ESSAYS ON CONSUMER FINANCE

by

KIHWAN BAE

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ABSTRACT OF THE DISSERTATION

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Dissertation Director:

Jennifer Hunt

My dissertation investigates economic incentives relevant to consumer financial services. I focus on two types of unsecured consumer loans primarily for credit-constrained consumers: student loans and consumer overdrafts. Currently in the U.S., the federal government supplies most student loans and applies strong disclosure rules for consumer overdrafts to address market failures due to asymmetric information. However, high student default rates and heavy overdraft fees demand improvements in these government interventions. Nevertheless, beneficial policy changes are hampered by insufficient understanding of student loan repayment behavior and market forces for overdraft fees. Chapter 1 helps fill this gap by demonstrating that stronger repayment incentives reduce defaults on federal student loans, and Chapters 2 and 3 reveal that competition is a key determinant of overdraft fees.

In Chapter 1, I examine how Tennessee's occupational license suspension policy affects student loan repayment. Using program changes in 2009 and 2013 as a quasi-experiment, my difference-in-differences and synthetic control estimation employing the College Scorecard Data shows that the license suspension program led to a surprisingly large reduction in federal student loan defaults: default rates fell by about 30% in Tennessee after the program. I also find suggestive evidence that these effects were largest among women and degree non-completers. While most studies have attributed high student loan default rates to low earnings or inability to repay, my study demonstrates that the incentive to repay is also important in explaining student loan defaults. This finding suggests that policymakers take into account the importance of repayment incentives to improve the sustainability of federal student loan programs.

In Chapter 2, I explore how competition affects overdraft fee revenue of U.S. banks.

Linking newly available overdraft fee revenue data in Call Reports to a competition index derived from branch deposits data, I demonstrate that banks facing higher competition generate more overdraft fee revenue per account than their peers facing lower competition. I use a historical competition index as an instrument for the current competition index to affirm the causality from competition to per-account overdraft fee revenue. These findings are consistent with a theory of bank risk-taking, developed by Marcus (1984) and Keeley (1990): an increase in competition reduces bank charter value, encouraging the bank to take more risk. In my study's context, the increased risk-taking involves supplying more overdraft credits or charging overdraft fees more aggressively at the expense of default or legal risk. In contrast to a general idea that competition benefits consumers, my study shows that competition among banks drives them to generate more overdraft fee revenue, likely hurting low-income consumers who are disproportionately exposed to overdraft fees.

In Chapter 3, I investigate a theoretical explanation for why competition among banks may reduce general deposit fees but raise overdraft fees. I theorize the effects of competition on the two types of deposit fees using a version of the Salop model where consumers are fully rational. In my model, banks provide a deposit account service and an overdraft service to high- and low-income consumers. I assume that low-income consumers are more likely to overdraw and are more sensitive to a difference in fees between competing banks than high-income consumers. My model predicts that the equilibrium overdraft fee rises as the number of banks increases. The economic logic is straightforward: since low-income consumers are more responsive to changes in fees and are more likely to pay the overdraft fee than high-income consumers, banks set the overdraft fee below the overdraft service costs in an equilibrium. As the number of banks in the market grows, each bank's revenue falls, and the banks respond by raising their overdraft fees in a new equilibrium.

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Dedication

To my family

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Introduction

My dissertation investigates economic incentives relating to consumer finance. Consumer finance, also known as household finance, asks "how households use financial instruments to attain their objectives" (Campbell 2006). In this dissertation, I focus on two financial instruments with a growing importance in the recent decade: student loans and consumer overdrafts.

Student loans are a major source of higher education financing in many countries. They enable credit-constrained young adults to invest in high-quality human capital accumulation through college education. Due to the lack of proper collateral for student loans, market provision is likely to fail (Friedman 1962). Moreover, student loans may reduce income inequality within and between generations, since low-income families are more likely to be credit constrained (Avery and Turner 2012). For these reasons, student loans are usually provided or guaranteed by governments. However, student loan debt has been growing fast and not been repaid well in many countries. Particularly, in the U.S., student loan debt has become the second largest and the most delinquent category of household debts (Federal Reserve Bank of New York 2019). To this end, it is crucial to look into student loan repayment behavior and relevant policies.

In Chapter 1, I examine a striking approach to reduce student loan default. Some states suspend the occupational licenses of individuals who default on their student loans. States aim to incentivize borrowers to repay student loans ("incentive effect"), but individuals who lose their license may also lose their job, hurting their ability to repay ("reduced earnings effect"). Popular views opposing the policy appear to presume the reduced earnings effect while ignoring the incentive effect. Using Tennessee's occupational license suspension program as a quasi-experiment, I demonstrate that the license suspension policy decreases student loan default rates, as policymakers hoped. My difference-in-differences and synthetic control estimation using the College Scorecard data shows that the license suspension program reduced three-year cohort default rates by 4 percentage points, which is 30% of the pre-treatment outcome in Tennessee.

