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The Effect of Membership Expansion on Credit Union Risk and Returns

By

Jordan van Rijn

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Jordan van Rijn

vanrijn@wisc.edu
608-215-3896

University of Wisconsin-Madison
Department of Agricultural and Applied Economics
427 Lorch St.
Madison, WI 53706

Credit Union National Association (CUNA)
5710 Mineral Point Rd.
Madison, WI 53705

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Abstract: In the past two decades, over a thousand credit unions converted to community charters, significantly increasing their pool of potential members. This study attempts to determine whether these conversions reduce risk by allowing credit unions to diversify their membership, or whether risk increases as the social capital of a tight common bond becomes diluted. We improve on previous cross-sectional approaches by utilizing a generalized difference-in-differences model with credit union and quarter fixed effects for the period 2002 to 2017, which allows us to control for unobserved time-invariant endogenous factors between credit unions. Contrary to previous findings in Ely (2014) and Frame et al. (2002), we find that conversion to community charter improves credit union returns (as measured by ROA, membership growth and loan growth), and lowers risk (as measured by the standard deviation of earnings and probability of liquidation or merger). Capital adequacy also decreases, but this is likely the result of active managers responding to a more diversified portfolio and not an exogenous outcome of charter conversion. There is no effect on the Z-score (probability of exhausting net worth), or indicators of interest rate exposure or asset quality.

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1. Introduction

In the past two decades, over one thousand federally chartered credit unions expanded their fields of membership by way of conversion to community charter. As opposed to charters that only permit credit unions to serve members that have a "common bond" of occupation or association—such as a common employer, church or profession—community charters allow credit unions to serve anyone within a specified geographic area, thereby substantially increasing their pool of potential members. Community charters have grown from just 6.5% of federally chartered credit unions in 1997 to 30.3% in 2017. However, commercial banking interests regularly oppose these developments and have filed various lawsuits attempting to restrict credit union membership expansion.[1] Therefore, an important question for regulators and policymakers is whether the expansion of credit unions' fields of membership is a positive or negative development for the overall health of the financial sector. This study investigates one component of this question: the impact of credit union membership expansion via conversion to community charter on credit union risk and returns. Specifically, we attempt to answer the questions: Does a larger and more diversified field of membership decrease risk for credit unions? Or does risk increase as the credit union's common bond and social capital become diluted? What are the effects on credit union growth and earnings? We find evidence that increases in credit union membership improve both credit union risk and returns, indicating that restricted fields of membership may act as a constraint that prevents Pareto improvements in the economy.

Credit unions are a substantial component of the global financial sector. The World Council of Credit Unions (2016) estimates that there are 68,882 credit unions operating in 109 countries with 236 million members, or approximately 14% of the world's economically active population (ages 15

[1] For example, see: https://bankingjournal.aba.com/2016/12/aba-sues-credit-union-regulator-over-field-of-membership-rule/

to 64). In many countries, this proportion is even higher, including 74% in Ireland, 29% in Ecuador, 18% in Australia, 36% in Jamaica, and 47% in Canada. In the U.S., credit unions are growing rapidly: between 1992 and 2016, credit union memberships grew from 63 million to 108 million, and total credit union financial market share increased from 5.6% to 6.8% (CUNA, September 2017). Furthermore, although banks still dominate most loan markets, in some areas credit unions are outperforming banks: for instance, in the first quarter of 2017, credit unions originated 26% of personal loans and 28% of auto loans, versus 16% and 25% for banks, respectively (Experian, 2017). Credit unions are also becoming more competitive in the mortgage market and increased their share of mortgage originations from just 6% in the first quarter of 2015 to 13% in the first quarter of 2017 (Ibid.).

Unlike banks and other financial organizations, credit unions are cooperative, not-for-profit depository institutions that serve a defined field of membership. Credit unions are also exempt from federal corporate income tax. The U.S. Treasury (2001) outlines five characteristics that distinguish credit unions from banks and thrifts, and are often used to justify the tax exemption: First, credit unions are member-owned and each member is entitled to one vote in electing members of the board of directors. Second, credit unions do not issue capital stock, and instead create capital via retained earnings. Third, credit unions rely on almost exclusively volunteer, unpaid boards of directors whom the members elect from the ranks of membership.[2] Although some states have created laws to allow compensation of board members, only 12 have elected to do so and the remuneration is typically modest (Fullbrook, 2015). Fourth, credit unions operate as not-for-profit institutions as opposed to shareholder-owned depository institutions. Therefore, all earnings are retained as capital or returned to members in the form of interest on share accounts, lower interest on loans, or other products and

[2] FCUA regulation 1761a allows paid compensation to one board member.

services (e.g., financial education). A number of studies confirm that credit unions charge lower rates on loans compared to other financial institutions, offer higher rates on deposits, and force banks to improve interest rates via competition (Feinberg & Rahman, 2001; Heinrich & Kashian, 2007; Tokle, 2005; Tokle, Fullerton & Walke, 2014).

Finally, the fifth distinguishing feature of credit unions outlined by the U.S. Treasury is that they may only accept as members individuals identified in a credit union's articulated field of membership. The Federal Credit Union Act of 1934 limited federal credit union membership to "individuals sharing a common bond of occupation, association, or geographic area" (NCUA, 2003). In 1982, the National Credit Union Administration (NCUA) interpreted this statute so as to allow certain types of credit unions to add multiple groups referred to as "select employee groups" (SEGs). Fearing significant credit union expansion and competition, commercial banking interest groups challenged the NCUA's interpretation of the common bond requirement. The case eventually made it to the Supreme Court, which issued a 1998 ruling that favored the banking industry's interpretation of the Federal Credit Union Act and restricted credit union membership to not more than one occupational group having a single common bond. However, that same year, the U.S. Congress passed the Credit Union Membership Access Act which revised the original Act of 1934 and made a variety of significant changes to credit union membership regulation (Ely, 2014).

The Federal Credit Union Membership Access Act (CUMAA) authorized credit unions to serve multiple associational and occupational groups, provided that each had its own common bond and was within a well-defined area near the credit union's office. It also authorized conversions to community charters, but these charters had to be within the limits of "well-defined local communities" (NCUA, 1998). Although the definitions of a "well-defined area" and "local community" were not made explicit by CUMAA, the NCUA clarified these terms in its *Chartering* *and Field of Membership Manual* published in 2003.[3] The NCUA also clarified that "community charters must be based on a single, geographically well-defined local community, neighborhood, or rural district where individuals have common interests and/or interact" (NCUA, 2003). Furthermore, the NCUA recognized four types of affinity on which a community charter could be based: persons who live in, worship in, attend school in, or work in the community. In addition, businesses and other legal entities within the community boundaries were also eligible for membership. Although there were previously credit unions chartered to serve certain geographic areas, the changes led to a significant increase in community charter conversions, including a peak of 138 in 2003 alone.

The NCUA and other policymakers argued that the expansion of credit union membership was necessary for the financial health of the industry, particularly to prevent risky concentration of loan portfolios in one occupational sector, firm or association. For instance, former NCUA Chairman Norm D'Amours argued that the legislation would allow "diversification of credit union membership in order to safeguard against economic conditions that affect specific groups or industries" (D'amours, 1998). The Assistant Secretary of the Treasury at the time, Rich Carnell, also testified that diversifying the membership base can make an institution "more resilient in the face of problems experienced by any one local employer" (Carnell, 1998). A 2006 Government Accountability Office (GAO) report similarly argued that the NCUA justified its approvals of community charter expansion in part because such expansions diversify the membership base and enhance safety and soundness (US GAO, 2006). Indeed, the original 1982 reinterpretation of the common bond requirement arose due to a large number of credit union closures from associated

[3] Effective May 2003: (1) any city, county, or political equivalent in a single political jurisdiction, regardless of population size, automatically meets the definition of a local community (previously, this was subject to a limit of 300,000 residents); (2) metropolitan statistical areas (MSAs) may meet the definition of local community provided the population does not exceed 1 million (previously, MSAs could not define a local community); and (3) contiguous political jurisdictions qualify as a local community if they contain 500,000 or fewer residents (previously, subject to a cap of 200,000).

business failures during the recession of the early 1980s. Credit unions associated with these businesses had limited memberships and subsequently experienced severe solvency issues when the businesses failed. CUNA estimated that some 500 federal credit unions failed or liquidated in 1981 alone (Frame, Karels & McClatchey, 2002).

On the other hand, there is an extensive economics literature that explains how the "social capital" in tight-knit communities enables lenders to overcome the traditional financial challenges of moral hazard and asymmetric information; therefore, increasing membership via charter conversion could in fact *increase* risk if this social capital becomes diluted (Besley & Coate, 1995; Ghatak & Guinnane, 1999; Karlan, D., 2007; Stiglitz, J. 1990). For example, in his testimony Carnell also noted that a tight common bond fosters low default rates "because of the effect that the default would have on friends, neighbors, or coworkers, and because of the shame associated with the default" (Carnell, 1998). Similarly, Kane and Henderschott (1996) point out that the extent and quality of private monitoring within credit unions is intensified by sponsors and volunteers who have inside information because they work with or live close to loan applicants. Lending decisions can incorporate this private information about the potential borrower and the financial condition of the employer, and defaults may be lower because of social pressure to repay loans.

Given the relatively small size of many credit unions, it is quite plausible that they would benefit from the social capital established among a tight-knit membership, such as credit unions associated with a church, business or neighborhood. Credit unions are significantly smaller than other financial institutions: between 2002 and 2017, the median federally-chartered credit union had just 2,300 members and only $11.5 million in total assets. (In comparison, the median bank size in 2017 is $210 million in assets.) As of 2017, 43% of credit unions have five or fewer employees, 20% have less than 1,000 members, and 28% have under $10 million in assets. Nonetheless, whether credit unions continue to benefit from social capital in today's developed, technology-driven financial sector is an open question, particularly in the U.S. For example, Walter (2006) argues that the widespread use of credit-reporting agencies, easy access to credit cards, and the advent of deposit insurance have diminished the advantages of lending within small groups that share a common bond.

