	0.0063***
	(2.88)	(0.33)	(8.48)	(6.74)	(5.20)	(7.76)	(6.88)	(6.39)	(6.05)
Return on Assets (ROA)	-0.354***	-0.304***	-0.728***	-0.139***	-0.0904***	-0.484***	-0.0617***	-0.0256	-0.300***
	(-9.98)	(-10.09)	(-6.55)	(-5.38)	(-4.40)	(-5.99)	(-3.79)	(-1.66)	(-6.15)
Cash	-0.0102***	-0.0096***	-0.0138***	-0.0128***	-0.0127***	-0.0152***	-0.0104***	-0.0103***	-0.0122***
	(-6.80)	(-5.44)	(-9.35)	(-8.78)	(-7.50)	(-8.86)	(-7.90)	(-6.73)	(-7.41)
Net-Long Term Assets	-0.0052***	-0.0046**	-0.0081***	-0.0080***	-0.0087***	-0.0076***	-0.0056***	-0.0063***	-0.0049***
	(-3.62)	(-2.23)	(-6.31)	(-6.03)	(-4.67)	(-5.49)	(-4.52)	(-3.62)	(-3.44)
Size	0.0031***	0.0047***	0.0003	0.0045***	0.0078***	0.0012	0.0050***	0.0086***	0.0019**
	(3.87)	(3.49)	(0.48)	(5.17)	(5.42)	(1.45)	(5.61)	(5.98)	(2.18)
ROA Volatility	0.673***	0.591***	1.315***	0.272***	0.254***	0.495***	-0.0294	-0.0024	-0.0757
	(8.12)	(6.80)	(6.67)	(3.23)	(2.82)	(4.31)	(-0.39)	(-0.03)	(-1.13)
Loan Growth	-0.0315***	-0.0321***	-0.0258***	-0.0144***	-0.0136***	-0.0163***	-0.0047***	-0.0036***	-0.0082***
	(-19.46)	(-19.55)	(-11.42)	(-10.34)	(-9.67)	(-7.27)	(-3.89)	(-2.86)	(-4.47)
Low Income	-0.0005	-0.0002	-0.0008**	-0.0010**	-0.0006	-0.0014***	-0.0008*	-0.0005	-0.0011***
	(-1.14)	(-0.26)	(-2.39)	(-2.01)	(-0.81)	(-3.58)	(-1.75)	(-0.78)	(-2.83)
State Charter	0.0000	-0.0020	0.0021	0.0006	-0.0001	0.0009	0.0006	0.0005	0.0017***
	(-0.01)	(-0.20)	(1.48)	(0.18)	(-0.02)	(1.39)	(0.30)	(0.13)	(4.54)
Unemployment	0.0418**	0.0357**	0.0288*	0.0384**	0.0293*	0.0371**	0.0647***	0.0493***	0.0820***
	(2.53)	(2.25)	(1.88)	(2.42)	(1.94)	(2.33)	(8.04)	(4.90)	(8.84)
CPI	0.0034	-0.0011	0.0174***	-0.0051	-0.0031	0.0037	-0.0223***	-0.0226**	-0.0169***
	(0.57)	(-0.12)	(4.01)	(-0.71)	(-0.28)	(0.50)	(-3.97)	(-2.58)	(-2.67)
Personal Income	-0.0092***	-0.0095**	-0.0085***	-0.0112***	-0.0148**	-0.0099***	-0.0074***	-0.0088**	-0.0071***
	(-3.15)	(-2.04)	(-3.97)	(-3.40)	(-2.61)	(-3.59)	(-3.16)	(-2.02)	(-3.32)
HPI	-0.0049***	-0.0044**	-0.0065***	0.0009	0.0016	0.0014	0.0093***	0.0075***	0.0126***
	(-3.09)	(-2.29)	(-4.77)	(0.42)	(0.60)	(0.67)	(5.22)	(3.38)	(6.66)
Constant	0.0844***	0.0889***	0.0556***	0.0970***	0.0825***	0.0787***	0.0842***	0.0637**	0.0764***
	(5.49)	(3.86)	(4.54)	(4.61)	(3.06)	(3.80)	(4.51)	(2.55)	(3.82)
Number of Observations	481745	319074	160625	415023	274373	138798	349268	230652	117104
R^2	0.664	0.658	0.529	0.765	0.765	0.569	0.834	0.836	0.675

Notes: This table provides results from the regression given by Equation 1 using data on all, small, and large credit unions from 2002Q2 until 2022Q4. All variables are defined in Appendix Table A.1. T-statistics are reported in parentheses where * is p<0.10, ** is p<0.05, and *** is p<0.01.