This study provides the first piece of empirical evidence on the economic impact of the controversial license suspension policy and is one of the first studies showing the importance of the incentive to repay federal student loans. While most studies have attributed high student loan default rates to low earnings or inability to repay, my study demonstrates that the incentive to repay is also important in explaining student loan defaults. This finding suggests that policymakers take into account the importance of repayment incentives for a sustainable federal student loan system.

Consumer overdrafts, the topic of Chapters 2 and 3, are a part of deposit account services that extend unsecured credits for short-term borrowing needs. According to the recent Call Reports, overdraft fees are a key source of deposit fee revenues of U.S. banks. But complex and heavy overdraft fees have raised consumer protection issues, which have led to a strong disclosure rule on consumer overdrafts in the Dodd-Frank Act of 2009. Despite the regulation, researchers have repeatedly found evidence on suboptimal or mistaken overdrafts (Stango and Zinman 2009, 2014, Alan et al. 2018) and subsequent checking account closures (Liu, Montgomery, and Srinivasan 2018, Campbell, Martínez-Jerez, and Tufano 2012). Moreover, financial regulators have documented that overdraft fees are mostly paid by a small fraction of low-income credit-constrained consumers (Consumer Financial Protection Bureau 2013, 2014, 2017b). Despite this, there has been little exploration of which factors lead banks to seek overdraft fee revenue.

In Chapter 2, I explore how competition among U.S. banks affects overdraft fee revenue. Using cross-sectional variation in competition, measured by the deposit-weighted state Herfindahl-Hirschman Index (HHI), I demonstrate that banks facing higher competition generate more overdraft fee revenue per account than their peers facing lower competition. Moreover, my estimation using a historical competition index as an instrument for the current competition index affirms the causality from competition to per-account overdraft fee revenue. These findings are consistent with a theory of bank risk-taking, developed by Marcus (1984) and Keeley (1990): an increase in competition reduces bank charter value, encouraging the bank to take more risk. In my study's context, the increased risk-taking involves supplying more overdraft credits or charging overdraft fees more aggressively at the expense of default or legal risk.

This is the first study uncovering a positive relationship between bank competition and overdraft fee revenue. In contrast to a general idea that competition benefits consumers, my study shows that competition among banks drives them to generate more overdraft fee revenue, likely hurting low-income consumers who are disproportionately exposed to overdraft fees. To mitigate this negative side-effect of bank competition on financially vulnerable consumers, regulators may need to consider stronger disclosure rules and consumer protection measures.

In Chapter 3, I investigate a theoretical relationship between the number of banks and the equilibrium overdraft fee using a version of the Salop model. In the model, banks provide a bundle of a generic deposit account service and an overdraft service to high- and low-income consumers. The banks charge a maintenance fee for the generic deposit account service and an overdraft fee for the overdraft service. I assume that low-income consumers are more likely to overdraw their deposit accounts and are more sensitive to a difference in fees between competing banks than high-income consumers. Then, the equilibrium overdraft fee rises as the number of banks increases. Because low-income consumers are more responsive to changes in fees and are more likely to pay the overdraft fee than high-income consumers, banks set the overdraft fee below the overdraft service costs in an equilibrium. As the number of banks in the market grows, each bank's revenue falls, and the banks respond by raising their overdraft fee in a new equilibrium. This study shows the possibility that competition leads to high overdraft fees even if no risk is involved in the overdraft service, and consumers are fully rational.

Overall, three chapters in this dissertation commonly show that studying economic incentive is crucial for understanding seemingly complex issues in consumer financial services. This understanding can be a foundation for evidence-based policies or prescriptive measures to improve consumer choice and social welfare.

Chapter 1

Incentivizing the Repayment of Student Loans: Evidence from Tennessee's Occupational License Suspension Program

1.1 Introduction

Higher education enrollment and graduation are increasing all over the world. As a result, student loans are increasing in many countries, especially the U.S. Outstanding student loans reached $1.5 trillion dollars in 2019, having become the second largest category of household debt following mortgage loans. Moreover, student loans are currently the most delinquent household debt (Federal Reserve Bank of New York 2019). Various approaches have been tried to reduce financial burdens or improve accountability of student loan borrowers.[1] On the one hand, the federal government offers income-based repayment plans and loan forgiveness programs to mitigate financial burdens and liquidity constraints on borrowers. Moreover, a growing number of states have been adopting free tuition programs for public colleges, and there is an ongoing nationwide debate on cancelling student debt. On the other hand, the federal government garnishes wages and social security benefits of defaulted borrowers in order to make them responsible for their student loan debt. Also, the government makes it almost impossible for borrowers to discharge student loan debt by declaring bankruptcy. A striking approach to reducing student loan defaults was recently tried

[1] Studies have found that student loan debt has negative effects on socio-economic outcomes: homeownership (Mezza et al. 2016, Bleemer et al. 2017, Cooper and Wang 2014, House and Berger 2015), graduate school enrollment (For, Liberman, and Yannelis 2017, Malcom and Down 2012, Zhang 2013), financial stability (Gicheva and Thompson 2015), marriage (Gicheva 2016), and fertility (Shao 2014).

by Tennessee: threatening to suspend occupational licenses for those who defaulted on their student loans. In the first paper to look at this program, I provide evidence on whether the program had an effect on student loan repayments and which subgroups of the population were most affected by the program.