This study uses NCUA "call report" quarterly panel data representing all federally chartered credit unions from 2002 to 2017 to empirically test whether membership expansion via conversion to community charter affects credit union risk and returns. Specifically, we attempt to determine whether conversion to community charters increases or decreases the risk profile of a credit union, and whether it influences the earnings and growth of the credit union. We focus on conversions to community charters as opposed to conversions from single- to multiple-group charters since conversions to community charters represent significant expansions in potential membership to all members within a specific geographic area. Adding an additional SEG or two typically does not significantly increase a credit union's membership or potential membership base. **Table 1** shows the mean and median number of members and potential members for federally chartered credit unions over the past decade (excluding the largest credit unions of over $500 million in assets). One can see that there is little difference between multiple- and single-chartered credit unions in memberships, and in fact the single-chartered credit unions often have more members and significantly larger potential membership fields.[4] However, community-chartered credit unions are over twice as large as multiple- or single-chartered credit unions at the median, and have significantly more potential members as well. Therefore, if there are risk reductions via expanded membership it is most likely to be found among credit unions that switch to a community charter.

[4] Regression analysis confirms that switching from single- to multiple-charter does not significantly increase the members or potential members of a credit union, on average. Therefore, there is no reason to expect a change in risk or returns due to a diversified portfolio via conversion to multiple-charter.

Table 2 shows the number of federal credit union community conversions each year from 1997 to 2017, and **Table 3** shows the number and percentage of credit unions by charter type. Federal community-chartered credit unions grew rapidly from 463 in 1997—representing just 6.5% of total federally-chartered credit unions—to 1,080 in 2017—or 30.3% of federally-chartered credit unions. Meanwhile, the number and percentage of single-group charters fell dramatically from 2,287 and 32.3% in 1997, to 700 and 19.6% in 2017, respectively. Therefore, for regulators and policymakers an important question is whether this significant transformation of the credit union industry has led to a more healthy and stable financial sector, or whether it has increased financial risk.

Although the question of credit union portfolio diversification has been considered in the literature—most notably by Ely (2014), Goddard et al. (2008), Esho et al. (2005) and Frame et al. (2002)—these studies suffer from the use of "bad controls" and endogeneity bias endemic to cross-sectional analysis (Angrist & Pischke, 2008). We contribute to the literature by using a generalized difference-in-differences model that exploits both quarter and credit union fixed effects. The fixed effects allow us to determine how credit union risk and returns change after conversion to a community charter, controlling for unobserved endogenous factors between credit unions that are likely correlated with outcome variables. Since the model focuses on variation within credit unions that change charter status over time, it also enables us to forego the use of bad control variables—such as the log of total assets—which are themselves affected by the independent variable of interest.

Contrary to Frame et al. (2002) and Ely (2014)—who conclude that expanded membership increases credit union risk and lowers earnings—we find evidence that conversions to community charters reduce risk and improve returns: the conversions lead to a reduction in the variability of earnings, a lower probability of liquidation or merger, higher earnings, and more growth in membership and loans. We also find that capital adequacy is reduced after community conversion, but this is likely due to credit unions holding greater capital pre-conversion in order to mitigate portfolio risk with a more concentrated portfolio, and then subsequently lowering capital after conversion under the more diversified portfolio. Therefore, on its own, the reduction in capital adequacy should not be seen as an indicator of greater credit union risk, and capital adequacy levels remain well above NCUA guidelines. However, these unobserved endogenous factors likely drive the contrary results found in Ely (2014) and Frame et al. (2002).

2. Theoretical background

At least since Markowitz (1952), it has been well understood in that diversifying a portfolio reduces idiosyncratic risk. We expect a similar outcome for credit unions that diversify their membership base by converting to a community charter. In other words, a more diversified membership base should lead to a more diversified loan portfolio. For example, a single-group-chartered credit union associated with a firm may convert to a community charter, which would allow it to serve anyone within a specified geographic boundary near the credit union, such as the entire town or city. These potential new members are now employed not just by one firm, but hundreds or thousands of different firms, whose outcomes are mostly uncorrelated with each other. For instance, if any one business fails or contracts, and the employees of that business are unable to pay their loans, the credit union continues to receive payments from the members that are employees of the other businesses. Therefore, one might expect that expansion of the membership base reduces credit union risk via a more diversified loan portfolio.

It may be less obvious why converting to a community charter could *increase* risk. Typically, financial intermediaries deal with two main challenges: asymmetric information and moral hazard. In this context, asymmetric information means that potential lenders do not have sufficient information regarding the creditworthiness of potential borrowers. In its extreme form, this may force lenders to increase interest rates in order to compensate for the potential risk associated with poor quality borrowers. However, this in turn can dissuade the good borrowers from soliciting loans, leaving only the questionable borrowers to apply (a phenomenon referred to as "adverse selection") (Akerlof, 1970; Stiglitz & Weiss, 1981). Moral hazard refers to the problem in which, ex-post, a borrower who receives a loan is not fully held responsible for repayment (e.g., unsecured loans, undercollateralized loans, no credit reporting) and spends the loan funds less wisely than he would have if held fully responsible, or feels less pressure to pay back the loan on-time and in full.

In the past three decades, an extensive literature has emerged that demonstrates how "social capital" enables lenders to overcome the problems of asymmetric information and moral hazard among tight-knit communities, such as in small towns or villages. Social capital is loosely defined by Robert Putnam (2000) as the "features of social organization, such as trust, norms and networks," and is shown to be particularly beneficial when lending is risky or prohibitively expensive (such as in rural areas of developing countries where loan sizes tend to be small, there is often insufficient collateral, and the lack of credit bureaus make monitoring costly). In this context, microfinance institutions have created unique lending structures, such as small solidarity groups of five or so members—or "village banks" of 20 to 30 members—that insure each other's loans, screen new members, and monitor each other to ensure proper use of funds and repayment. Although not identical to the context of U.S. credit unions—where there is deposit insurance, well established credit bureaus, and easy access to credit cards—there are many similarities between microfinance organizations in developing countries and credit unions in the U.S., particularly smaller credit unions with single-bond charters.

First, credit unions may exploit local knowledge about potential borrowers, or their employer. For instance, a credit union serving members associated with a single firm may know inside information about the financial stability of the employer, or the work-ethic, character, history, and relative salaries of the employees. A credit union associated with a church may refuse to lend to an applicant that is a known alcoholic or gambler. Alternatively, this credit union may offer a loan to a new immigrant with no credit history since the community has come to know him or her as hard-working, ethical and duly employed. This local knowledge can help facilitate screening of applicants that have little or questionable credit history, and enable credit unions to offer loans when other lenders may not. Many authors have demonstrated how local information can be exploited to help lenders overcome problems of asymmetric information and adverse selection (Armendáriz de Aghion & Gollier, 2000; Ghatak & Guinnane, 1999; Van Tassel, 1999).

Second, members of small credit unions may be in a better position to monitor each other's behavior—such as the proper use of loan funds or imprudent expenditures when a loan is already past-due—and encourage repayment. If relationships are particularly tight—such as among close friends or family members—there may even be forms of co-insurance, such as members acting as co-signers on a loan for other members, or helping friends or family members make payments if they experience a setback. Various authors demonstrate how intragroup credit insurance and peer-monitoring reduces the incentive for risk-taking, thereby allowing lenders to overcome moral hazard, reduce competitive interest rates, and increase lending to otherwise excluded individuals (Armendáriz et al., 2000; Conning, 1999; Stiglitz, 1990; Varian, 1990).

Finally, the threat of social penalties for not paying a loan or becoming delinquent may encourage on-time repayment. For example, Besley and Coate (1995) focus on the role of social penalties in the case of default, which may reduce the incentive for moral hazard. They determine that if a microfinance group is formed from communities with a high degree of social connectedness, the cost of upsetting other members in the community can be significant. In the credit union context, this may arise if a member faces some form of social stigma or exclusion for late- or non-payment of a loan. The punishment may even be self-imposed; for example, a borrower may not want to let down or disappoint others in the credit union that are his friends, co-workers or family members that he sees on a daily basis, or he may feel guilty if he falls behind on a loan. Similarly, given his intimate connection with the credit union, the borrower may feel a particular sense of responsibility to the credit union for believing in him and giving him a chance when other lenders would not, and feel remorse if he does not fulfill his loan contact.

Therefore, relatively small and well-connected communities that constitute a credit union's membership base may be able to exploit social capital to help reduce risk and facilitate lending that may not otherwise occur. However, if this credit union opens up to significantly more members from outside the established community via charter conversion, it may face challenges assessing good credit risks, and relying on monitoring and social penalties for on-time repayment. For example, if the new members are not employees of the same firm, followers of the same church, or close neighbors, the credit union no longer has inside information about their character, income or background, can no longer rely on regular interactions for monitoring, and may find that the new members feel less loyal and obligated to the credit union and its membership, reducing the potential for social penalties. Under these circumstances, conversion to a community charter could in fact increase the risk faced by the credit union.

3. Literature review & contribution

3.1. Previous studies on credit union membership and revenue diversification

A number of previous studies have investigated the relationship between credit union membership and revenue diversification and risk. Frame, Karels and McClatchey (2002) use NCUA call report data from 1997 to study the relationship between credit union charter type and risk. Through cross-sectional regression analysis, the authors find that occupational credit unions—relative to other single-bond credit unions—have fewer loan delinquencies but hold higher levels of capital. Furthermore, the presence of multiple SEGs is negatively related to credit union capital ratios and positively related to loan-to-share ratios and loan delinquencies. The authors note that the results may be driven by diluted informational advantages associated with tight common bonds, or the tendency for credit unions to reduce capital ratios when concentration risk is lower.