Table 6: Earnings Risk Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Small Only	Large Only	All	Small Only	Large Only	All	Small Only	Large Only
	1-Year	1-Year	1-Year	3-Year	3-Year	3-Year	5-Year	5-Year	5-Year
Loan Interest Income	-0.0007***	-0.0006***	-0.0008***	-0.0005***	-0.0003***	-0.0007***	-0.0003***	-0.0001*	-0.0006***
	(-4.62)	(-3.44)	(-3.66)	(-4.56)	(-2.73)	(-4.00)	(-3.81)	(-1.74)	(-4.90)
Other Interest Income	0.0007***	0.0006**	0.0003	-0.0001	-0.0001	0.0001	-0.0002	-0.0003**	0.0002
	(2.85)	(2.63)	(1.12)	(-0.43)	(-0.72)	(0.43)	(-1.51)	(-2.01)	(0.99)
Fee Income	0.0003	-0.0001	0.0005	0.0008***	0.0006**	0.0005	0.0012***	0.0011***	0.0007***
	(0.78)	(-0.16)	(1.34)	(2.76)	(2.00)	(1.41)	(6.58)	(5.63)	(2.72)
Other Operating Income	0.0015***	0.0004	0.0016***	0.0020***	0.0011***	0.0018***	0.0020***	0.0012***	0.0016***
	(2.88)	(0.89)	(3.37)	(5.22)	(3.14)	(4.57)	(7.55)	(5.49)	(5.96)
Investment Gains	0.0011**	0.0010	0.0003	0.0003	0.0002	-0.0001	-0.0002**	-0.0002**	-0.0005***
	(1.99)	(1.65)	(0.64)	(1.11)	(0.68)	(-0.34)	(-2.23)	(-2.03)	(-3.21)
Fixed Asset Income	0.0008	-0.0006	0.0016**	-0.0006	-0.0014*	0.0004	-0.0009*	-0.0012*	-0.0001
	(0.95)	(-0.55)	(2.07)	(-0.97)	(-1.72)	(0.68)	(-1.75)	(-1.96)	(-0.15)
Other Noninterest Income	-0.0009	-0.0008	-0.0012	-0.0001	0.0000	-0.0005	0.0002	0.0002	-0.0001
	(-0.89)	(-0.87)	(-1.34)	(-0.23)	(-0.05)	(-1.48)	(0.85)	(0.82)	(-0.62)
Net Worth	-0.0106***	-0.0125***	-0.00967***	-0.0175***	-0.0205***	-0.0154***	-0.0175***	-0.0205***	-0.0172***
	(-8.42)	(-9.10)	(-5.67)	(-16.51)	(-17.02)	(-10.26)	(-21.49)	(-22.33)	(-14.05)
Delinquent Loans	-0.0106***	-0.0098***	-0.0433***	-0.00425***	-0.0039***	-0.0194***	-0.0016***	-0.0015***	-0.0068***
	(-13.19)	(-12.70)	(-10.23)	(-8.10)	(-7.73)	(-8.85)	(-4.12)	(-3.99)	(-5.25)
Membership Growth	0.0003***	0.0005***	-0.0007***	-0.0001**	0.0001	-0.0008***	-0.0001**	-0.0001	-0.0004***
	(2.88)	(4.81)	(-2.77)	(-2.06)	(1.19)	(-4.22)	(-2.58)	(-1.02)	(-3.36)
Cash	-0.0010***	-0.0012***	0.0002	-0.0004***	-0.0006***	0.0002	-0.0002**	-0.0003**	0.0000
	(-4.98)	(-6.56)	(0.61)	(-2.87)	(-3.87)	(0.74)	(-2.03)	(-2.63)	(0.10)
Net-Long Term Assets	-0.0004***	-0.0007***	-0.0004**	-0.0003**	-0.0004**	-0.0006***	-0.0001	-0.0001	-0.0003**
	(-2.83)	(-3.87)	(-2.24)	(-2.29)	(-2.29)	(-3.74)	(-0.67)	(-0.98)	(-2.09)
Size	0.0005***	0.0003**	-0.0002*	0.0000	-0.0006***	-0.0003**	-0.0005***	-0.0012***	-0.0006***
	(5.61)	(2.49)	(-1.85)	(-0.22)	(-3.83)	(-2.48)	(-4.96)	(-8.70)	(-4.69)
ROA Volatility	-0.0227***	-0.0168**	-0.0332**	0.0025	0.0002	0.0078	0.0190***	0.0105**	0.0412***
	(-2.83)	(-2.11)	(-2.11)	(0.37)	(0.02)	(0.74)	(4.01)	(2.11)	(5.22)
Loan Growth	0.0025***	0.0024***	0.0025***	0.0013***	0.0013***	0.0011***	0.0005***	0.0006***	0.0003
	(8.50)	(8.79)	(5.08)	(6.55)	(7.24)	(3.51)	(5.43)	(5.98)	(1.44)
Low Income	0.0002***	0.0002**	0.0002***	0.0003***	0.0002***	0.0003***	0.0002***	0.0001**	0.0002***
	(2.95)	(2.23)	(3.62)	(5.34)	(3.81)	(6.10)	(4.48)	(2.58)	(5.51)
State Charter	0.0011	0.0022***	-0.0009	0.0006	0.0017***	-0.0010*	0.0000	0.0004**	-0.0010***
	(1.09)	(4.28)	(-1.30)	(0.88)	(5.27)	(-1.94)	(-0.00)	(2.36)	(-2.72)
Unemployment	-0.0095***	-0.0127***	-0.0023	-0.0064**	-0.0078***	-0.0027	-0.0098***	-0.0096***	-0.0092***
	(-3.27)	(-3.90)	(-1.38)	(-2.47)	(-3.00)	(-1.45)	(-11.66)	(-9.76)	(-9.47)
CPI	-0.0071***	-0.0083***	-0.0024***	-0.0064***	-0.0088***	-0.0023**	-0.0019***	-0.0031***	0.0006
	(-6.97)	(-5.82)	(-2.87)	(-6.08)	(-5.35)	(-2.44)	(-3.53)	(-3.24)	(1.01)
Personal Income	0.0007	0.0006	0.0007**	0.0019***	0.0026***	0.0015***	0.0010***	0.0014***	0.0009***
	(1.40)	(0.77)	(2.17)	(4.08)	(3.16)	(3.67)	(4.46)	(2.81)	(3.81)
HPI	0.0009***	0.0014***	-0.0003	-0.0006*	-0.0004	-0.0015***	-0.0015***	-0.0012***	-0.0021***
	(3.17)	(4.11)	(-0.89)	(-1.70)	(-1.07)	(-4.36)	(-7.63)	(-5.25)	(-9.51)
Constant	0.0183***	0.0270***	0.0125***	0.0186***	0.0298***	0.0111***	0.0191***	0.0298***	0.0130***
	(8.30)	(9.58)	(6.41)	(6.30)	(8.24)	(4.54)	(9.41)	(11.25)	(6.74)
Number of Observations	493728	320602	171065	426596	275752	148978	360328	231899	126903
R^2	0.375	0.366	0.382	0.548	0.544	0.536	0.692	0.687	0.684

Notes: This table provides results from the regression given by Equation 1 using data on all, small, and large credit unions from 2002Q2 until 2022Q4. All variables are defined in Appendix Table A.1. T-statistics are reported in parentheses where * is p<0.10, ** is p<0.05, and *** is p<0.01.

Further Segmentation of Small Credit Unions

In addition to examining the differences between small and large credit unions, further examination is used for evidence of small credit unions undergoing further segmentation. The market is subdivided for small credit unions into three groups: institutions less than $2 million in total assets, $2 million to less than $10 million in total assets, and $10 million to $50 million in total assets. These groups correspond to the smallest three "peer groups" identified by the NCUA.

Univariate Analysis

Figure 4 illustrates the average loan portfolio composition for the smallest three market segments. Panel A provides mean measures for the smallest institutions, with under $2 million in total assets. These credit unions are characterized by loan portfolios that have a majority investment in unsecured, member loans (37%) and almost half the loans for automobiles (19% new, 29% used car loans). These credit unions in the smallest sector of the market invest little in credit card loans, real estate loans or business loans. In comparison, credit unions with between $2 million and $10 million in total assets, provided in Panel B, employ a slightly more aggressive investment strategy on average. Approximately 2% of the average loan portfolio is in credit card debt, and 10% is in some type of real estate loan. This segment is highly engaged in automobile lending, with 58% average investment in new and used car loans, and 20% unsecured member loans. Further highlighting how size influences investment strategy, those credit unions with between $10 million and $50 million in total assets, provided in Panel C, averaged 4% credit card loans, 31% in real estate-related loans, 46% in new and used car loans, and only 11% in unsecured loans to members.

Gomez-Biscarri, et al. (2021) found that expansion of business lending by credit unions greater than $50 million in total assets significantly increased the institution's risk exposure. The results confirm that over the sample period small credit unions did not highly engage in this segment of the market, nor did they make large investments in credit card debt. Instead, they employed strategies that, at the smallest institutions, focused on unsecured and automobile loans to members. As the size of the institution's average loan portfolio grew, the strategy changed to reflect greater lending in real estate-related loans and less emphasize on unsecured member debt. The results indicate there are significant differences in loan portfolio composition for credit unions with less than $50 million in total assets, evidence of increasing market segmentation over the sample period.

While not as dramatic as the differences in loan portfolio composition, the segmentation of the small credit union market clearly shows significant differences in sources of income as total assets rise. The smaller the institution, the greater the percentage of total income derived from loan interest. Institutions with less than $2 million in total assets on average generated 73% of their income from loan interest, while those between $10 million and $50 million derived 64% of their income from loan interest. Income from fees follows a similar trend. The smallest segment generated 5% of income from fee activities on average, the intermediate group about 8%, and the group between $10 and $50 million about 12%. Esho et al. (2005) found that an increased reliance on fee income was positively correlated with an increase in credit union risk. Figure 5 illustrates the differences in income sources based on size of total assets.

Univariate analysis is presented next on the small credit union sample. Panel A and B of Table 7 compare the smallest segment of the credit union market, those with less than $2 million in total assets, against the segment with between $2 million and $50 million in total assets. *P*-values from the tests for differences of mean loan and income source values indicate that the null hypothesis of no differences in mean is rejected for all loan types. Panel C and D of Table 7 reports the results of testing for loan portfolio components between the middle segment, between $2 and $10 million in total assets, against those institutions with less than $2 million and greater than $10 million in total assets. *P*-values indicate that the null hypothesis of no difference in mean values can be rejected for the average asset composition across all loan and income portfolio components. These results provide support for the contention that the market of small credit unions is not homogeneous in terms of strategies. Finally, Panel E and F of Table 7 reports the results of testing for loan portfolio components between those institutions with assets greater than $10 million versus those with less than $10 million in assets. The null hypothesis of no difference in means of loan portfolio components is rejected.