The suspension of a license is typically a type of disciplinary action against licensees for malpractice or wrongdoing. But a special provision for student loan default was suggested to reduce student loan defaults in the early 1990s and adopted in some states (Farrell 1990). License suspension for student loan default may raise borrowers' incentive to repay student loans by adding to the expected cost of student loan defaults ("incentive effect") (Yannelis 2017). Conversely, license suspension itself may reduce defaulters' earnings and prolong the default by preventing them from practicing in the licensed occupation ("reduced earnings effect") (New York Times 2017). Hence, it is important to assess these opposing effects to see whether the license suspension policy is socially desirable. Surprisingly, however, little is known about the economic impact of license suspension policies, and the policy has been both implemented and revoked without a solid evidentiary foundation.

Tennessee established the License Review program to suspend occupational licenses for student loan defaulters in 2009 and expanded it in 2013. Given that no other states made any such policy change in that period, I use Tennessee's License Review program as a quasi-experiment to identify its effects. For identification, I employ both difference-in-differences and synthetic control methods. The difference-in-differences method compares the outcome of borrowers who attended colleges in Tennessee with those who attended colleges in control states before and after the program establishment. The synthetic control method constructs a synthetic Tennessee and then compares post-treatment outcomes between Tennessee and synthetic Tennessee. Due to the lack of data, I do not use the individual licensing information of the borrowers, and as a result the estimation identifies the program's effects on borrowers as a whole rather than licensees only.

The study overcomes two important empirical challenges. The first challenge is the lack of information on whether and how states enforce their license suspension laws for student loan default. Among the 23 states that have at some point enacted the license suspension laws, some states have reportedly never enforced the laws while other states have suspended a large number of licenses (New York Times 2017). To address this issue, I exploit information from two different sources. First, for the case of Tennessee, I use public documents of a former federal student loan guarantee agency in Tennessee to clarify how Tennessee enforced its license suspension laws under the License Review program. Next, for a cross-state comparison, I use data on adverse licensing actions against medical practitioners, which are the most commonly licensed occupations across states in the U.S. According to the data in the National Practitioner Data Bank (NPDB), the number of medical practitioner license suspensions due to student loan default substantially varies even among states with license suspension laws. More importantly, the data indicates that Tennessee dwarfs all other states in medical practitioner license suspensions due to student loan default after 2009, and suggests that no other state made a comparable policy change between 2003 to 2015.

The second empirical challenge is the lack of publicly available data on student loan repayment outcomes, which has been a major obstacle for many researchers working on student loans. For this study, I employ the College Scorecard Data (CSD), a newly available institution-level administrative dataset. For each postsecondary education institution in the U.S., the CSD provides cohort default rates and repayment rates of federal student loan borrowers. The dataset also contains the repayment rates by demographic subgroups, such as family income, gender, and degree completion status. Cohort default rates measure the fraction of borrowers who have ever defaulted two or three years after entering repayment, while repayment rates quantify the fraction of borrowers who have made progress towards repayment within two years after entering repayment. I examine the occupational license suspension program's effects on both outcome measurements.

By the nature of the outcome measurements, my estimations on cohort default rates and repayment rates identify different types of effects of the occupational license suspension program. Because repayment rates are positively affected by the incentive effect and negatively affected by the reduced earnings effect, estimation on repayment rates quantifies the net effect of the program. In contrast, cohort default rates are not influenced by the reduced earnings effect because the reduction in earnings due to a license suspension does not occur until after a default. Once a borrower defaults on student loans, the borrower is counted as a defaulter for the computation of cohort default rates. Therefore, estimation on default rates measures a pure incentive effect which is not confounded by the reduced earnings effect.

The primary finding of this study is that Tennessee's License Review program reduced student loan default rates by a surprisingly large amount. Based on difference-in-differences estimates, the program reduced three-year cohort default rates by 4 percentage points, or 30% of the pre-treatment outcome in Tennessee. This is a remarkable figure because the occupational license suspension program were not applied to borrowers who do not have occupational licenses, and only about one-third of borrowers might have occupational licenses in Tennessee. This implies that defaults may have been reduced by as much as 90% among license holders. Estimations using subsamples by institution type reveal that borrowers from public or for-profit institutions contributed to the improvement in cohort default rates more than those from private nonprofit institutions. Synthetic control estimates of cohort default rates are similar to difference-in-difference estimates.