Esho, Kofman and Sharpe (2005) investigate whether diversification in credit union product mix and increased reliance on fee income affect the risk profile and performance of Australian credit unions. The authors use cross-sectional regressions and define six risk measures, including the Z-score and probability of breaching regulatory capital (Reg-Z)[5], the coefficient of variation of earnings, the standard deviation of the return on assets, and the degree of total leverage. The authors also go through great lengths to control for significant merger activity among Australian credit unions, and ultimately conclude that credit unions with a highly concentrated product mix have lower returns. However, the effect on risk depends on the type of new products offered: increased

[5] The Z-score represents the number of standard deviations below mean ROA at which the institution would deplete its net worth (Z-score=(ROA + Net worth/total assets)/SD-ROA). Reg-Z simply subtracts the minimum capital requirement from the numerator, typically 8.0% or 6.0%.

residential lending decreases risk while an increase in the revenue share of transaction fees increases risk.

Similar to Esho et al., Goddard, McKillop and Wilson (2008) estimate the impact of revenue diversification on financial performance but for U.S. credit unions during the period 1993 to 2004. The authors use NCUA quarterly call report data to estimate cross-sectional regressions with a variety of control variables, as well as regressions with instrumental variables to control for endogeneity issues related to credit union management. They find that higher reliance on non-interest income is associated with higher earnings volatility; however, a more diversified portfolio is associated with lower volatility (with the net effect being insignificant).

More recently (and more related to our research), Ely (2014) tests for differences in risk across credit unions with different field of membership types. Specifically, he compares risk outcomes for credit unions with single-bond, multiple-bond and community charters. The main outcome variables of interest are the Z-score, capital ratio and variation of earnings. Ely employs a cross-sectional regression analysis with a variety of control variables, and improves on Frame et al. (2002) by employing a difference-in-differences specification to capture switches in field of membership between 2004 and 2007. However, panel data is only used for two periods, so the difference-in-differences approach relies on the identification assumption of parallel trends between 2004 and 2007. Ely concludes that credit unions that switched from single-bond to broader field-of-membership types operate with greater risk, as measured by more volatile earnings, lower capital ratios, and higher (negative) Z-scores. Furthermore, Ely finds lower ROA and net-worth ratios at community and multiple-bond credit unions relative to single-bond credit unions.

3.2. Econometric challenges and contribution

Identifying a causal effect of credit union field of membership expansion on credit union risk and performance is inherently challenging due to the potential for endogeneity, particularly with respect to the management of the credit union. For example, any proactive credit union CEO will manage his or her loan portfolio and financial ratios in response to changes in perceived risk; therefore, changes in ratios that are easily managed are not necessarily exogenous outcomes due to a treatment or change in policy, but choice variables of the credit union's management. Capital adequacy—or net-worth divided by total assets—is a perfect example. NCUA considers a credit union to be "well capitalized" if this ratio is above 7.0%. However, a credit union manager may choose to increase this ratio well above this threshold by holding more retained earnings, as Frame et al. (2002) rightly point out. A savvy CEO of a single-bond credit union that recognizes concentration risk would likely maintain a higher capital ratio than a CEO of a well-diversified community-chartered credit union. Indeed, this is exactly what we find in the data. **Table 4** shows that between 2002 and 2017, the mean and median capital adequacy ratios were 16.7% and 14.8% for single-bond chartered credit unions, and 11.3% and 10.4% for community-chartered credit unions. If we were to conclude from this simple comparison that community-chartered credit unions are therefore riskier due to their lower capital adequacy ratios, we would be ignoring the effect of management's role in managing risk. Therefore, any cross-sectional analysis that does not properly take this endogeneity into account will suffer from unobserved variable bias. Unfortunately, it is unlikely that adding control variables at the credit union level is sufficient to address this endogeneity issue, since the extent to which a credit union responds to perceived risk is likely to depend on characteristics of the credit union manager (e.g., aptitude, education, risk-aversion), or credit union board (e.g., progressiveness, diversity, experience). And these variables are typically unavailable in the call reports or other sources of credit union data.

One approach to resolve this concern is to use instrumental variables. If one can find an instrument that is correlated with credit union risk or returns and the independent variable of interest, but is not correlated with any other unobserved variables that affect outcomes of interest (exclusion restriction), then it can be used to identify the causal effect. However, these instruments are extremely difficult to find. Goddard et al. (2008) use the ratio of actual members of a credit union to potential members as an instrument for the ratio of non-interest income to operating income, and justify its use by showing that the instrument is relatively uncorrelated with financial performance indicators. However, even small correlation between the instrument and unobserved financial indicators can cause significant bias (Wooldridge, 2010), and the authors report correlation coefficients that are nearly one-third the size of the correlation between the instrument and the outcome variable of interest (-0.290 and -0.090). Intuitively, one can imagine that as the ratio of actual members to potential members increases, it may be more difficult to attract new members (as the market becomes saturated), thereby increasing costs, influencing marketing strategies, or affecting other related variables that would be unobserved and correlated with the outcome variables of interest.

Without a proper instrument, the next best econometric approach would be to utilize the panel data structure of the call report data. One can exploit the repeated observations of credit unions each quarter by running a generalized difference-in-differences model with credit union and period fixed effects. The model is similar to Goenner (2016), who utilizes credit union and quarter fixed effects for the period 2010 to 2014 to estimate the impact of new loan participation rules on credit union returns. With this approach, variation comes from credit unions that change their treatment status (e.g., convert to a community charter), and the advantage is that the estimation only relies on variation *within* credit unions over time. Therefore, any unobserved endogenous factors *between* credit unions—such as managerial ability, size, location, technology, progressiveness, etc.—are controlled for. In other words, the identification strategy compares the same credit union before and after changing converting to community charter, and controls for any aggregate time trends between quarters. As long as the unobserved heterogeneity within credit unions is constant between quarters—a fairly reasonable assumption—it is removed from the error term by first differencing.

To the best of our knowledge, the approach that comes closest to this methodology in the relevant literature is that of Ely (2014); however, he only uses two panels, so must rely on the strong assumption of parallel trends between 2004 and 2007. In other words, for his identification strategy to be valid, the changes in unobserved variables that may influence credit union risk is constant for credit unions that expand their field of membership and those that do not between the time periods. Unfortunately, three years is a relatively extended period and it is likely that the assumption is violated, which would bias any results. For example, one possible violation could be that the "treatment" credit unions that decide to change charters were already preparing for growth and expansion, and implemented strategies to this effect; whereas, the "control" credit unions that remain as single-bond charters may be content without growing and simply serving their current members. The former may begin investing retained earnings in marketing campaigns and outreach—thereby lowering capital adequacy and increasing leverage—while the latter may prefer safety and soundness, and a higher capital adequacy ratio. Therefore, the purpose and mission of the two credit unions are quite different, and the trends in risk and performance outcomes are likely to be different as well, violating the parallel trend assumption. Ultimately, it is rather easy to tell a story in which the parallel trends assumption is violated in this case.

One relatively simple solution is to exploit the additional data points before and after the "treatment" in a fixed effects model with credit union and period fixed effects. In this case, the parallel trends assumption need only hold for each quarter (as opposed to three years), and any important unobserved credit-union level variables are first differenced after each period. Returning to our example, if the more ambitious credit union decides to change charter type, this difference between the credit unions will be controlled for after each quarter. Therefore, in this case, the parallel trends assumption is much more likely to hold. Indeed, as demonstrated below, the approach leads to significantly different findings than in Ely (2014).

In addition to endogeneity concerns, previous studies also suffer from the use of "bad controls", or control variables that affect both independent and dependent variables (Angrist & Pischke, 2008). In other words, these variables could plausibly be dependent variables in themselves. This is endemic in econometric studies of credit union risk and performance. For example, many studies (including those cited above) include *total assets* or *log of total assets* as a control for credit union size. The intuition is that the structure of larger credit unions is significantly different from smaller ones, and these differences must be controlled for. Although the intuition is correct, *total assets* is also likely to be influenced by the independent variable of interest.

Intuitively, if an econometrician wanted to study the effect of a change in charter type on earnings, an expansion of field of membership via conversion to community charter would increase total assets via new memberships and savings, which in turn would affect credit union ROA through the interest and fees on the new loans and related products and services. In other words, much of the increase in earnings may be *through* the change in assets. In fact, we would expect credit unions that switch to community charters to grow in asset size as their memberships increase. To test whether this indeed occurs in the call report data, we regress *log of total assets* on a community charter dummy with credit union and period fixed effects and find a positive and highly significant coefficient on the community charter dummy, suggesting a significant positive effect of community charter conversion on credit union assets, as expected. Therefore, it does not make sense to use *log of total assets* as an independent control variable, since it is not in fact independent of the main causal variable of interest.

To further explore this question and the potential ramifications of using *log of total assets* as a control variable, using our 2002 – 2017 call report data we run a simple cross-sectional regression of ROA on an indicator variable for whether a credit union has a community charter (with robust standard errors). Then, we compare the results of the same regression after including a "bad control"—the log of total assets—following the convention in the literature. We find that the coefficient on ROA completely flips signs—it is 0.0040 and significant at the 95% confidence level without log of total assets, and *negative* 0.0054 and significant at the 90% confidence level when including log of total assets. Comparable results of this exercise are found even after including a variety of other control variables.[6] Therefore, we can see that the use of bad controls can considerably change our results and conclusions, and must be careful when considering which control variables to include in our econometric specifications.

The generalized difference-in-differences model helps us with determining which control variables to include, since repeated panel data with many frequent time periods makes many control variables unnecessary (besides credit union and period fixed effects), since they are unlikely to vary significantly within credit unions between time periods. Specifically, since the variation used for identification comes from within credit unions and is differenced every quarter, any control variables

[6] We omit detailed results of this analysis for concision, but can provide them on request. Alternatively, interested readers can perform similar exercises with the publicly available call report data.

used to control for unobserved variation between credit unions are first-differenced after each period and their inclusion does little to change the regression results. However, since bad controls are still correlated with the outcome variable, they absorb much of the variation and can create bias. For example, if we repeat our previous exercise of regressing ROA on a community charter dummy variable, but now include quarter and credit union fixed effects, the coefficient on ROA still flips signs (although it is only statistically significant in the regression that does not include total assets).