Matching Estimation

Similar to the baseline findings, results are reported based on matching estimation for the three small credit union segments. The format is the same as discussed previously with the exception that the sample is only credit unions with less than $50 million in total assets. The results are presented in Table 8 where Panel A is for the eight loan types and Panel B is for the seven income sources. The matching occurs based on credit unions in one of each of the three brackets compared to the other small credit unions. Panel A details a segmentation among loan products even among small credit unions. The results indicate that credit unions with assets from $10 to $50 million, the largest of the small credit union segments, make more SBA, credit cards, real estate, and business loans compared to the smallest credit unions. Likewise, the smallest credit unions specialize in other unsecured loans. Credit unions with assets between $2 and $10 million tend to make more vehicle loans than other credit unions. Panel B provides the results for the seven income sources and shows continued segmentation between small credit unions. The largest of the small credit union segments have less income from loan interest, investment gains, and fixed assets. Whereas the smallest credit unions have less income from fee income and other operating income.

Credit and Earnings Risk

As a final analysis, the results examining contributions to credit and earnings risk are presented by breaking the sample into the small credit union groups in Tables 9 and 10, respectively. Columns 1 through 3 present the results when the dependent variable is the one-year forward risk, columns 4 through 6 for the three-year ahead risk, and finally columns 7 through 9 for the 5-year forward risk.

Unsecured loans are a significant contributor to credit risk for the smallest credit unions, as these are the groups that initiate the majority of these loans. New vehicle loans contribute less to credit risk for credit unions with assets of $2 million and over. This is interesting as the middle group made more of these loans, but they contribute less risk. Used vehicle loans contribute to more credit risk for the smallest credit unions. Real estate loans contribute less credit risk for the larger credit unions, a product that they make more loans in compared to others. Finally, business loans contribute to more credit risk for credit unions with between $10 and $50 million in assets. Results when the dependent variable is the 3- and 5-year ahead credit risk are similar, albeit at lower levels of significance.

Table 10 reports the results when the dependent variable is earnings risk. The results show that loan interest income is negatively related to earnings risk for credit unions with assets between $10 and $50 million. However, these credit unions make significantly less income from this source. Other interest income contributes more to earnings risk for credit unions regardless of size. For the credit unions with between $2 and $10 million in assets, they make significantly more of their income from this source, which could be troubling. Looking at longer earnings risk, fee income and other operating income contribute to more credit risk for credit unions with over $2 million in assets.

Summary and Conclusions

The literature on credit union performance indicates that, using $50 million as the line of demarcation, small and large credit unions have pursued different investment strategies regarding types of loans and sources of income. Testing for these historical differences using data from a recent twenty-year period provides results which confirm the persistence of these size differences. However, while many credit unions continue to grow in total asset size seeking additional geographic market share, changes are also occurring in the small credit union market.

This paper extends the literature by segmenting the market for small credit unions into three distinct groups based on total asset size, employing statistical tests for differences in loan portfolio components and income sources. The empirical results suggest that the traditional market of “small” credit unions with less than $50 million in total assets is not homogeneous. T-tests for differences in mean values of loan components and income sources support the idea that institutions with less than $2 million in total assets pursue quite different strategies for profitability and income than those with $2 million to $10 million, as well as those between $10 million and $50 million. Likewise, comparisons of the strategies pursued by the two larger components of the small credit union market indicate significant differences as well. The conclusion is that the lower total asset portion of the credit union industry continued to segment during the sample period from 2002-2022, with significantly different strategies employed by managements depending on the total asset size of the institution.

These different loan products and income sources are examined to determine drivers for credit and earnings risk, respectively. The differences are documented by how loan products and income sources relate to credit and earnings risk across the different total asset segments. The findings show that certain types of loans and income contribute differently depending on the size of the institution, even when partitioning the small credit unions into smaller segments. The results from this research provide strong evidence that the overall U.S. credit union market continues to segment, including institutions with under $50 million in total assets. Further research is warranted for credit unions under $50 million in total assets based on differentiation of regulation, profitability, and risk exposure.