The program also improved student loan repayment rates. Difference-in-difference estimation shows that the program raised one-year repayment rates by 4.5 percentage points, or 9.3% of the pre-treatment outcome in Tennessee. This means that some Tennessee licensees paid down their student loans to avoid a license suspension. Estimations using subsamples by institution type reveal that borrowers from public or private nonprofit institutions improved their repayment rates while those from for-profit institutions did not. Furthermore, estimations on demographic subgroup repayment rates show that the program had a broad-based effect regardless of family income, but that it mostly affected degree non-completers and had larger effects on females than males.

These findings have several policy implications. First, occupational license suspension provides licensees with a strong incentive to repay their loans. It may be because the risk of losing a job due to license suspension substantially raises expected costs of student loan default. Next, heightening repayment incentives can be an effective way to improve the sustainability of federal student loan programs. Interestingly, however, most states have recently repealed occupational license suspension laws for student loan defaulters. This is primarily because state governments no longer have a financial incentive to reduce student loan defaults. Since federal student loan programs transitioned from the Federal Family Education Loan (FFEL) to the Direct Loan in 2010, state governments do not guarantee student loans any more and do not bear financial losses from student loan defaults. Despite these changes, the federal government, which bears all financial costs from student loan defaults, may have an incentive to revisit license suspension policy in cooperation with state governments that administer occupational regulation. Therefore, it is still important to understand the policy's economic impacts and overall welfare implications.

This study is relevant to the literature on consumer default and bankruptcy. Early studies on bankruptcy reforms have recognized that consumer default and bankruptcy is determined not only by the ability to repay but repayment incentives.[2] Several studies have recently found that after the Great Recession, some households with negative home equity strategically defaulted on their mortgage loans even though they had the ability to repay the loans.[3] In regard to student loans, two studies have recently examined how repayment incentives affect student loan default or bankruptcy.[4] Darolia and Ritter (2017) have shown that the removal of private student loan bankruptcy discharge in 2005 had little effect on Chapter 7 bankruptcy filing behavior. Conversely, Yannelis (2017) has shown that the removal of federal student loan bankruptcy discharge in 1998 and the intensification of wage garnishment in 2006 reduced federal student loan defaults. Being consistent with the second study, my study adds to empirical evidence that the incentive to repay is crucial to explaining consumer default.

1.2 Tennessee's Occupational License Suspension Program

1.2.1 Background

The federal government used not to lend student loans directly to borrowers. Instead, under the Federal Family Education Loan program (FFEL), banks made federal stu-

[2] Domowitz and Eovaldi (1993), Gropp, Scholz, and White (1997), Fay, Hurst, and White (2002), Gross and Souleles (2002), Albanesi and Nosal (2018).

[3] Guiso, Sapienza, and Zingales (2013), Gerardi et al. (2017).

[4] Many other studies on student loan default have focused on the importance of the ability to repay rather than the incentive to repay student loans. Several studies have found that relatively poor returns on a degree from a for-profit school are a leading cause of high student loan default rates (Deming, Goldin, and Katz 2012, Looney and Yannelis 2015, Armona, Chakrabarti, and Lovenheim 2019). Also, other studies have shown that negative earnings shocks in the Great Recession increased student loan defaults, and that income-based repayment plans have been effective in mitigating student loan defaults or delinquencies (Mueller and Yannelis 2019, Herbst 2018).

dent loans, which were guaranteed by student loan guaranty agencies and reinsured by the Department of Education. Because most student loan guaranty agencies were state agencies, both the federal and state governments could lose money if borrowers default on federal student loans. Amid a surge in student loan default rates around 1990, the Department of Education proposed occupational license suspension policies in an effort to improve borrowers' accountability and reduce fiscal costs due to student loan defaults (Farrell 1990). In the 1990s to the early 2000s, states enacted license suspension laws that allow state agencies and licensing boards to suspend, revoke, or deny occupational licenses if licensees fail to repay student loans. As shown in Appendix Table 1.A1, 23 states have license suspension laws for student loan defaulters as of 2014.

The license suspension laws, however, have increasingly become unpopular in the recent years. Sixteen states have repealed the license suspension laws since 2015. These dramatic changes are motivated by the recognition of potentially undesirable effects of the license suspension laws to people without means to repay their student loans.[5] More importantly, however, states no longer have a financial incentive to maintain the license suspension laws. As federal student loan programs evolved from the FFEL to the Direct Loan program around 2010, state agencies do not guarantee new student loans any more, and existing guaranteed loans have been substantially diminishing over time.[6]

1.2.2 Tennessee's License Review Program

Tennessee's License Review program, an administrative procedure, was set up around July 2009 to enforce Tennessee occupational license suspension laws for student loan default, which bad become effective in July 1999 but had not been enforced (Tennessee Student Assistance Corporation 2010).[7]. Tennessee Student Assistance Corporation (TSAC), the student loan guarantee agency in Tennessee at that time, determines which Tennessee licensees are in default on a federal student loan and notifies them of their default status. If a licensee does not properly respond to the notice, the

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5 New York Times (2017), Texas Tribune (2018), Dieterle, Weissmann, and Watson (2018).