However, with this model we must be careful with getting the standard errors right. Bertrand, Duflo and Mullainathan (2004) emphasize that in difference-in-differences models with many time periods it is likely that the error term is not independently and identically distributed, and errors for a given individual (cluster) may be correlated over time (i.e., serial correlation). The authors illustrate how conventional difference-in-differences standard errors may grossly understate the standard deviation of the estimated treatment effects, leading to overestimation of significance levels. Bertrand et al. (2004) recommend clustering at the level of the individual fixed effect (in our case, clustering at the credit union level) in order to produce consistent standard errors. Therefore, we use cluster-robust standard errors to account for heteroskedasticity and serial correlation. This approach is similar to Goenner (2016).

Given this background, our paper contributes to the literature by utilizing a generalized difference-in-differences model over 15 years (58 quarter-periods), with cluster-robust standard errors in order to more rigorously investigate the potential causal relationship between expanded fields of membership and credit union risk and returns. Using this approach, contrary to previous studies, we find that expanding fields of membership via conversion to community charter reduces risk as measured by the standard deviation of earnings and the probability of liquidation or merger, has no significant effect on Z-scores, and improves credit union returns as measured by ROA, membership growth and loan growth. Although capital adequacy falls, this is likely a decision of credit union managers to lower capital ratios due to reduced concentration risk, and is more than offset by the increase in ROA. We do also find that the loan-share ratio increases; however, this is expected with an increase in loans and members, and should not in itself be an indicator of increased risk.

4. Data & methodology

The main dataset used for this study is the NCUA's public "call report" data, which all U.S. credit unions are required to file with the NCUA on a quarterly basis.[7] This data contain detailed credit union financial information, as well information regarding credit union products and services. Due to significant changes in the reporting of Type of Membership (TOM) codes and community charter definitions prior to 2002, our sample consists of call report data from 2002 to 2017 (58 quarter-periods). This interval encompasses the changes that the NCUA published in 2003 in its *Chartering and Field of Membership Manual,* which clarifies what constitutes a community charter, how to convert to a community charter, and the geographic and population limitations of a "community" (NCUA, 2003). We combine this data with internal data from the Credit Union National Association (CUNA) to add a number of additional credit-union level and CEO-level control variables. The charter type data is only available for federally-chartered credit unions over this time period; therefore, we do not include state-chartered credit unions in our sample. As of June 2017, there were 3,566 federally-chartered credit unions, compared with 2,245 state-chartered credit unions. Due to significant consolidation of the credit union industry, the numbers of state- and

[7] Call report data is available at: https://www.ncua.gov/analysis/Pages/call-report-data/quarterly-data.aspx

federally-chartered credit unions have decreased substantially in the past two decades. Thus, at the beginning of our sample in 2002 there were 6,031 federally-chartered credit unions. The total observations used for analysis (number of federally chartered credit unions each period multiplied by number of periods) is 290,723.

We focus on two main types of outcomes: risk and returns. Given the previously mentioned endogeneity concerns, it is important to carefully consider measures of credit union risk. The NCUA uses CAMEL ratings to assess credit union risk and solvency, which consist of "Capital", "Asset quality", "Management", "Earnings" and "Liquidity/Asset-Liability management." Each composite CAMEL rating is given a numerical value of 1 to 5, with a rating of "1" indicating sound indicators and no major concerns, and a "5" indicating extremely unsafe and unsound practices and conditions (NCUA, 2007). We find Sollenberger and Schneckenburger's (1994) overview of credit union risk and return areas helpful for the interested reader.

Below are the financial indicators that we use in our analysis. We note that although there are many indicators for each risk and return area, given the high degree of correlation between them, we confine our analysis to just one or two, but the results are generally robust to the use of alternative related indicators:

Table 5. Financial Variables Used in Regressions

Performance Area	Ratio
	Risk
Capital Adequacy	Net worth ratio = net worth / total assets
Asset Quality	Delinquency ratio = delinquent loans / total assets
Asset Quality	Charge-offs ratio = net charge-offs / average loans
Asset Quality	Unsecured loans / total assets
Interest Rate Exposure	Mortgage-assets ratio = mortgage assets / total assets
Liquidity	Loan-share ratio = total loans / total shares
	Returns
Earnings	Return on assets (ROA) = net income / average assets
Earnings	Growth in net income = % change in net income
Growth	Membership growth = % change in memberships
Growth	Loan growth = % change in loans

In addition to these variables, a number of other indicators have been used in the finance literature to measure the financial risk of credit unions, including the standard deviation of ROA (SD(ROA)) and the Z-score (Boyd et al., 1993; Ely, 2014; Esho et al. 2005). The standard deviation of earnings (SD(ROA)) is an indicator of the variability of earnings, and the Z-score indicates probability of bankruptcy. The Z-score is defined as the number of standard deviations below mean ROA at which the credit union would deplete its net worth:

$$\textit{Z-score} = \frac{ROA + Capital\ adequacy}{SD(ROA)}$$

According to the Federal Credit Union Act, the capital level below which the NCUA considers a credit union "undercapitalized" is 6.0%; therefore, the Z-score is often modified to incorporate this minimum threshold (Ely, 2014; Esho et al., 2005):

$$\textit{Reg-Z} = \frac{ROA + Capital\ adequacy - 0.06}{SD(ROA)}$$

Since SD(ROA), and therefore Z-score and Reg-Z, cannot be calculated for a single period, we calculate the SD(ROA) over three- and five-year periods. Our main specification includes the three-year period measure, although the results are robust to a five-year calculation as well.[8]

As should be clear, many of these financial indicators are interrelated and correlated. For example, if loan growth is high, in the short-run this increases the loan-share ratio (all else equal), and will influence capital adequacy through both the numerator and denominator. Furthermore, practically all of these indicators can in some way be influenced by the credit union manager. For instance, if the capital adequacy ratio is getting too low, a CEO might attempt to retain more capital, lower expenses or slow growth. If interest rate exposure is too high, a CEO could sell some mortgages to the secondary market. If delinquencies are too high, a CEO may decide to charge-off more delinquent loans. However, a credit union CEO's ability to influence these indicators is not unlimited and depends on the credit union's size and circumstances.

Nonetheless, any regression analysis must consider the interconnectedness and correlation between the financial indicators, and the degree to which a credit union manager may choose to change variables in response to a treatment. If outcome variables in separate regressions are in fact correlated, then these regressions are not in fact independent. For example, Ely (2014) includes separate regressions with Z-score and Reg-Z as dependent variables; however, these variables are highly correlated with a correlation coefficient between the two of 0.94.

We focus our analysis on only one or two important financial indicators that represent each area of risk and return, but are relatively uncorrelated. Although we recognize that outcome variables may be highly correlated—such as loan growth and earnings—we report both results to provide a

[8] We prefer the shorter time period since there is less likelihood that the standard deviation includes a significant period of time after which a credit union has changed its charter.

more complete picture of the impact of charter conversion on credit union outcomes. For example, if capital adequacy goes down but ROA goes up, this may simply indicate that credit unions are using capital for growth and expansion, and may not indicate an increase in risk, as simply looking at capital adequacy would indicate. **Table 6** shows the correlation matrix for important credit union variables used in this analysis. One can immediately see the high correlation between various credit union indicators. For example, the correlation coefficients between *log members*, *log loans,* and *log net-income* are all higher than 80%.

Although we include many of these outcome variables in our regressions for illustrative purposes and to gain a more complete picture of the effect of community charter conversion on credit union risk and returns, we place more emphasis on risk variables that the credit union CEO is less likely to be able to directly control, and that are less correlated with other financial indicators. The *Z-score* falls into this category, since it depends not only on capital adequacy but also earnings and the variability of earnings. A credit union executive may attempt to improve the Z-score by increasing capital adequacy, but this may in turn inhibit earnings, thereby lowering the Z-score. Therefore, a manager's control over this indicator is somewhat more limited.

In addition to the *Z-score,* the *standard deviation of ROA* is also less likely to be easily influenced by a credit union's CEO, since it represents the extent to which a credit union's earnings fluctuate with the business cycle or other shocks that are out of the manager's control. Similarly, we include *probability of liquidation or merger* as an additional important risk variable. As mentioned, there has been significant consolidation of the credit union industry with many credit unions forced to merge or liquidate due to increased competition, technological advances, and recessions (Frame, Karels & McClatchey, 2002; Wheelock & Wilson, 2013). In fact, these mergers are often strongly encouraged by the NCUA (Bauer, Miles & Nishikawa, 2009). Therefore, this variable is a good indicator as to whether a credit union is positioned well enough to withstand downward trends in performance or negative shocks. One can see in the correlation matrix that these two variables have relatively less correlation with other credit union-level variables. In fact, neither show correlation coefficients of higher than 3.1%; whereas, except for *Z-score* all other variables on the matrix have correlation coefficients of at least 10.0% or higher with one or more other variables on the matrix. This provides us with our preferred indicators of risk: *Z-score, SD(ROA)* and *probability of liquidation or merger*.