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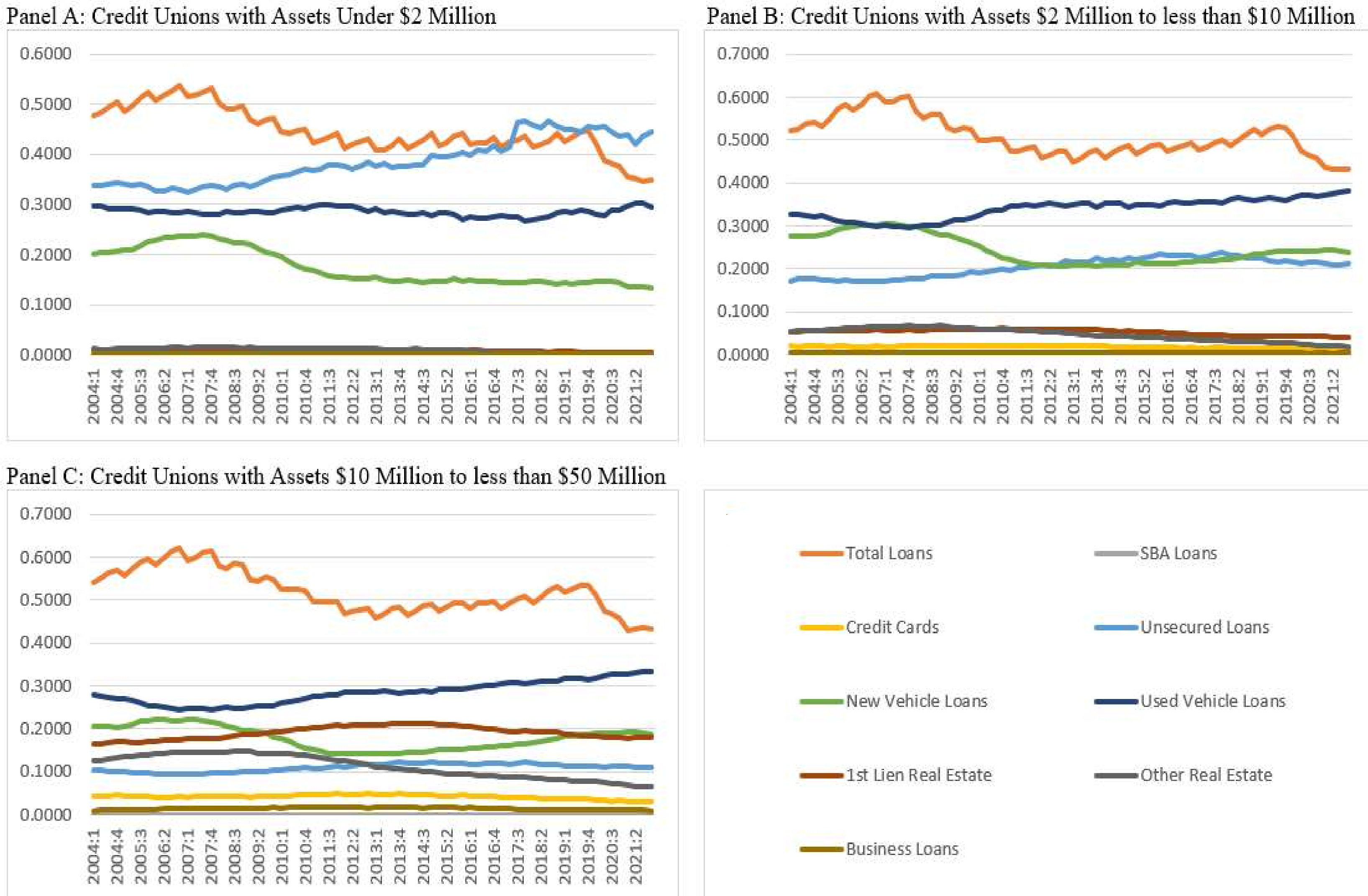
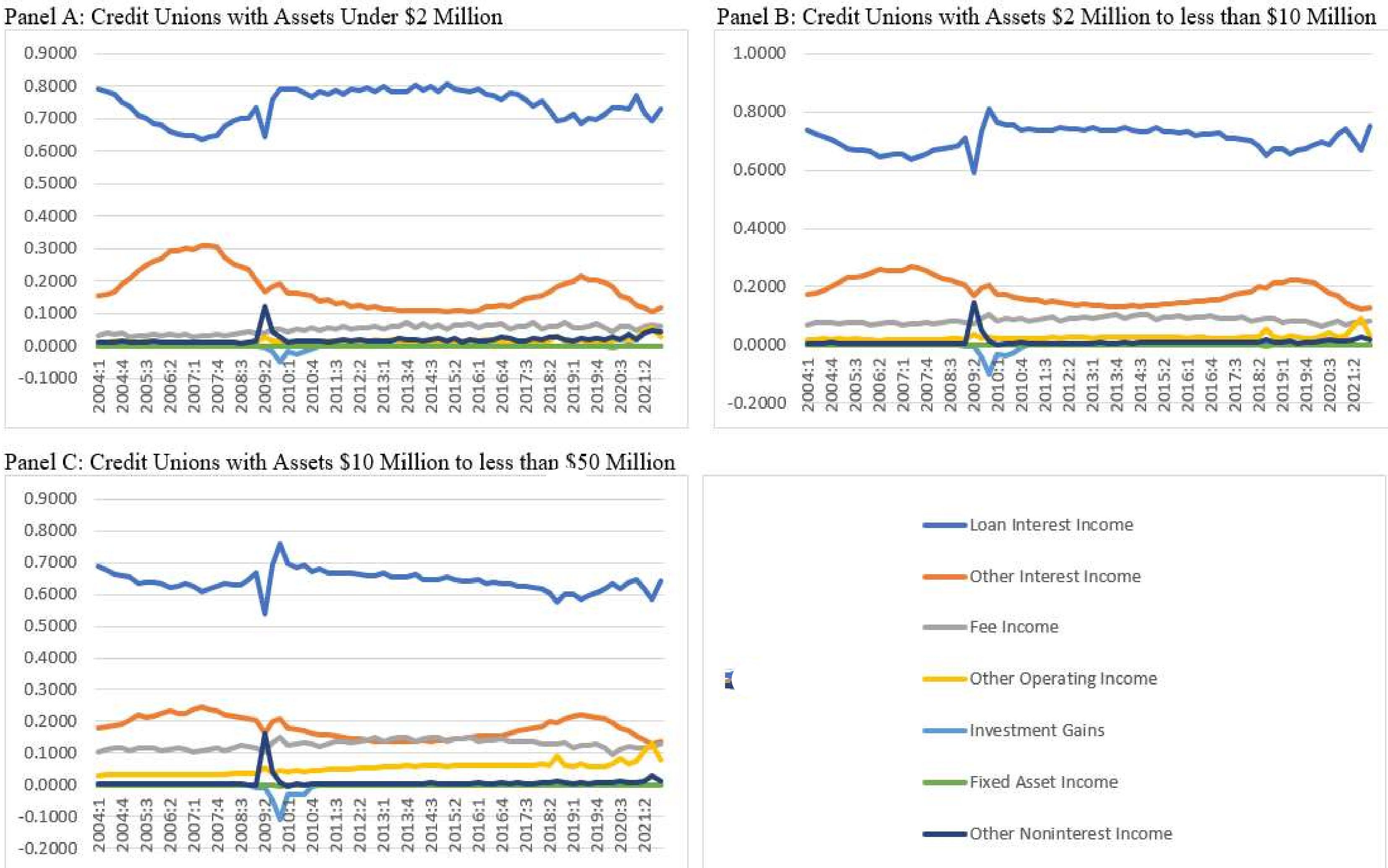
Fig. 4. Loan composition for small credit unions



Notes: Data on loans was gathered from the NCUA Call Reports and aggregated across credit unions based on their size, measured by total assets, that quarter. Variables are defined in Appendix Table A.1.

Fig. 5. Income sources for small credit unions



Notes: Data on income sources was gathered from the NCUA Call Reports and aggregated across credit unions based on their size, measured by total assets, that quarter. Variables are defined in Appendix Table A.1.

Table 7: T-tests of Differences in Means for Small Credit Unions

	$2 Million > Assets		$2 Million <Assets < $50 Million			
	Number of Observations	Mean	Number of Observations	Mean	Difference	P-Value
Panel A: Loan Types						
SBA Loans	64649	0.0000	287326	0.0001	0.0000	0.0000
Credit Cards	77841	0.0037	328959	0.0325	-0.0288	0.0000
Unsecured Loans	77841	0.3615	328959	0.1450	0.2165	0.0000
New Vehicle Loans	77841	0.1929	328959	0.2165	-0.0236	0.0000
Used Vehicle Loans	77841	0.2876	328959	0.3033	-0.0156	0.0000
1st Lien Real Estate	77841	0.0090	328959	0.1286	-0.1195	0.0000
Other Real Estate	77841	0.0110	328959	0.0880	-0.0770	0.0000
Business Loans	77841	0.0012	328959	0.0098	-0.0086	0.0000
Panel B: Income Sources						
Loan Interest Income	75705	0.7409	322913	0.6738	0.0671	0.0000
Other Interest Income	75705	0.1857	322913	0.1836	0.0020	0.0025
Fee Income	75705	0.0434	322913	0.1050	-0.0615	0.0000
Other Operating Income	75705	0.0133	322913	0.0374	-0.0241	0.0000
Investment Gains	75705	-0.0023	322913	-0.0037	0.0014	0.0000
Fixed Asset Income	75705	0.0000	322913	-0.0003	0.0003	0.0000
Other Noninterest Income	75705	0.0167	322913	0.0077	0.0091	0.0000

	$2 Million <Assets < $10 Million		Assets < $2 Million and > $10 Million			
	Number of Observations	Mean	Number of Observations	Mean	Difference	P-Value
Panel C: Loan Types						
SBA Loans	121146	0.0000	230829	0.0001	-0.0001	0.0000
Credit Cards	141923	0.0190	264877	0.0313	-0.0123	0.0000
Unsecured Loans	141923	0.1939	264877	0.1825	0.0114	0.0000
New Vehicle Loans	141923	0.2584	264877	0.1871	0.0713	0.0000
Used Vehicle Loans	141923	0.3324	264877	0.2831	0.0493	0.0000
1st Lien Real Estate	141923	0.0534	264877	0.1337	-0.0803	0.0000
Other Real Estate	141923	0.0515	264877	0.0850	-0.0335	0.0000
Business Loans	141923	0.0047	264877	0.0099	-0.0052	0.0000
Panel D: Income Sources						
Loan Interest Income	138856	0.7087	259762	0.6747	0.0340	0.0000
Other Interest Income	138856	0.1866	259762	0.1826	0.0040	0.0000
Fee Income	138856	0.0806	259762	0.1000	-0.0194	0.0000
Other Operating Income	138856	0.0226	259762	0.0383	-0.0157	0.0000
Investment Gains	138856	-0.0038	259762	-0.0033	-0.0005	0.0000
Fixed Asset Income	138856	-0.0001	259762	-0.0003	0.0002	0.0000
Other Noninterest Income	138856	0.0086	259762	0.0098	-0.0012	0.0000