6 According to the Federal Student Aid Portfolio Summary, outstanding FFEL loans ($271.6 billion) is less than a quarter of outstanding direct loans ($1,198.4 billion) as of March 31, 2019.

7 Tennessee Public Acts, 1999, Chapter No. 476

TSAC asks the licensing board to suspend the person's license. If the person later pays their balances in full or enters into a repayment plan approved by the TSAC, the agency requests the licensing board to reinstate the person's license.[8] The program applied to both FFEL loan borrowers and Direct loan borrowers. Also, the program affected Tennessee licenses of both in-state and out-of-state residents.

Tennessee then expanded the program with new legislation taking effect in July 2013.[9] The program initially applied to licenses issued by licensing boards under the Tennessee Department of Commerce and Insurance and the Tennessee Department of Health. After the expansion, all Tennessee licensees, including teacher licenses under the Tennessee Department of Education and attorney licenses under the Tennessee Supreme Court, fell under the program. Ultimately, the program ended in April 2018, as the phase out of FFEL loans lowered the state's financial gains from recovered loans below administrative costs for the program.

Kleiner and Vorotnikov (2017) show that the proportion of licensees among all workers in Tennessee is 23%, close to the national average of 22%. According to the 2015 National Survey of College Graduates (NSCG), student loan borrowers are 30% more likely to have an active license or certificate than non-borrowers.[10] The two pieces of information together indicate that the License Review program is likely to have affected about a third of student loan borrowers in Tennessee. The program may have affected a broad range of occupations. Table 1.1 shows that Tennessee licensees are distributed across various occupation categories. Among them, healthcare, education, sales, and business related occupations have a larger share of licensed workers than other occupations, and therefore these occupations are likely to have been influenced more by the program.

Public records on the License Review program provide further details on Tennessee's enforcement activities and loan recoveries from defaulted loans. Tennessee Student Assistance Corporation (2016) shows that the agency sent out 8,864 notification letters to Tennessee licensees in default on a federal student loan from fiscal years

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8 Rules of Tennessee Student Assistance Corporation Chapter 1640-01-23 (Procedure Affecting Professional Licenses) provides more details on the procedure of license suspension for student loan default.

9 Tennessee Public Acts, 2012, Chapter No. 519

10 According to the 2015 NSCG, 40% of college graduates who have borrowed for their degrees have a license or certificate while 31% of those who have not borrowed for their degrees have an active license or certificate.

2010 to 2015; subsequently, 5,492 licenses were suspended, and 3,943 licenses were reinstated during the same period. As shown in Figure 1.1, the number of default notices, license suspensions and reinstatements gradually increased over time, and they surged upon the program expansion in 2013. According to Tennessee Student Assistance Corporation (2013), licensees in 105 license types had received at least one default notice as of August 31, 2013. Among them, nurses, cosmetologists, security guards, teachers, and salesmen received a relatively larger number of default notices and subsequent license suspensions than other licensees, as shown in Table 1.2. In regard to loan recoveries under the program, Tennessee Student Assistance Corporation (2016) reveals that more than 1,000 defaulted borrowers paid their loan in full and $77 million were recovered from defaulted loans from July 2009 to March 2016. However, looking only at these changes in Tennessee without accounting for counterfactual outcome changes may be inappropriate to determine the causal effects of the program. Therefore, I use the difference-in-differences and synthetic control method to quantify the causal effects.

1.2.3 Significance of Tennessee's Program

There is substantial heterogeneity among occupational license suspension policies for student loan default. Some states have the laws for all licenses while other states have them for certain licenses such as medical practitioner licenses. More importantly, states vary in the enforcement of their license suspension laws. Given the lack of a register of license suspensions for all types of licenses in all states, I use the National Practitioners Data Bank (NPDB) to compare the number of medical practitioner license suspensions for student loan default across states in the U.S. Medical practitioners are the most commonly licensed occupation and typically fall under the license suspension laws for student loan defaulters. According to the NPDB data, medical practitioner license suspensions due to student loan default are concentrated in a handful of states including Tennessee, Illinois, and Texas, as shown in Figure 1.2.[11] This het-

[11] State licensing boards are required by the law to report license suspensions of all medical practitioners to the NPDB since March 2010. Before the point, it is not compulsory for the licensing boards to report license suspensions of medical practitioners except physicians and dentists. In spite of that, the NPDB data contains a large number of records on license suspensions of medical practitioners other than physicians and dentists before 2010. For a comparison of the number of medical practitioner license suspension due to student loan default with that for other reasons in each period, see Appendix Table 1.A2.

erogeneity makes it desirable to focus on a specific state which actively enforces the license suspension laws in order to identify the impacts of license suspension for student loan default.