Our main econometric model is a linear two-way fixed effects model with credit union and quarter fixed effects. Specifically, the estimating equation is:

$$y_{i,t+4} = \gamma_i + \delta_t + \beta C_{it} + \rho \boldsymbol{X}_{it} + \varepsilon_{it} \qquad (1)$$

where i denotes a credit union, t denotes a quarter, y_{it} is the outcome of interest for credit union i, C_{it} is an indicator variable for whether credit union i has a community charter in period t, γ_i is a credit union fixed effect, δ_t is a period fixed effect, $\boldsymbol{X}_{it}$ represent control variables, and ε_{it} is a stochastic error term. Standard errors are clustered at the credit union level to account for heteroskedasticity and serial correlation (Bertrand et al., 2004; Goenner, 2016). Our outcome variable is estimated for 4 and 12 quarters forward (1 and 3 years) to account for adjustment periods after charter conversion. In other words, we would not expect a conversion to community charter to have an immediate effect on outcome variables, but only after a period of time as the new members join. This is common practice in econometric analysis of credit unions (e.g., Goddard et al., 2016; Huang & Kisgen, 2013; Palvia et al., 2015).

The credit union fixed effect captures time-invariant credit union-specific factors that are potentially correlated with omitted explanatory variables, such as managerial ability or board progressiveness. To the extent that these do not vary within quarters in a manner that is correlated with outcomes, the credit union fixed effect is able to control for these unobserved factors. However, variation for identification comes from changes in C_{it}, so the model's power is driven by credit union conversions to community charter. Between 2002 and 2017 there were 709 such conversions, with the majority (576) occurring between 2002 and 2010 (**Table 2**). The time fixed effect captures common time trends or shocks, such as changes in the business cycle, unemployment, growth, or recessions.

Since we already account for credit union and quarter fixed effects, additional covariates are unlikely to significantly affect the outcome variables. Furthermore, any covariates should not be "bad controls" and must, therefore, not be significantly influenced by charter conversions in and of themselves. We note that the vast majority of relevant financial and other variables in the call report data fall into this category. Therefore, we include only a few exogenous control variables from internal CUNA data. These include an indicator for whether the CEO is *female*, based on literature that shows that females are, on average, more risk-averse, less competitive and less overconfident compared to males, and that these gender differences affect financial management and performance of banks and firms (Barber & Odean, 2001; Charness & Gneezy, 2012; Faccio et al., 2016; Huang & Kisgen, 2013; Palvia et al., 2015). We also include the duration in quarters that a female CEO has been active, and the duration of time since a credit union first started. The latter variable is included to account for newer credit unions being less likely to have retained earnings from previous years, and older credit unions being more established and experienced at managing risk. Although this represents our preferred model, subsequent robustness checks demonstrate that the main findings are robust to including and excluding these and other control variables.

5. Estimation results & robustness checks

5.1. Empirical results

We estimate our main model (1) for both 1-year and 3-year periods after conversion to community charter. First, we test the effect of conversion to community charter on potential memberships and memberships in order to demonstrate that the conversions do in fact lead to a larger, more diverse field of membership. **Table 8** shows that conversion to community charter significantly increases potential membership, as expected.[9] On average, the conversion increases *potential members* by 305,054—a 123% increase—creating a very large new pool of potential members. **Table 8** also shows that *log members* is positive and significant, suggesting a 7.4% increase in membership one year after conversion to a community charter. Although the membership increase may appear modest, this figure is over three times the average annual credit union membership growth rate of 2.4% between 1992 and 2016. Therefore, conversion to community charter increases both the pool of potential members and the actual membership of a credit union. We note that similar results do not hold for conversion from single-bond to multiple-bond charters; therefore, contrary to Ely's (2014) analysis, we should not necessarily expect changes in credit union risk or returns due to increased membership via conversion to multiple-bond charter, on average.

Table 9 displays the risk outcomes for the 1-year period after conversion. As expected, the capital adequacy ratio is significant and negative, suggesting a decrease of 0.79 percentage points in the net worth ratio after conversion to a community charter. However, despite this decrease, there is no statistically significant effect on the Z-score (although the coefficient is negative). On the other hand, our other main two indicators of credit union risk—*period liquidation or merger* and

[9] *Log Potential Members* and *Potential Members* are measured in time *t* as opposed to *t + 4*, since the increase in potential membership should be immediate after conversion.

SD(ROA)—are statistically significant and negative, suggesting a reduction in the probability of liquidation or merger of 0.32%, and a reduction in the variability of earnings of 0.30%. To get some sense as to the magnitude of these coefficients, from 1997 to 2017, the average annual liquidation rate was 3.4%; therefore, the figure of 0.32% represents roughly 10% of the annual liquidation rate, a non-trivial reduction in the probability of liquidation. Regarding the variability of earnings, the mean SD(ROA) in our sample is 1.06%, and the median is 0.35% (**Table 4**). Therefore, a reduction of 0.30% represents 28.3% of the variability in earnings at the mean, and 85.7% at the median. In other words, at the median, conversion to community charter reduces the standard deviation of earnings from 0.35% to 0.05%.

There is also some indication that credit unions are diversifying their portfolios of income after conversion, as the *fee income ratio* is positive and statistically significant, suggesting a 1.6 percentage point increase in fee income as a percentage of total assets. However, as Esho et al. (2005) and Goddard et al. (2008) show, fee income diversification does not necessarily lead to decreased risk, as the relationship depends on credit union size and the source of fee income. As this is not the main focus of our paper, we simply include *fee income ratio* to illustrate that increased membership appears to diversify the credit union income stream as well, which could be a source of decreased risk and higher returns. On the other hand, the conversion appears to decrease liquidity via the *loan-share ratio*, as the coefficient on this indicator is significant and positive, suggesting a 2.1 percentage point increase after conversion, on average. The *delinquency ratio* is also positive and significant, although only at the 90 percent confidence level. The coefficients on *mortgage-assets ratio*, *unsecured-assets ratio* and the *charge-offs ratio* are all positive but insignificant, suggesting no statistically significant effect of charter conversion on interest rate exposure or asset quality.

With the caveat that the return outcomes are highly correlated, **Table 10** shows that one-year return indicators are all positive, and two of the three coefficients are statistically significant. As mentioned, our other return variable—*membership growth*—is also positive and significant. The coefficient on *ROA* suggests that conversion to community charter increases ROA by 0.36 percentage points—a fairly substantial amount considering median ROA in the sample frame of 0.61. In addition to the increases in ROA and membership, the conversion also appears to increase loans by 13.7%. This increase in loans may very well explain the rise in the loan-share ratio, since with fast loan growth the loan-share ratio will mechanically also rise (unless for some reason deposits increase even faster, which is unlikely). However, this is not necessarily an indication of increased risk. Indeed, from the median loan-share ratio at the time of conversion of 70.0%, an increase of 2.1 percentage points would be a relatively modest rise and still well within reasonable levels (the current U.S. credit union industry loan-share ratio as of November 2017 is 81.8%) (CUNA, November 2017).

The three-year risk and return outcomes (**Tables 11 - 12**) are mostly consistent with the one-year outcomes; however, the coefficients vary in magnitude somewhat. We also note that the sample is slightly smaller since many credit unions do not have data for 3 years after conversion (i.e., credit unions that converted in 2015, 2016 or 2017). Nonetheless, we note a few changes from the 1-year results: the coefficient on *Z-score* remains insignificant but is now positive, and the coefficient on the *delinquency ratio* is positive but no longer statistically significant. Among the return variables, *log net income* is now positive and statistically significant, suggesting a 10.2% increase in net income three years after conversion to community charter. Overall, the results are consistent with the 1-year outcomes, but also suggest that there is no long-run effect on delinquencies for converting to a community charter.

Overall, the results indicate that conversion to community increases potential members and membership, as expected. Furthermore, the conversion unambiguously increases credit union earnings and significantly increases the loan portfolio. Despite a decrease in capital adequacy, there is no effect on the Z-score, but credit unions that convert have significantly lower variation of earnings and a lower probability of liquidation or merger. These results indicate that the conversion decreases credit union risk; however, liquidity also decreases—perhaps mechanically due to the increased loan portfolio—and there is some weak evidence that delinquencies increase, although the effect disappears after three years.

5.3. Robustness checks

5.3.1. Naïve model: Quarter & State Fixed Effects

As an initial robustness check and for comparison purposes we run a "naïve" econometric model without credit union fixed effects but with period and state fixed effects. This allows us to include some of the *between* credit union variation that we lose in the previous model, but the approach also opens the model up to more of the endogeneity issues discussed above, such as omitted variable bias. Nonetheless, the state fixed effects control for state-level time invariant factors that may influence outcomes, such as state-level laws or regulations, economic trends, or natural disasters.

Specifically, the new estimating equation is:

$$y_{its} = \theta_s + \delta_t + \beta C_{its} + \rho \boldsymbol{X}_{its} + \varepsilon_{its} \tag{2}$$

Where now s denotes the state where the credit union is located in period t, and all other variables are as in (1). Standard errors are now heteroskedasticity-consistent (Huber-White) standard errors. Note that we estimate all outcome variables in period t (as opposed to $t + 4$) since most of the variation is from between credit unions. Although “naïve”, the inclusion of the period and state fixed effects make this a relatively powerful model and still an improvement on many cross-sectional approaches found in the literature, as it controls for both quarter- and state-level time invariant unobserved effects with many periods, states and credit union observations. However, there may be unobserved variable bias within states that we cannot fully account for, so it is not our preferred model.

Table 13 displays the results for risk indicators. Consistent with outcomes from the previous model (1), community-chartered credit unions have significantly lower capital adequacy ratios. There also continues to be evidence of a diversified income stream, as *fee income ratio* is positive and significant. Furthermore, the coefficients on *SD(ROA)* and *Period Liquidation or Merger* continue to be statistically significant and negative, providing further evidence of reduced risk with an increased membership pool for credit unions with community charters. However, the *loan-share ratio* is also higher, as is the *mortgage-assets ratio,* indicating potentially lower liquidity and greater concentration risk (although this may simply be due to smaller credit unions offering mortgages for the first time after conversion). The *charge-offs ratio* coefficient is also positive and statistically significant; however, the *delinquency ratio* is negative and statistically significant. In fact, given the trade-off credit union managers face between delinquencies and charge-offs, we note that the magnitude of the decrease in the delinquency ratio is substantially larger than the increase in charge-offs. Furthermore, the *unsecured-assets ratio* is now highly statistically significant and negative, suggesting an improvement in asset quality.