	$10 Million<Assets < $50 Million		Assets < $10 Million			
	Number of Observations	Mean	Number of Observations	Mean	Difference	P-Value
Panel E: Loan Types						
SBA Loans	166180	0.0001	185795	0.0000	0.0001	0.0000
Credit Cards	187036	0.0428	219764	0.0136	0.0292	0.0000
Unsecured Loans	187036	0.1079	219764	0.2533	-0.1453	0.0000
New Vehicle Loans	187036	0.1847	219764	0.2352	-0.0506	0.0000
Used Vehicle Loans	187036	0.2812	219764	0.3165	-0.0353	0.0000
1st Lien Real Estate	187036	0.1856	219764	0.0377	0.1479	0.0000
Other Real Estate	187036	0.1157	219764	0.0371	0.0786	0.0000
Business Loans	187036	0.0136	219764	0.0035	0.0101	0.0000
Panel F: Income Sources						
Loan Interest Income	184057	0.6474	214561	0.7201	-0.0727	0.0000
Other Interest Income	184057	0.1814	214561	0.1863	-0.0049	0.0000
Fee Income	184057	0.1233	214561	0.0675	0.0558	0.0000
Other Operating Income	184057	0.0486	214561	0.0193	0.0293	0.0000
Investment Gains	184057	-0.0037	214561	-0.0033	-0.0004	0.0001
Fixed Asset Income	184057	-0.0004	214561	-0.0001	-0.0003	0.0000
Other Noninterest Income	184057	0.0069	214561	0.0115	-0.0045	0.0000

Notes: This table presents t-tests for the smallest three groups of credit unions across loan types from 2004Q1 until 2021Q4. Variables are defined in Appendix Table A.1

Table 8: Matching Results for Small Credit Unions

Panel A: Loan Types	SBA Loans	Credit Cards	Unsecured Loans	New Vehicle Loans	Used Vehicle Loans	1st Lien Real Estate	Other Real Estate	Business Loans
Under $2 Million	-0.0001***	-0.0103***	0.0892***	-0.0526***	-0.0147***	-0.0304***	-0.0137***	-0.0020***
	(-4.45)	(-32.70)	(31.31)	(-35.57)	(-8.13)	(-25.08)	(-23.11)	(-7.01)
$2 Million to $10 Million	-0.00003***	-0.0080***	0.0130***	0.0312***	0.0150***	-0.0331***	-0.0125***	-0.0014***
	(-5.44)	(-36.28)	(14.15)	(43.00)	(17.98)	(-52.03)	(-24.24)	(-9.28)
$10 Million to $50 Million	0.0001***	0.0195***	-0.0600***	-0.0344***	-0.0210***	0.0807***	0.0221***	0.0050***
	(20.00)	(63.60)	(-58.04)	(-43.89)	(-22.62)	(71.43)	(24.44)	(16.14)

Panel B: Income Sources	Loan Interest Income	Other Interest Income	Fee Income	Other Operating Income	Investment Gains	Fixed Asset Income	Other Noninterest Income
Under $2 Million	0.0703***	-0.0242***	-0.0385***	-0.0120***	0.0038***	0.0001***	-0.0013*
	(33.01)	(-10.98)	(-37.51)	(-21.58)	(11.08)	(3.29)	(-1.79)
$2 Million to $10 Million	0.0070***	0.0102***	-0.0084***	-0.0099***	0.0004*	0.0002***	-0.0001
	(8.55)	(13.92)	(-18.70)	(-36.44)	(1.92)	(7.06)	(-0.39)
$10 Million to $50 Million	-0.0330***	-0.0286***	0.0406***	0.0241***	-0.0016***	-0.0004***	0.0004
	(-32.11)	(-26.39)	(72.01)	(71.46)	(-10.19)	(-14.06)	(1.42)

Notes: This table presents t-tests for the smallest three groups of credit unions across income sources from 2004Q1 until 2021Q4. Variables are defined in Appendix Table A.1.

Table 9: Credit Risk Results

	(1) Under $2 mil 1-Year	(2) $2-$10 mil 1-Year	(3) $10-$50 mil 1-Year	(4) Under $2 mil 3-Year	(5) $2-$10 mil 3-Year	(6) $10-$50 mil 3-Year	(7) Under $2 mil 5-Year
SBA Loans	-0.2680	-0.3570	-0.0337	-0.7400	-0.2980	-0.1360	-0.1560
	(-0.35)	(-1.06)	(-0.33)	(-1.28)	(-1.50)	(-0.77)	(-0.33)
Credit Cards	0.0915	0.0215	-0.0035	0.0725	0.0153	-0.0117	0.0492
	(1.25)	(1.56)	(-0.53)	(1.14)	(1.08)	(-1.66)	(1.15)
Unsecured Loans	0.0120***	0.0142***	0.0075	0.0052	0.0142***	0.0022	0.0013
	(3.05)	(3.07)	(1.38)	(1.62)	(3.44)	(0.41)	(0.42)
New Vehicle Loans	0.0068	-0.0123***	-0.0113***	0.0086	-0.0095**	-0.0083**	0.0128
	(0.71)	(-2.68)	(-3.66)	(0.87)	(-2.20)	(-2.56)	(1.34)
Used Vehicle Loans	0.0170**	-0.0007	-0.0006	0.0222**	-0.0036	-0.0014	0.0197**
	(2.11)	(-0.15)	(-0.20)	(2.48)	(-0.87)	(-0.49)	(2.16)
1st Lien Real Estate	-0.0120	0.0006	-0.0083***	0.0075	0.0036	-0.0093***	0.0088
	(-0.63)	(0.11)	(-2.83)	(0.37)	(0.62)	(-3.21)	(0.47)
Other Real Estate	0.0083	-0.0134*	-0.0074**	0.0175	-0.0093	-0.0064*	0.0080
	(0.35)	(-1.95)	(-2.23)	(0.81)	(-1.51)	(-1.95)	(0.34)
Business Loans	-0.0362	-0.0034	0.0228***	-0.0133	0.0043	0.0221**	-0.0031
	(-1.25)	(-0.33)	(2.84)	(-0.42)	(0.51)	(2.59)	(-0.10)
Net Worth	0.119***	0.0498***	0.0141*	0.134***	0.0646***	0.0342***	0.121***
	(3.94)	(4.34)	(1.68)	(3.92)	(5.30)	(3.50)	(3.46)
Membership Growth	-0.0095***	0.0008	0.0067***	-0.0019	0.0044***	0.0074***	0.0009
	(-3.04)	(0.54)	(5.90)	(-1.29)	(4.95)	(7.20)	(0.39)
Return on Assets (ROA)	-0.247***	-0.242***	-0.332***	-0.0586	-0.0477	-0.124***	-0.0478
	(-3.89)	(-7.19)	(-8.36)	(-1.27)	(-1.46)	(-3.99)	(-1.24)
Cash	-0.0144***	-0.0059***	-0.0078***	-0.0223***	-0.0080***	-0.0088***	-0.0198***
	(-2.86)	(-3.46)	(-6.25)	(-4.29)	(-4.67)	(-6.63)	(-3.95)
Net-Long Term Assets	0.0056	-0.0080**	-0.0051***	-0.0159*	-0.0106***	-0.0035**	-0.0190**
	(0.51)	(-2.28)	(-3.41)	(-1.72)	(-3.40)	(-2.34)	(-2.38)
Size	0.0029	0.0076***	0.0034***	0.0174***	0.0093***	0.0043***	0.0213***
	(0.48)	(4.41)	(3.20)	(2.70)	(5.11)	(3.54)	(3.22)
ROA Volatility	0.537***	0.565***	0.720***	0.2810	0.273***	0.417***	0.1060
	(3.07)	(5.34)	(6.72)	(1.44)	(2.84)	(3.93)	(0.55)
Loan Growth	-0.0341***	-0.0252***	-0.0238***	-0.0153***	-0.0082***	-0.0120***	-0.0027
	(-11.02)	(-13.54)	(-13.99)	(-6.29)	(-6.25)	(-7.61)	(-1.14)
Low Income	-0.0022	-0.0011	0.0005	0.0004	-0.0015	0.0000	0.0022
	(-0.57)	(-1.14)	(1.09)	(0.10)	(-1.52)	(-0.02)	(0.59)
State Charter	0.0000	-0.0070***	0.0004	0.0000	0.0000	0.0034	0.0000
	(.)	(-7.75)	(0.03)	(.)	(.)	(0.53)	(.)
Unemployment	0.0128	0.0454***	0.0349***	0.0262	0.0514***	0.0546***	0.0143
	(0.25)	(2.94)	(3.21)	(0.49)	(3.36)	(4.35)	(0.28)
Inflation	-0.0553*	-0.0162	0.0065	-0.0483	-0.0179	0.0012	-0.0294
	(-1.93)	(-1.27)	(1.05)	(-1.38)	(-1.30)	(0.14)	(-0.85)
Personal Income	0.0164	-0.0051	-0.0100***	0.0013	-0.0079	-0.0112***	-0.0189
	(1.11)	(-0.74)	(-3.02)	(0.07)	(-1.08)	(-2.77)	(-1.07)
HPI	-0.0105	-0.0019	-0.0043***	0.0084	0.0067**	0.0031	0.0106
	(-1.30)	(-0.85)	(-3.40)	(0.76)	(2.03)	(1.49)	(1.04)
Constant	0.1390	0.0622*	0.0756***	-0.0142	0.0277	0.0570***	0.0785
	(1.25)	(1.98)	(4.40)	(-0.11)	(0.97)	(2.96)	(0.64)
Number of Observations	43215	86475	123233	34177	73302	106615	27741
R^2	0.616	0.638	0.581	0.741	0.74	0.673	0.811