Tennessee's License Review program has several merits for this study compared to other states' policies. First, Tennessee enforced license suspension laws for student loan default most strictly among all states in the era of the License Review program. Figure 1.2 shows that a majority of medical practitioner license suspensions due to student loan default in the nation in 2010-2018 happened in Tennessee, despite Tennessee's small population compared with Illinois and Texas. Next, the introduction of the License Review program is a seismic policy change in Tennessee. There is no medical practitioner license suspension due to student loan default in Tennessee in 1999-2008, which confirms Tennessee's non-enforcement of the license suspension laws before the License Review program. Lastly, no other states seem to have changed their policy on license suspension for student loan default to an extent comparable with Tennessee's policy change. Until Montana repealed its own license suspension laws in 2015, license suspension laws in other states had remained largely unchanged. The number of medical practitioner license suspensions due to student loan default is similar before and after 2009 for all other states except Texas, as seen in Figure 1.2. The change in Texas is larger than other states, but it still not comparable with the change in Tennessee. For these reasons, I focus on Tennessee's License Review program as an archetype of a license suspension policy for student loan default.

1.3 Data

1.3.1 Data Sources and Measurement

I employ administrative information on postsecondary institutions and student loan repayment outcomes from the College Scorecard Data (CSD). The CSD provides cohort default rates of every U.S. higher education institution, which is obtained from the Federal Student Aid (FSA) office under the Department of Education. The original data source of cohort default rates is the National Student Loan Data System (NSLDS), the Department of Education's central database for student aid. Cohort default rates are defined as the fraction of borrowers who are in default within a cohort default period among borrowers entering repayment in a fiscal year. The cohort default period of a fiscal year cohort begins on the first date of the fiscal year, and it ends on the last date of the following fiscal year for two-year cohort default rates and on the last date of the second following fiscal year for three-year cohort default rates.[12]

Two-year cohort default rates are measured for fiscal year 1995 (FY1995) cohort to FY2011 cohort, which makes them appropriate for analyzing the effects of the establishment of the License Review program in 2009. But due to the lack of data from FY2012 cohort on, it is impossible to analyze the effects of the program expansion in 2013 using two-year cohort default rates. Conversely, three-year cohort default rates are measured for FY2009 cohort to FY2015. This means that it is possible to use the three-year measurement to examine the effects of both the program establishment and expansion.[13]

The CSD also contains one-year repayment rates derived from the NSLDS. One-year repayment rates are defined as the fraction of borrowers entering repayment in a fiscal year who are not in default, and with loan balances that have declined as of the end date of the following fiscal year since entering repayment. So, the repayment rates measure a success of student loan repayments more narrowly than cohort default rates. For example, borrowers deferring repayments for economic hardship reasons do not default on student loans but still fail to reduce their loan balances. Also, the repayment rates are based solely on undergraduate loans, which makes them not directly comparable to cohort default rates based on both undergraduate and graduate loans.[14]

One-year repayment rates are available as two-year rolling averages for the combination of FY2006 and FY2007 (FY2006/FY2007) cohorts to FY2013/FY2014 cohorts. More importantly, unlike cohort default rates, repayment rates are given by demo-

[12] For example, the two-year cohort default rates of fiscal year 2010 cohort is the number of borrowers entering repayment in fiscal year 2010 (October 1, 2009 to September 30, 2010) who are in default by the end date of fiscal year 2011 (September 30, 2011) divided by the number of borrowers entering repayment in fiscal year 2010; the three-year cohort default rates of fiscal year 2010 cohort is the number of borrowers entering repayment in fiscal year 2010 who are in default by the end date of fiscal year 2012 (September 30, 2012) divided by the number of borrowers entering repayment in fiscal year 2010.

[13] The Department of Education changed the official measurement of school performance from two-year cohort default rates to three-year cohort default rates around 2010. It has released two-year cohort default rates only for fiscal year cohorts up to FY2008 cohort, both two- and three-year cohort default rates for FY2009 to FY2011 cohorts, and three-year cohort default rates only from FY2012 on.

[14] For more detailed comparisons between cohort default rates and repayment rates, see Appendix Table 1.A3.

graphic subgroups, for example, by family income, gender, and education program completion status. A high-income family is defined by the NSLDS as having income above $75,000; middle-income means family income between $30,000 to $70,000; and low-income means family income below $30,000, based on the Free Application for Federal Student Aid (FAFSA).

Figure 1.3 shows national trends of cohort default rates and one-year repayment rates. Two-year cohort default rates are about 5% for cohorts entering repayment in the early 2000s and gradually increase to 10% by the FY2011 cohort. Three-year cohort default rates peak at about 15% for the FY2010 cohort and trend down for later cohorts. Two-year rolling averages of one-year repayment rates sharply decline from 64% for FY2006/FY2007 cohorts (plotted as a dot between 2006 and 2007) to 40% for FY2012/FY2013 cohorts.