Finally, similar to Ely (2014) and Frame et al.’s (2002) findings, the coefficient on *Z-score* is negative and statistically significant. This illustrates our point that cross-sectional analysis may lead some researchers to conclude that conversion to community charter *increases* the probability of bankruptcy. Nonetheless, as argued above, this is likely driven by credit union managers actively managing their portfolios and reducing capital adequacy at more diversified community-chartered credit unions. As demonstrated with the generalized difference-in-differences model, if we only focus on variation within credit unions that have actually changed their charters, we find no statistically significant effect of conversion to community charter on the Z-score.

Table 14 displays the results for the return outcomes, and strongly confirms the findings from the previous model. All coefficients are statistically significant and positive, but the magnitudes are substantially larger than the coefficients in the previous model. This points to the fact that some of the positive variation is likely driven by the between variation—which is subject to significant omitted variable bias—and some is driven by the within variation. The generalized difference-in-differences model allows us to parse out the variation that is less prone to bias by focusing on the within variation. Nonetheless, this model confirms that conversion to community charter has strongly positive effects on credit union growth and earnings—and some indicators of risk—although the coefficients here are likely biased.

5.3.2. Small versus large credit unions

One might expect that the smallest credit unions are more likely to have tight-knit communities and receive the risk reduction benefits from a common bond and social capital, relative to larger credit unions. **Table 7** displays summary statistics for credit unions that converted to community charter from the period in which they converted. The mean and median number of members for these credit unions are 15,577 and 8,396, and the mean and median total assets are $112,000,000 and

$55,300,000. Therefore, these credit unions are in fact larger than the typical credit union, and it is possible that they are already too large to benefit from social capital. This may be why we see little evidence of a decrease in risk from conversion to community charter. However, in order to test this more rigorously, we re-run our estimating equation (1) for a one-year period for only credit unions below the median member size at the time of conversion (8,396). This reduces the sample to 443 credit unions that convert their charter types, with a median membership of 3,609, still somewhat large but well within the limits of a moderately-sized village or firm in which we might expect greater social capital.

Table 15 displays the regression results for financial indicators related to risk. All coefficients are in the same direction as in the full model, with similar statistical significance, except for the coefficient on *delinquency ratio,* which is no longer significant (although this may simply be due to the reduced sample size). Using this approach, we find no evidence that smaller credit unions face a greater chance of an increase in risk due to conversion to community charter, and in fact some of the reductions in risk are even larger than with the full sample. For example, the coefficients on *SD(ROA)* and *period liquidation or merger* are both larger in magnitude than with the full sample—and the coefficients on *charge-offs ratio* and *delinquency ratio* are both smaller in magnitude—which is the opposite of what we might expect if smaller credit unions had more social capital. However, this result may simply point to the fact that very small credit unions typically do not convert to community charters in our data. It could be, for example, that CEOs of smaller credit unions are simply content with serving a limited membership base, or they may recognize the benefits of social capital and choose not to convert. Therefore, our findings cannot be generalized to extremely small credit unions of, say, under 500 or 1,000 members, where there is likely to be a greater degree of social capital

5.3.3. Mergers

As **Table 3** demonstrates, there has been significant consolidation of the credit union industry. Federally chartered credit unions decreased a full 50% in the past two decades, from 7,081 in 1997 to 3,566 in 2017. This consolidation occurs largely from underperforming credit unions liquidating and leaving the market entirely or, as is more common, merging with other, typically larger and well-performing credit unions. Bauer, Miles and Nishikawa (2009) analyze credit union mergers and hypothesize that most mergers are instigated by regulators in order to avert using insurance funds to bail out failing institutions. The authors argue that merger activity helps stabilize the credit union industry, as riskier credit unions are merged with healthier ones.

This creates a form of selection bias in econometric analysis using call report data if not properly accounted for. The challenge is that a credit union that absorbs a liquidated credit union has the same name and identification in the data, but its loan portfolio, assets and financial indictors now include the failed credit union. Researchers have dealt with this econometric issue in a number of different ways, including removing credit unions with many mergers from the data, excluding the merger quarter from time series, excluding all merged credit unions, and treating the merged credit union as one credit union *before* the merger (Bauer et al., 2008; Ely, 2014; Esho et al, 2005; Goenner, 2016).

Ultimately, mergers are more concerning in cross-sectional analysis when significant variation comes from between credit unions. Since our model focuses on variation *within* credit unions, merger activity is unlikely to bias the results significantly unless, for example, mergers coincide with community conversions. We find very few cases of this occurring in our data. Nonetheless, to be thorough, we re-run our regressions on a sample of credit unions that include a new credit union identifier if a merger includes the acquisition of a smaller credit union that is larger than 10% of the acquiring credit union's assets. We reason that the acquisition of a relatively small credit union of under 10% of assets is unlikely to significantly affect credit union risk or performance. As expected, there are no substantial differences in the results, and all coefficient signs and statistical significance are as before, with only modest changes in coefficient magnitudes.[10] The findings are similar to those found in Goenner (2016), who with a similar model finds no significant effect of merger activity on credit union returns.

5.3.4. Control variables

As discussed above, the generalized difference-in-differences model focuses on variation within credit unions as opposed to between credit unions, so additional control variables commonly used in the literature will generally have little influence on the results. However, for robustness, we also re-run our model with a variety of additional controls and find that the results generally hold up. For example, when we include *log of total assets* as an additional control variable to model (1), all the coefficients are of similar magnitude and statistical significance. The only change is the coefficient on *ROA*, which remains positive but is no longer statistically significant.

It is also possible that the control variables included in model (1)—a dummy variable for a female CEO, the duration of a CEO's tenure, and the duration that the credit union has been active—are in fact "bad controls" themselves. It is somewhat difficult to imagine how these variables could be influenced by conversion to community charter; however, it is possible if, for example, credit unions that convert to community charter also tend to change their CEO around the same time for

[10] Regression output from this and the remaining robustness checks are omitted for concision but available upon request.

reasons that are correlated with the decision to convert. For instance, a credit union's board of directors might want a more experienced CEO to help with the transition, or to lead new marketing and expansion efforts, or to help create new products and services tailored to the new members. Therefore, as a final robustness check we rerun specification (1) without any control variables. The results are very close to the original model: all coefficients have similar signs, magnitude and levels of statistical significance.

6. Conclusion

The credit union industry—which serves nearly one-third of the U.S. population—has significantly transformed in the past two decades. Federal credit unions have decreased 50% from 7,081 in 1997 to 3,566 in 2017, yet the percentage of credit unions with community charters has increased from 6.5% to 30.3%—substantially increasing credit unions' pool of potential members. Despite opposition from community banking interests, regulators and policymakers justified this expansion by arguing that community charter conversions decrease risk by creating a more diversified membership base and loan portfolio. On the other hand, exposing credit unions to substantially more new members may dilute the social capital associated with a tight common bond, thereby increasing risk. As credit union market share continues to increase, and more credit unions seek to expand their fields of membership, it is important that policymakers understand how this shifting landscape affects risk in the financial sector.

This study attempts to determine how credit union risk and returns are affected by conversions from single- and multiple-bond charters to community charters. We improve on previous attempts by utilizing a generalized difference-in-differences model with credit union and quarter fixed effects to isolate the effect of community conversion on risk and return outcomes, thereby controlling for time-invariant unobserved endogenous factors. Contrary to previous findings (Ely, 2014; Frame et al., 2002), we find that conversions to community charter unambiguously improves credit union returns as measured by ROA, membership growth and loan growth, and decreases risk, as measured by the standard deviation of earnings and the probability of liquidation or merger. Furthermore, we find no effect of charter conversion on the Z-score (probability of exhausting capital), and little indication that conversion affects interest rate exposure or asset quality. Although we also find an increase in the loan-share ratio and decrease in capital adequacy, these results are likely due to the increased loan growth associated with conversion, and the endogenous decision of management to reduce net worth due to a safer, more diversified portfolio.

However, an important caveat is in order: we note that the median credit union to convert to a community charter in our sample had 8,396 members and $55,300,000 in assets at the time of conversion, which is significantly larger than the typical credit union; therefore, the results may not necessarily hold for the smallest credit unions that may have tighter common bonds, such as credit unions with fewer than 1,000 members. Furthermore, the results are *on average*, and some credit unions—even the larger ones—may not necessarily find the same benefits to conversion. It is likely that credit unions that converted to community charters were already implementing various policies and practices to help make the conversion successful, such as marketing campaigns, adding new products and services, or hiring additional employees. CEOs at these credit unions might also be particularly ambitious, experienced or skilled. This creates a form of selection bias that the model cannot entirely account for. In other words, we cannot determine for sure whether the risk reductions and improvements in earnings were due to a more diverse portfolio or, for example, more capable credit union managers that make the decision to convert. Although this should not significantly bias the results of our analysis, it does call into question its external validity. In other words, successful conversions to community charters might not occur among credit unions that are not prepared and well-managed. Nonetheless, save randomly assigning charter types to credit unions, as far as we are aware, this is the best empirical approach to date in determining the effect of conversion to community charter on credit union risk and returns.

Caveats aside, for many moderate- to medium-sized credit unions, this study demonstrates that there may be significant benefits to community charter conversion. The findings imply that the transformation of the U.S. credit union industry towards a greater proportion of community charters and expanded fields of membership is a positive development for the financial sector. In general, it appears to reduce risk and improve credit union returns, the latter of which can be used for better interest rates and more products and services for consumers. The reduced risk also puts less pressure on the NCUA to encourage mergers or use insurance funds. Given the common trade-off between risk and returns, it is particularly noteworthy that both the earnings and risk profile of credit unions improve after conversion. This may indicate that the restricted fields of membership acts as a constraint on credit unions, and may prevent Pareto improvements in the economy. In other words, the increased fields of membership appear to benefit credit unions, members and the NCUA, without making any of these actors worse off.