Notes: This table provides results from the regression given by Equation 1 using data on all, small, and large credit unions from 2002Q2 until 2022Q4. All variables are
T-statistics are reported in parentheses where * is p<0.10, ** is p<0.05, and *** is p<0.01.

Table 10: Earnings Risk Results

	(1) Under $2 mil 1-Year	(2) $2-$10 mil 1-Year	(3) $10-$50 mil 1-Year	(4) Under $2 mil 3-Year	(5) $2-$10 mil 3-Year	(6) $10-$50 mil 3-Year	(7) Under $2 mil 5-Year	(8) $2-$10 mil 5-Year	(9) $10-$50 mil 5-Year
Loan Interest Income	0.0003	0.0000	-0.0004**	0.0000	-0.0002	-0.0001	0.0000	-0.0002	-0.0001
	(1.00)	(0.12)	(-2.03)	(0.09)	(-1.24)	(-0.94)	(-0.15)	(-0.99)	(-0.68)
Other Interest Income	0.0018***	0.0013***	0.0007***	0.0003	0.0000	0.0001	-0.0002	-0.0002	-0.0002
	(4.28)	(3.51)	(2.68)	(0.82)	(0.02)	(0.27)	(-0.90)	(-0.94)	(-1.09)
Fee Income	0.0008	-0.0004	-0.0007*	0.0000	0.0009*	0.0006*	0.0007	0.0010**	0.0006**
	(1.04)	(-0.76)	(-1.94)	(0.06)	(1.90)	(1.75)	(1.46)	(2.58)	(2.40)
Other Operating Income	0.0011*	0.0002	-0.0002	0.0002	0.0008**	0.0008**	0.0003	0.0008**	0.0009***
	(1.71)	(0.46)	(-0.67)	(0.34)	(2.08)	(2.40)	(0.71)	(2.37)	(3.74)
Investment Gains	0.00171*	0.0008	0.0007	0.0009	0.0001	0.0003	-0.0002	-0.0002	-0.0001
	(1.89)	(1.52)	(1.35)	(1.35)	(0.28)	(1.21)	(-0.57)	(-1.00)	(-0.40)
Fixed Asset Income	0.0054	-0.0005	-0.0006	-0.0008	-0.0018	-0.0008	-0.0022	-0.0019	-0.0004
	(0.95)	(-0.20)	(-0.58)	(-0.18)	(-0.99)	(-0.91)	(-0.52)	(-1.30)	(-0.59)
Other Noninterest Income	0.0020**	0.0004	0.0001	0.0009*	0.0006	0.0004	0.0002	0.0005	0.0004
	(2.65)	(0.89)	(0.40)	(1.72)	(1.56)	(1.42)	(0.46)	(1.34)	(1.54)
Net Worth	-0.0158***	-0.0081***	-0.0072***	-0.0247***	-0.0182***	-0.0185***	-0.0239***	-0.0200***	-0.0198***
	(-7.53)	(-5.74)	(-5.50)	(-12.33)	(-11.30)	(-11.43)	(-12.72)	(-16.15)	(-16.05)
Delinquent Loans	-0.0069***	-0.0198***	-0.0223***	-0.0027***	-0.0081***	-0.0091***	-0.0013***	-0.0034***	-0.0047***
	(-8.60)	(-12.85)	(-12.25)	(-4.79)	(-7.17)	(-9.17)	(-3.38)	(-3.82)	(-6.22)
Membership Growth	0.0010***	0.0007***	-0.0001	0.0003***	0.0002	-0.0005***	0.0002*	-0.0001	-0.0004***
	(4.59)	(2.81)	(-0.38)	(3.15)	(1.32)	(-3.68)	(1.79)	(-0.98)	(-3.50)
Cash	-0.0015***	-0.0011***	-0.0004	-0.0003	-0.0006***	-0.0003	0.0001	-0.0005***	-0.0002
	(-4.63)	(-4.90)	(-1.54)	(-1.02)	(-3.44)	(-1.38)	(0.26)	(-3.50)	(-1.65)
Net-Long Term Assets	-0.0009	-0.0008***	-0.0006***	0.0001	-0.0005*	-0.0004**	0.0003	-0.0003	-0.0003**
	(-1.48)	(-3.06)	(-2.97)	(0.16)	(-1.91)	(-2.21)	(0.74)	(-1.40)	(-2.07)
Size	0.0000	0.0005**	-0.0002*	-0.0023***	-0.0005*	-0.0008***	-0.0028***	-0.0011***	-0.0012***
	(0.01)	(2.53)	(-1.76)	(-6.11)	(-1.95)	(-4.59)	(-7.91)	(-5.53)	(-8.08)
ROA Volatility	-0.0015	-0.0080	0.0045	-0.0046	-0.0092	0.0095	0.0007	-0.0018	0.0105
	(-0.11)	(-0.74)	(0.41)	(-0.44)	(-1.01)	(1.17)	(0.07)	(-0.23)	(1.55)
Loan Growth	0.0015***	0.0027***	0.0024***	0.0006***	0.0015***	0.0016***	0.0001	0.0007***	0.0009***
	(6.39)	(10.30)	(11.11)	(4.02)	(8.12)	(6.05)	(0.86)	(5.90)	(4.88)
Low Income	-0.0002	-0.0002*	0.0002***	-0.0001	-0.0001	0.0002***	-0.0002	-0.0001	0.0002***
	(-0.63)	(-1.86)	(2.71)	(-0.26)	(-0.95)	(4.15)	(-0.96)	(-0.75)	(3.74)
State Charter	0.0000	-0.0006***	0.0022**	0.0000	0.0000	0.0014**	0.0000	0.0000	0.0001
	(.)	(-3.67)	(2.14)	(.)	(.)	(2.29)	(.)	(.)	(1.28)
Unemployment	-0.0175***	-0.0144***	-0.0113***	-0.0128***	-0.0101***	-0.0120***	-0.0093***	-0.0067***	-0.0099***
	(-4.14)	(-5.50)	(-6.18)	(-3.80)	(-5.78)	(-9.18)	(-3.16)	(-5.03)	(-8.58)
Inflation	-0.0083***	-0.0054***	-0.0024***	-0.0114***	-0.0078***	-0.0035***	-0.0062*	-0.0044***	-0.0007
	(-5.26)	(-3.88)	(-3.01)	(-4.77)	(-5.57)	(-2.93)	(-1.95)	(-3.94)	(-0.67)
Personal Income	-0.0018**	-0.0016**	-0.0011**	0.0024*	0.0014*	0.0008	0.0020	0.0014**	0.0009*
	(-2.24)	(-2.08)	(-2.61)	(1.86)	(1.79)	(1.37)	(1.16)	(2.47)	(1.82)
HPI	0.0028***	0.0015***	0.0012***	-0.0011	-0.0008*	-0.0008**	-0.0018***	-0.0010***	-0.0011***
	(5.06)	(4.87)	(5.35)	(-1.56)	(-1.86)	(-2.41)	(-2.90)	(-3.31)	(-4.11)
Constant	0.0557***	0.0357***	0.0260***	0.0730***	0.0403***	0.0303***	0.0619***	0.0331***	0.0224***
	(8.13)	(10.47)	(11.50)	(11.05)	(11.29)	(10.60)	(8.78)	(11.17)	(8.23)
Number of Observations	43472	87072	123900	34401	73826	107238	27932	64105	96336
R^2	0.369	0.423	0.427	0.539	0.587	0.585	0.649	0.711	0.711