Apart from student loan repayment outcomes, the CSD includes information on institution type and state obtained from the Integrated Postsecondary Education Data System (IPEDS). It also indicates whether an institution is public, private nonprofit, or for-profit, and whether it is a four-year, two-year, or less than two-year institution. Additionally, I use state unemployment rates obtained from the Bureau of Labor (BLS) Statistics.

1.3.2 Study Sample

I primarily use state-by-year observations for estimation, which I aggregate from institution-by-year observations, weighting by the institution cohort size in the CSD. Because the CSD uses different definitions of cohort default rates for institution-by-year observations with the cohort size fewer than 30, these observations must be excluded from the aggregation.[15] Institutions whose campuses are located in multiple states are also excluded from the analysis, since they cannot be used for cross-state comparisons.[16]

Therefore, I use three state-by-year panels: a two-year cohort default rates panel,

[15] The number of borrowers in all institutions with fewer than 30 borrowers is less than 1% of all borrowers in each year, and so excluding these small institutions has little effect on estimation results.

[16] This restriction to the sample effectively exclude all for-profit schools with a regional or nationwide network. The final sample includes student loan repayment outcomes of about 80% of borrowers who attended 77% of institutions in the CSD.

a three-year cohort default rates panel, and a one-year repayment rates panel.[17] The panels have different lengths due to the limited availability of each outcome. Table 1.3 shows summary statistics of each panel. In Tennessee, compared with other states, cohort default rates are higher, one-year repayment rates are lower, the proportion of borrowers who attended for-profit institutions is lower, unemployment rates are higher, and the number of borrowers is similar.

1.4 Empirical Methodology

1.4.1 Identification

I employ both difference-in-differences and synthetic control methods to identify the program's causal effects on student loan repayment outcomes. The difference-in-differences method identifies the causal effects under the assumption that outcomes of Tennessee and other states have common trends. Given that only Tennessee is treated and its outcomes are not outliers of other states' outcomes, the synthetic control method provides a systematic way of determining a control group and constructing counterfactual outcomes. I use both methods and compare estimation results to check the robustness.

I primarily identify the program's effect after its establishment in 2009 and conduct some analysis on the additional effect of its expansion in 2013. Considering the timing of the program establishment and the cohort default period of each fiscal year cohort, I classify FY2008 and preceding cohorts as pre-establishment cohorts and FY2009 and following cohorts as post-establishment cohorts.[18] Similarly, I categorize FY2011 and earlier cohorts as pre-expansion cohorts and later cohorts as post-expansion cohorts. For the most part of my analysis, treatment means the program establishment, and pre- and post-treatment means pre- and post-establishment. An exception is for difference-in-difference estimations on three-year cohort default rates. Due to the lack of data on this outcome for pre-establishment cohorts, I use the FY2009 cohort as

[17] When constructing the state-by-year panel, I use all institution-by-year observations regardless of whether an institution has existed for the entire panel period. However, an alternative state-by-year panel that is constructed using a consistent set of institutions for the entire panel period gives similar estimation results.

[18] For example, the two-year cohort default period of the FY2008 cohort begins on Oct. 1, 2007 (the first date of FY2008) and ends on Sep. 31, 2009 (the last date of FY2009). The measurement period of one-year repayment rates is the same to the two-year cohort default period.

pre-treatment cohort and later cohorts as post-treatment cohorts when measuring the program's effect on three-year cohort default rates.

I examine the program's effects on two types of student loan repayment outcomes: cohort default rates and repayment rates. Cohort default rates are a formal measurement used by the Department of Education to sanction schools from receiving federal aid, while repayment rates are a complementary measurement focusing on repayment success. Both of them are of interest from the license suspension program's perspective. The program directly targets borrowers in default, so default rates are relevant to analyze whether the program prevents borrowers from defaulting on student loans. However, the program's ultimate goal is to improve student loan repayments, hence repayment rates are also informative to quantify the extent to which the program encourages borrowers to repay their debt.

Estimations on cohort default rates and repayment rates identify different types of effects on different sets of borrowers. Estimations on cohort default rates measure the program's incentive effect on the student loan default of undergraduate and graduate borrowers. Because cohort default rates are not affected by any repayment of borrowers who ever defaulted on student loans, the incentive effect is not confounded by reduced earnings effect from actual license suspensions, which do not occur until after a default. In contrast, estimations on repayment rates quantify the program's net effects, of the incentive and reduced earnings effects, on the repayment success of undergraduate borrowers excluding those in school or military service.