The results also have implications for other countries that are considering questions of credit union field of membership expansion; for example, credit unions that are closely tied to the agricultural sector in developing countries, or that are based on relatively restricted common bonds. These credit unions—and their members—may benefit from the risk reductions and increased returns associated with a more diverse pool of clients; however, we caution that the U.S. context is unique in having well-developed credit bureaus, deposit insurance, widespread use of computers and the internet, and relatively easy access to credit cards and other forms of credit. These factors may very well make the social capital of a tight common bond less relevant in determining credit worthiness and facilitating loan repayment in today's economy.

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Table 1. Memberships & Potential Memberships by Charter Type
Federally Chartered Credit Unions with Total Assets Under $500 million, 2006 - 2016

Memberships							Potential Memberships						
	Single		Multiple		Community			Single		Multiple		Community	
Year	Mean	Median	Mean	Median	Mean	Median	Year	Mean	Median	Mean	Median	Mean	Median
2016	6,978	2,895	6,056	2,781	9,925	6,278	2016	227,692	15,000	57,601	8,000	267,952	107,653
2015	6,855	2,814	6,042	2,773	9,903	6,195	2015	213,254	13,000	53,764	7,500	260,325	104,390
2014	6,714	2,711	6,039	2,743	9,849	5,996	2014	193,507	11,000	51,848	7,500	250,435	100,000
2013	6,616	2,632	6,058	2,721	9,829	5,776	2013	179,046	10,000	50,250	7,195	241,364	100,000
2012	6,472	2,559	6,051	2,734	9,766	5,736	2012	161,940	10,000	49,923	7,000	230,919	95,000
2011	6,360	2,460	6,016	2,722	9,811	5,671	2011	145,847	8,000	46,688	6,696	230,834	90,000
2010	6,364	2,407	6,126	2,749	10,074	5,865	2010	145,847	8,000	46,688	6,696	230,834	90,000
2009	6,287	2,347	6,195	2,771	10,051	5,760	2009	137,950	7,500	44,072	6,500	227,648	80,975
2008	6,232	2,284	6,226	2,793	10,261	5,715	2008	129,975	7,000	42,756	6,500	226,145	80,000
2007	6,204	2,226	6,307	2,878	10,328	5,666	2007	120,871	6,000	43,047	6,500	215,102	75,000
2006	6,119	2,126	6,577	2,892	10,313	5,642	2006	110,820	6,000	43,253	6,500	193,573	65,000

Table 2. Credit Union Community Conversions
Federally Chartered Credit Unions, 1997 - 2017

Year	Single to Community	Multiple to Community	Other to Community	Total
2017	26	2	1	29
2016	17	1	1	19
2015	8	1	0	9
2014	14	2	0	16
2013	16	0	0	16
2012	15	2	2	19
2011	23	2	0	25
2010	17	1	0	18
2009	16	2	1	19
2008	26	6	0	32
2007	40	3	0	43
2006	63	5	0	68
2005	87	8	0	95
2004	71	6	1	78
2003	125	9	4	138
2002	78	6	1	85
2001	85	8	3	96
2000	92	10	5	107
1999	65	5	3	73
1998	63	5	7	75
1997	10	0	1	11
Totals:	957	84	30	1,071

Table 3. Credit Union Charter Type

Federally Chartered Credit Unions, 1997 - 2017

Year	Community CUs		Single Group		Multiple Group		Total CUs
	#	%	#	%	#	%	#
2017	1,080	30.3%	700	19.6%	1,547	43.4%	3,566
2016	1,070	29.1%	740	20.1%	1,613	43.9%	3,678
2015	1,099	28.5%	782	20.3%	1,690	43.9%	3,854
2014	1,118	27.8%	834	20.7%	1,775	44.1%	4,028
2013	1,142	27.3%	885	21.1%	1,845	44.1%	4,187
2012	1,164	26.7%	939	21.5%	1,924	44.1%	4,366
2011	1,171	25.8%	993	21.9%	1,999	44.1%	4,531
2010	1,171	25.2%	1,037	22.3%	2,053	44.2%	4,650
2009	1,181	24.7%	1,094	22.9%	2,094	43.8%	4,783
2008	1,184	23.9%	1,172	23.6%	2,151	43.4%	4,956
2007	1,165	22.8%	1,231	24.1%	2,243	43.8%	5,118
2006	1,132	21.3%	1,328	25.0%	2,338	44.1%	5,306
2005	1,084	19.7%	1,413	25.7%	2,459	44.8%	5,493
2004	1,008	17.7%	1,499	26.4%	2,623	46.1%	5,685
2003	910	15.5%	1,598	27.3%	2,765	47.2%	5,863
2002	819	13.6%	1,722	28.6%	2,882	47.8%	6,031
2001	739	11.9%	1,842	29.6%	2,993	48.0%	6,230
2000	649	10.0%	1,977	30.6%	3,149	48.7%	6,465
1999	580	8.7%	2,136	31.9%	3,245	48.4%	6,703
1998	513	7.4%	2,228	32.3%	3,340	48.4%	6,903
1997	463	6.5%	2,287	32.3%	3,477	49.1%	7,081

**Notes:* The sum of community, single group and multiple group charter types does not add to 100% due a small percentage of associational credit unions. Yearly numbers are from mid-year (end of 2nd quarter).

Table 4. Summary Statistics by Charter Type

Federally Chartered Credit Unions, 2002 - 2017

Full Sample				Community Charter				Single Bond Charter			
Variables	Mean	Median	S.D.	Variables	Mean	Median	S.D.	Variables	Mean	Median	S.D.
Capital Adequacy	0.1368	0.1192	0.0674	Capital Adequacy	0.1134	0.1042	0.0437	Capital Adequacy	0.1668	0.1483	0.0810
SD(ROA)	0.0106	0.0035	0.4589	SD(ROA)	0.0059	0.0031	0.0217	SD(ROA)	0.0231	0.0043	1.1110
Mortgage-Assets Ratio	0.2242	0.1646	0.2356	Mortgage-Assets Ratio	0.3648	0.3669	0.2269	Mortgage-Assets Ratio	0.1179	0.0000	0.1971
Loan-Share Ratio	0.6523	0.6641	0.5807	Loan-Share Ratio	0.6803	0.6954	0.1921	Loan-Share Ratio	0.5930	0.5843	0.2732
Chargeoff Ratio	0.0039	0.0016	0.0159	Chargeoff Ratio	0.0037	0.0022	0.0106	Chargeoff Ratio	0.0038	0.0008	0.0179
Delinquency Ratio	0.0122	0.0058	0.0239	Delinquency Ratio	0.0090	0.0053	0.0140	Delinquency Ratio	0.0119	0.0055	0.0238
Z-Score	205.7	80.3	7,418.8	Z-Score	149.0	82.1	800.1	Z-Score	219.3	78.4	5,049.8
ROA	0.0037	0.0061	0.4884	ROA	0.0046	0.0052	0.0260	ROA	-0.0046	0.0043	1.1839
Members	10,229	2,300	59,563	Members	13,997	6,124	27,261	Members	6,496	911	12,249
Total Assets (millions)	$86.8	$11.5	$678.0	Total Assets (millions)	$124.0	$40.6	$324.0	Total Assets (millions)	$77.4	$4.7	$1,440.0

Table 5. Financial Variables Used in Regressions

Performance Area	Ratio
	Risk
Capital Adequacy	Net worth ratio = net worth / total assets
Asset Quality	Delinquency ratio = delinquent loans / total assets
Asset Quality	Charge-offs ratio = net charge-offs / average loans
Interest rate exposure	Mortgage-assets ratio = mortgage assets / total assets
Liquidity	Loan-share ratio = total loans / total shares
	Returns
Earnings	Return on assets (ROA) = net income / average assets
Growth	Membership growth = % increase in memberships
Growth	Loan growth = % increase in loans

Table 6. Correlation Matrix
Federally Chartered Credit Unions, 2002 - 2017

	Log members	Log loans	Log potential members	Total assets	SD(ROA)	Capital Adequacy	Z-score	Period liquid./merger	Loan-share ratio	Delinquency ratio	Charge-off ratio	Unsecured / Total Assets	Log net-income	ROA	Fee income ratio	Mortgage-assets ratio
Log members	1.000															
Log loans	0.945	1.000														
Log potential members	0.869	0.822	1.000													
Total assets	0.292	0.270	0.224	1.000												
SD(ROA)	-0.022	-0.026	-0.016	-0.003	1.000											
Capital Adequacy	-0.393	-0.389	-0.399	-0.061	0.031	1.000										
Z-score	-0.001	0.000	-0.003	0.002	-0.002	0.027	1.000									
Period liquidation / merger	-0.026	-0.027	-0.019	-0.004	0.000	0.007	0.002	1.000								
Loan-share ratio	0.190	0.315	0.189	0.067	-0.001	0.062	-0.016	-0.004	1.000							
Delinquency ratio	-0.250	-0.259	-0.207	-0.032	0.026	0.129	-0.018	0.016	0.209	1.000						
Charge-off ratio	0.031	0.022	0.033	0.015	0.003	-0.016	-0.009	0.003	0.082	0.080	1.000					
Unsecured / Total Assets	-0.255	-0.279	-0.251	-0.026	0.011	0.201	-0.020	0.007	0.203	0.280	0.104	1.000				
Log net-income	0.832	0.852	0.703	0.256	-0.020	-0.270	-0.029	-0.026	0.219	-0.224	0.010	-0.227	1.000			
ROA	-0.061	-0.080	-0.046	0.007	0.027	0.129	-0.017	0.000	0.090	0.078	0.002	0.106	0.122	1.000		
Fee income / total income	0.439	0.357	0.475	0.027	-0.008	-0.278	-0.015	-0.008	0.114	-0.100	0.046	-0.077	0.294	-0.028	1.000	
Mortgage-assets ratio	0.571	0.639	0.542	0.128	-0.015	-0.291	0.003	-0.016	0.114	-0.173	-0.036	-0.344	0.536	-0.070	0.149	1.000