Notes: This table provides results from the regression given by Equation 1 using data on all, small, and large credit unions from 2002Q2 until 2022Q4. All variables are defined in Appendix Table A.1. T-statistics are reported in parentheses where * is p<0.10, ** is p<0.05, and *** is p<0.01.

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Appendix Table A.1

Variable	**Definition**
Panel A: Loan Types	
SBA Loans	Small Business Administration (SBA) loans to total loans
Credit Cards	Credit cards loans to total loans
Unsecured Loans	Unsecured loans minus credit cards to total loans
New Vehicle Loans	New vehicle loans to total loans
Used Vehicle Loans	Used vehicle loans to total loans
1st Lien Real Estate	First lien mortgage real estate loans and lines of credit to total loans
Other Real Estate	Other real estate loans and lines of credit to total loans
Business Loans	Member and nonmember business loans to total loans
Panel B: Income Sources	
Loan Interest Income	Interest income from loans to total income defined as the sum of total interest income and total noninterest income
Other Interest Income	The sum of total investment income and total trading profits to total income
Fee Income	Fee income to total income
Other Operating Income	Total other operating income to total income
Investment Gains	Total investment gains or losses to total income
Fixed Asset Income	Income from the sale of fixed assets to total income
Other Noninterest Income	Other noninterest income defined as the sum of derivatives income, merger income, and other nonoperating income to total income
Panel C: Credit Union Variables	
Net Worth	Net worth over total assets
Delinquent Loans	Total amount of loans delinquent two or more months over total loans
Membership Growth	Quarterly growth in current CU members
Return on Assets (ROA)	Net income divided by total assets
Cash	The total of cash on hand, cash on deposit, and cash equivalents plus investments with less than one-year remain maturity divided by total assets
Net-Long Term Assets	The sum of real estate loans which will not refinance, reprice, or mature within five years, commercial loans, investments with remaining maturities of more than three years, National Credit Union Share Insurance Fund deposit, land, and building, and other fixed assets divided by total assets
Size	Natural log of total assets
ROA Volatility	Standard deviation of ROA across the previous three years
Loan Growth	One quarter growth rate in total loans and leases
Low Income	A dummy variable equal to one if the CU has a low-income designation, and zero otherwise
State Charter	A dummy variable equal to one if the CU has a state charter, and zero otherwise
Unemployment	Quarterly unemployment rate in the state of the CU headquarters gathered from monthly data provided by the BLS and averaged to the quarterly level
CPI	The natural log of the quarterly consumer price index (CPI) in the census region of the CU headquarters gathered from the BLS
Personal Income	The natural log of quarterly personal income in the state of the CU headquarters gathered from the Bureau of Economic Analysis
HPI	The natural log of the quarterly Federal Housing Finance Agency Housing Price Index (HPI) in the state of the CU headquarters
Panel D: Risk Measures	
Credit Risk	Future credit risk measured as the average value of the quarterly observations of nonperforming loans and charge-offs over the following one year, or five years.
Earnings Risk	Future earnings risk measured as the average value of the quarterly observations of net income to total assets (ROA) over the following one year, or five years.

The Weather Outside is Frightful! Extreme Weather Effects on Residential Real Estate Transaction Prices

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Abstract

The effects of extreme weather events on the transaction price of residential real estate are modeled for Chatham County and the City of Savannah in coastal southeastern Georgia. Extreme weather events as characterized by National Weather Service issuance of warnings and watches for hurricanes, tornadoes, tropical storms and severe thunderstorms reduce the sale price of homes. Further, heterogeneous effects of temperature on home sale prices are identified. Cold temperature reduces home sale price but hot days do not have a statistically significant effect on transaction prices. Precipitation is also found to reduce transaction price.

JEL Classification: Q51, Q54
Keywords: Hedonic, extreme weather, warnings, watches

Introduction

The impact of weather on transaction outcomes has attracted researcher interest and empirical estimation since the 1950s (Steele 1951). More recently, growing public discussion of climate change is concurrent with consideration of extreme weather events on economic activity. For example, in the months and years following an extreme weather event, housing prices in the southeastern Unites States respond to hurricanes (Below, Beracha, and Skiba, 2017; Saginor, 2017; Morgan, 2007), and in the south and Midwest, respond to tornadic activity (Donadelli et al., 2020). In the western United States, other weather-related extreme events such as wildfire risk are capitalized into home prices (Donavan, Champ, and Butry, 2007; Loomis, 2004).

The presence of short-run weather effects on the sale price of residential real estate is the focus of this investigation. The lack of literature on this topic has been pointed out by Gourley (2021) and Livy (2020). This work extends that of Livy (2020) which focused on temperature and Gourley (2021) which focused on temperature and precipitation. Livy (2020) finds that temperature deviations from normal result in negative but heterogeneous effects on the sale price of home in Franklin County, Ohio. Specifically, transaction prices are more responsive to hotter temperature as compared to colder temperature. Gourley (2017) finds precipitation has heterogeneous effects on sale price, but only during the summer and cold temperature increases sale price in winter.

The analysis below includes temperature and precipitation effects on transaction prices but extends empirical modeling to include extreme weather events as characterized by National Weather Service issuance of warnings and watches for hurricanes, tropical storms, tornadoes and severe thunderstorms.

Weather-related conditions are capitalized into home sales prices. The results suggest that extreme weather events reduce transaction price by one percent. Precipitation in the amount of two standard deviations above the mean reduces transaction price 1.3% compared to periods without rain. Colder temperature reduces transaction price while hotter temperature does not have a statistically significant effect on home sale price.

Data and Empirical Design

Home sale data used in this study are from the Multiple Listing Service of Chatham County, Georgia. This includes the city of Savannah. Data were available on virtually all agent-assisted transactions from 2007-2019 and are rich enough to allow for a wide array of physical home characteristics (see Table 1). The location of each home is controlled for through the use of 89 dummy variables, each representing a different 6-digit zip code constructed from truncating available 9-digit zip codes. Yearly and seasonal controls are also included.

Information on storm watches and warnings was obtained from the Iowa Environmental Mesonet maintained by Iowa State University. Daily weather information data was obtained for the National Weather Service reporting station at the Savannah-Hilton Head International Airport.

The primary variable of interest is *Storm*, a binary variable set equal to one if there was a hurricane, tornado, tropical storm, or severe thunderstorm warning or watch issued by the National Weather Service in the 15 to 45 day period prior to the closing date of the house sale.

The National Association of Realtors (2021) reported the mean search time for homebuyers is eight weeks and homebuyers contacted a realtor three weeks into their search, on average. Homebuyers viewed a median of nine homes during the search. The time of interest during which weather conditions could matter is the period leading up to when the *last home viewed* prompted an offer to buy during the five weeks while homebuyers had the assistance of a realtor and the closing date. It is assumed that an offer to purchase a home would occur toward the end of the five-week period once the realtor showed a home satisfying the preferences of the buyer. Further, because Anenberg and Laufer (2017) find the last one-third of homes (among their sample of 1.9 million home sales) delist in the two weeks before the closing date, the period of time during which weather conditions could affect home prices is truncated to end 15 days before the close date. Thus, homebuyer search behavior for a transaction of interest is considered to be concentrated in the 15 to 45 days prior to the closing date.

Additional controls for weather conditions on home sales prices include variables characterizing precipitation and temperature: *Precip, Avg_hdd,* and *Avg_cdd. Precip* is defined as the average level of precipitation, per day in inches, over the time window of 15 to 45 days prior to the close of the home. In general, a heating or cooling degree day measures the day's average temperature deviation from 65 degrees Fahrenheit. *Avg_hdd* is the average of this value below 65 degrees in the period of 15 to 45 days before closing and thus a measure of how cold the weather was in this period. *Avg_cdd* is the mean of this value above 65 degrees in the 15 to 45 days before closing and thus a measure of how warm the weather was in this period. Table 1 provides variable definitions and summary statistics.

Table 1. Summary statistics

Variable	Description	Mean	Std Dev	Min	Max
Price	sale price of home	246,661.7	178,847.4	40,000	1,500,000
Storm	equals 1 if a tornado warning/watch, severe thunderstorm warning/watch, tropical storm warning/watch, or hurricane warning/watch present in the 15-45 day window prior to close	0.299	0.458	0	1
Precip	avg. inches of precipitation per day in 15-45 day window prior to close	0.133	0.087	0	0.44
Avg_hdd	avg. heating degree day value in the 15-45 day window prior to close	4.036	5.160	0	21.8
Avg_cdd	avg. cooling degree day value in the 15-45 day window prior to close	7.702	7.021	0	21.43
Summer	equals 1 if home sold in June-August	0.304	0.460	0	1
Fall	equals 1 if home sold in Sept-Nov	0.215	0.411	0	1
Winter	equals 1 if home sold Dec-Feb	0.201	0.401	0	1
Spring	equals 1 if home sold March-May (reference group)	0.280	0.449	0	1
Condo	equals 1 if home is a condo or townhouse	0.164	0.370	0	1
Beds	number of bedrooms	3.156	0.817	1	10
Baths	number of bathrooms	2.451	0.951	1	10
Fireplace	equals 1 if the home has at least one fireplace	0.557	0.497	0	1
Ceiling	equals 1 if the home has 9 foot ceilings (or higher)	0.207	0.405	0	1
Granite	equals 1 if the home has granite counter tops	0.137	0.344	0	1
Garage_spaces	number of garage spaces	1.106	1.007	0	8
Sqft	square footage of house	1948.29	886.46	304	9792
Age	age of house in years	35.687	31.504	2	226
Pool	equals 1 if house has a swimming pool	0.062	0.242	0	1
y2007-y2019	yearly fixed effects (y2007 is reference group)				
z1-z89	6-digit zip code fixed effects (z1 is reference group)				

Number of observations: 47,479

The data were restricted to homes selling for $40,000 or more and $1.5 million or less. Observations with missing or illogical values were excluded. Analysis includes 47,479 observations and the average home had 1,948 square feet, three bedrooms, two bathrooms, and sold in for $246,661.

A hedonic pricing model (Rosen 1974) is used to estimate the marginal impacts of the independent variables. The model is specified as:

$$\text{Ln}(price_{it}) = a + BX_{it} + CZ_{it} + DW_{it} + e_{it}$$

Where X_{it} is a vector of physical characteristics of the house, Z_{it} is a vector of variables controlling for the timing of the sale, and W_{it} is a vector of weather condition variables and e_{it} is a white noise error. The marginal effects of the independent variables are the vectors of estimated parameters B, C, and D. The model is estimated via OLS with robust standard errors.

Results

Estimates of the empirical model are provided Table 2. Twelve yearly fixed effects and 88 six-digit zip code locational control fixed effects are included in the model but omitted from Table 2 for brevity.

Table 2: Results

Dependent Variable: *ln(price)*	Coefficient	Std. Error
Storm	-0.0100***	0.0031
Precip	-0.0411**	0.0165
Avg_cdd	0.0001	0.0004
Avg_hdd	-0.0016***	0.0005
Summer	0.0105**	0.0053
Fall	-0.0125*	0.0071
Winter	-0.0328***	0.0041
Condo	-0.0376***	0.0052
Beds_total	0.0515***	0.0112
Beds_total_sq	-0.0144***	0.0016
Baths_total	0.1235***	0.0096
Baths_total_sq	-0.0807***	0.0016
Fireplace	0.0810***	0.0033
Ceiling	0.0476***	0.0028
Granite	0.1080***	0.0032
Garage_spaces	0.0801***	0.0021
Sqft	0.0006***	0.0000
Sqft_sq	0.0000***	0.0000
Age	-0.0023***	0.0002
Age_sq	0.0000***	0.0000
Swimpool	0.0740***	0.0056
y2008-2019	included but results omitted	
z2-z89	included but results omitted	
n=	47,479	
R-sq=	0.794	

***, **, and * indicating statistical significance at 1%, 5%, and 10% level respectively

Coefficients on the physical characteristics of the homes and timing of sale variables are of the expected sign and consistent with existing literature. Characteristics such as increased square footage, the presence of desirable amenities (swimming pool, granite countertops, etc.), additional bathrooms, and additional garage spaces are associated with higher sale price. Condominiums and older homes, as well as homes sold in winter, have reduced transaction prices.

Turning to the weather condition variables, extreme weather events, as characterized by *Storm*, result in a one percent decline in sales price when a warning or watch was issued by the National Weather Service in the 15 to 45 day window before the closing date of the sale. Extreme weather events are present in thirty percent of the transactions.

Increased precipitation has a negative impact on sales price. Compared to clear periods, a 30-day period that saw average rainfall two standard deviations above the mean would lead to a 1.3% decrease in sales price.

Colder temperature reduces sales price by 0.16% for each degree of increase in the mean number of heating degree days in the 15 to 45 day window before the closing date of the sale. At the mean value of *Avg_hdd*, this translates into a reduction in price of 0.65%. Extremely cold temperatures (two standard deviations above the mean for *Avg_hdd*) imply a 2.3% lower transaction price.

Hotter temperature, measured by cooling degree days, is not statistically significant in the model.

Conclusion

The above findings extend the work of Livy (2020) and Gourley (2021) in capturing the short-run effect of weather conditions in hedonic pricing models of residential real estate by including extreme weather (hurricanes, tropical storms, tornadoes and severe thunderstorms) events along with temperature and precipitation. The primary finding is that extreme weather events reduce the sale price of residential real estate by one percent.

With respect to the findings of Livy (2020) and Gourley (2021) pertaining to temperature, there is consistency in that weather effects are present in hedonic pricing models of residential real estate, but the results herein suggest in the generally warm weather climate of coastal Georgia, cold weather days are negatively capitalized into housing prices, but not hot weather days.

This contrasts with the results of Livy (2020) which found that home prices are more sensitive to hot weather than cold weather in the more northerly climate of central Ohio. Lastly, Gourley (2021) finds cold weather increases the price of houses during the winter. This latter result may be because Gourley's data is from Jefferson County, Colorado which is within a 75 minute drive to eight major ski resorts in the Colorado Rockies (Bustic, Hanak, and Vallette, 2011).

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