Table 7. Summary Statistics for CUs that Convert to Community Charter

Federally Chartered Credit Unions, 2002-2017

Variables	Obs	Mean	Median	St. Dev.	Min	Max
Capital Adequacy	886	0.1198	0.1096	0.0407	0.043	0.481
SD(Earnings)	886	0.0037	0.0026	0.0040	0.0005	0.0657
Mortgage-Assets Ratio	886	0.3623	0.3617	0.2043	0.000	0.956
Loan-Share Ratio	886	0.6938	0.7004	0.1641	0.230	1.415
Chargeoff Ratio	886	0.0029	0.0022	0.0034	-0.006	0.040
Delinquency Ratio	886	0.0063	0.0045	0.0065	0.000	0.048
Z-Score	886	155.69	103.99	205.55	2.86	3,906.82
ROA	886	0.0068	0.0070	0.0062	-0.043	0.032
Members	886	15,577	8,396	22,643	254	274,418
Total Assets	886	$112,000,000	$55,300,000	$222,000,000	$342,362	$3,460,000,000

Table 8. Generalized Difference-in-Differences Model

1-year Membership Outcomes of Change to Community Charter

	(1)	(2)	(3)
VARIABLES	Log Potential Members	Potential Members	Log Members
Community Charter Dummy	1.232***	305,054***	0.0739***
	(0.060)	(71,206)	(0.0125)
Period FE	X	X	X
CU FE	X	X	X
Observations	212,374	232,901	212,417
R-squared	0.189	0.003	0.010
Number of credit unions	5,349	5,504	5,349

Notes. Standard errors clustered by credit union in parentheses. Control variables include an indicator for whether the credit union CEO is female, the duration of the CEO's tenure, and the duration that the credit union has been active. *** p<0.01, ** p<0.05, * p<0.1

Table 9. Generalized Difference-in-Differences Model
1-year Risk Outcomes of Change to Community Charter

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	SD(ROA)	Z Score	Period Liquid/Merger	Capital Adequacy	Loan Share Ratio	Mortgage-Assets Ratio	Unsecured-Assets Ratio	Charge-offs Ratio	Delinquency Ratio	Fee Income Ratio
Community Charter Dummy	-0.00298***	-9.834	-0.00324***	-0.00788***	0.0206***	0.0052	0.00125	0.00026	0.000562*	0.0159***
	(0.0011)	(19.58)	(0.0008)	(0.0012)	(0.0062)	(0.0053)	(0.0014)	(0.0002)	(0.0003)	(0.0030)
Period FE	X	X	X	X	X	X	X	X	X	X
CU FE	X	X	X	X	X	X	X	X	X	X
Observations	212,291	211,979	212,417	212,417	212,396	212,247	212,417	212,417	212,417	212,393
R-squared	0.001	0.011	0.009	0.103	0.025	0.067	0.015	0.003	0.010	0.042
No. of credit unions	5,320	5,316	5,349	5,349	5,349	5,347	5,349	5,349	5,349	5,349

Notes. Standard errors clustered by credit union in parentheses. Control variables include an indicator for whether the credit union CEO is female, the duration of the CEO's tenure, and the duration that the credit union has been active. *** p<0.01, ** p<0.05, * p<0.1

Table 10. Generalized Difference-in-Differences Model

1-year Returns Outcomes of Change to Community Charter

	(1)	(2)	(3)
VARIABLES	Log Net Income	ROA	Log Loans
Community Charter Dummy	0.059	0.00359**	0.137***
	(0.0374)	(0.0014)	(0.0162)
Period FE	X	X	X
CU FE	X	X	X
Observations	165,319	212,417	212,247
R-squared	0.276	0.000	0.083
No. of credit unions	5,226	5,349	5,347

Notes. Standard errors clustered by credit union in parentheses. Control variables include an indicator for whether the credit union CEO is female, the duration of the CEO's tenure, and the duration that the credit union has been active. *** p<0.01, ** p<0.05, * p<0.1

Table 11. Generalized Difference-in-Differences Model

3-year Risk Outcomes of Change to Community Charter

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	SD(ROA)	Z Score	Period Liquid/Merger	Capital Adequacy	Loan Share Ratio	Mortgage-Assets Ratio	Unsecured-Assets Ratio	Charge-offs Ratio	Delinquency Ratio	Fee Income Ratio
Community Charter Dummy	-0.00163***	22.4	-0.00247***	-0.00453***	0.0162***	0.0030	0.00022	0.00003	0.00057	0.00775***
	(0.0004)	(31.24)	(0.0009)	(0.0012)	(0.0061)	(0.0049)	(0.0015)	(0.0002)	(0.00036)	(0.0026)
Period FE	X	X	X	X	X	X	X	X	X	X
CU FE	X	X	X	X	X	X	X	X	X	X
Observations	173,054	172,806	173,149	173,149	173,131	173,044	173,149	173,149	173,149	173,128
R-squared	0.001	0.012	0.009	0.117	0.019	0.045	0.015	0.002	0.012	0.030
No. of credit unions	4,959	4,932	4,960	4,960	4,958	4,956	4,960	4,960	4,960	4,960

Notes. Standard errors clustered by credit union in parentheses. Control variables include an indicator for whether the credit union CEO is female, the duration of the CEO's tenure, and the duration that the credit union has been active. *** p<0.01, ** p<0.05, * p<0.1

Table 12. Generalized Difference-in-

3-year Returns Outcomes of Change to Community Charter

	(1)	(2)	(3)	(4)
VARIABLES	Log Net Income	ROA	Log Members	Log Loans
Community Charter Dummy	0.102**	0.00346***	0.0623***	0.107***
	(0.0399)	(0.0006)	(0.0114)	(0.0155)
Period FE	X	X	X	X
CU FE	X	X	X	X
Observations	131,113	173,149	173,149	173,044
R-squared	0.282	0.001	0.010	0.065
No. of credit unions	4,806	4,960	4,960	4,956

Notes. Standard errors clustered by credit union in parentheses. Control variables include an indicator for whether the credit union CEO is female, the duration of the CEO's tenure, and the duration that the credit union has been active. *** p<0.01, ** p<0.05, * p<0.1

Table 13. Period & State Fixed Effects Model

Risk Outcomes

VARIABLES	(1) SD(ROA)	(2) Z Score	(3) Period Liquid/Merger	(4) Capital Adequacy	(5) Loan Share Ratio	(6) Mortgage-Assets Ratio	(7) Unsecured-Assets Ratio	(8) Charge-offs Ratio	(9) Delinquency Ratio	(10) Fee Income Ratio
Community Charter Dummy	-0.00877***	-29.97***	-0.0015***	-0.0265***	0.0534***	0.122***	-0.0249***	0.00024***	-0.00184***	0.0501***
	(0.0022)	(6.19)	(0.0003)	(0.0002)	(0.0010)	(0.0011)	(0.0003)	(0.0001)	(0.0001)	(0.0007)
Period FE	X	X	X	X	X	X	X	X	X	X
State FE	X	X	X	X	X	X	X	X	X	X
Observations	232,773	232,441	232,901	232,901	232,878	232,655	232,901	232,901	232,901	232,871
R-squared	0.002	0.002	0.011	0.092	0.151	0.255	0.133	0.008	0.036	0.140

Notes. Robust standard errors parentheses. Control variables include an indicator for whether the credit union CEO is female, the duration of the CEO's tenure, and the duration that the credit union has been active. *** p<0.01, ** p<0.05, * p<0.1

Table 14. Period & State Fixed Effects Model
Return Outcomes

	(1)	(2)	(3)	(4)
VARIABLES	Log Net Income	ROA	Log Members	Log Loans
Community Charter Dummy	0.937***	0.00524**	0.915***	1.156***
	(0.0106)	(0.0024)	(0.0063)	(0.0085)
Period FE	X	X	X	X
State FE	X	X	X	X
Observations	183,117	232,901	232,901	232,655
R-squared	0.269	0.001	0.282	0.296

Notes. Robust standard errors in parentheses. Control variables include an indicator for whether the credit union CEO is female, the duration of the CEO's tenure, and the duration that the credit union has been active. *** p<0.01, ** p<0.05, * p<0.1

Table 15. Generalized Difference-in-Differences Model
1-year Risk Outcomes of Change to Community Charter (small credit unions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	SD(ROA)	Z Score	Period Liquid/Merger	Capital Adequacy	Loan Share Ratio	Mortgage-Assets Ratio	Unsecured-Assets Ratio	Charge-offs Ratio	Delinquency Ratio	Fee Income Ratio
Community Charter Dummy	-0.00406**	-14.49	-0.00337**	-0.00990***	0.0206**	0.0106	0.00185	0.00013	0.00049	0.0207***
	(0.0016)	(19.99)	(0.0013)	(0.0018)	(0.0089)	(0.0075)	(0.0019)	(0.0002)	(0.00049)	(0.0046)
Period FE	X	X	X	X	X	X	X	X	X	X
CU FE	X	X	X	X	X	X	X	X	X	X
Observations	160,060	159,758	160,179	160,179	160,158	160,009	160,179	160,179	160,179	160,155
R-squared	0.001	0.010	0.011	0.104	0.021	0.050	0.015	0.002	0.008	0.038
No. of credit unions	4,354	4,349	4,383	4,383	4,383	4,381	4,383	4,383	4,383	4,383

Notes. Standard errors clustered by credit union in parentheses. Control variables include an indicator for whether the credit union CEO is female, the duration of the CEO's tenure, and the duration that the credit union has been active. *** p<0.01, ** p<0.05, * p<0.1