1.4.2 Difference-in-Differences Method

Difference-in-differences method compares the change in outcome of student loan borrowers who attended Tennessee colleges with those who attended colleges in control states, using state-by-year panel data.

$$Outcome_{st} = \beta(Tennessee_s \cdot Post_t) + \lambda_t + \alpha_s + \gamma X_{st} + \epsilon_{st}$$

where s indexes state, t indexes fiscal year cohort, $Outcome_{st}$ is cohort default rates or repayment rates, $Tennessee_s \cdot Post_t$ is the dummy for post-treatment cohorts in Tennessee, λ_t is cohort fixed effects, α_s is state fixed effects, X_{st} is a set of control variables, and ϵ_{st} is the error term.

The control group for Tennessee consists of 47 states and the District of Columbia. Illinois and Texas are excluded from the control group, since they appear to have changed the enforcement of their license suspension laws around the time of Tennessee's policy change. Other states with license suspension laws are not excluded for the following reasons: all of them had enacted the license suspension laws by 2003, their enforcement seems not have changed around 2009, and none of them repealed the laws until 2015. Therefore, there is little concern of estimation bias from including them in the control group.

The explanatory variable of interest is the dummy for post-treatment cohorts in Tennessee. Under the common trend assumption between Tennessee and control states, OLS estimation of β in the model with state means yields a difference-in-difference estimate of causal effects of the Tennessee's policy change. Pre- and post-treatment cohorts vary by outcome variables given their limited availability. For estimations on two-year cohort default rates, I compare FY2007 and FY2008 cohorts (pre-treatment) with FY2009 to FY2011 cohorts (post-treatment). For estimations on one-year repayment rates, I compare FY2007/FY2008 cohorts (pre-treatment) with FY2009/FY2010 to FY2013/FY2014 cohorts (post-treatment). For estimations on three-year cohort default rates, I compare the FY2009 cohort (pre-treatment) with FY2010 to FY2015 cohorts (post-treatment). Because the FY2009 cohort is likely to have been partially affected by the program, the estimations may cause underestimation of the causal effect. To isolate the additional effect of the program expansion, I also compare estimates on the FY2011 cohort (pre-expansion) with those on FY2012 to FY2015 cohorts (post-expansion).

Control variables X include the proportion of borrowers who attended for-profit institutions, the proportion of borrowers who attended two-year or less than two-year institutions, and state unemployment rates. The first two variables are included to account for heterogeneity in institution types across states. It is well known that those who attended for-profit schools are much more likely to default than public or private nonprofit schools (Deming, Goldin, and Katz 2012, Looney and Yannelis 2015, Armona, Chakrabarti, and Lovenheim 2019). State unemployment rates are expected to control for state-specific labor market conditions, which may affect borrowers' ability to repay student loans.

I cluster standard errors by state. It is known that clustered standard errors are underestimated for the difference-in-differences estimation with a small number of treated groups (Conley and Taber 2011, MacKinnon and Webb 2017, Ferman and Pinto 2019, MacKinnon and Webb 2019). Because Tennessee is the only treated group in this study, the inference based on the clustered standard errors may inflate the statistical significance of estimated coefficients. However, there are no alternative inference methods with proper statistical power.

1.4.3 Synthetic Control Method

To complement the difference-in-differences method, I also employ the synthetic control method. The synthetic control is a convex combination of comparison states in a donor pool that closely match pre-treatment characteristics including pre-treatment outcomes (Abadie and Gardeazabal 2003, Abadie, Diamond, and Hainmueller 2010, Abadie, Diamond, and Hainmueller 2015).

I focus on matching pre-establishment characteristics between Tennessee and synthetic Tennessee and comparing post-establishment outcomes between them. Matching pre-expansion characteristics may give a different version of synthetic Tennessee for an analysis of the program expansion effect. However, given that the program establishment and expansion happened within a few years, the program establishment effect may have phased in for post-establishment pre-expansion cohorts and hence matching trends in outcomes of these cohorts may be improper. Hence, I only consider synthetic Tennessee based on pre-establishment characteristics.

Synthetic Tennessee is represented as a vector of synthetic weights for each state in the donor pool, which is determined to minimize mean squared prediction errors (MSPE) from a prediction of Tennessee's pre-treatment characteristics using comparison states' characteristics. The donor pool for synthetic Tennessee consists of the control states from the difference-in-differences analysis. Suppose that m pre-treatment characteristics, so-called predictors, are used for the prediction. Then MSPE is defined as

$$MSPE = \sum_{m=1}^{k} (X_{1m} - X_{0m}W)^2$$

where X_{1m} is m-th predictor of Tennessee, X_{0m} is a row vector of m-th predictor of comparison states in the donor pool, and W is a column vector of synthetic weights for comparison states.

Using three kinds of pre-treatment characteristics together, I construct a unique synthetic Tennessee for estimations on all three outcome variables. The first kind of predictors are cohort default and repayment rates of pre-establishment cohorts. I match two-year cohort default rates of FY2006, FY2007, and FY2008 to account for the trend of cohort default rates right before the policy became effective. I also match the average of two-year cohort default rates at the period of the highest national cohort default rates (FY1995-FY1997) and at the period of the lowest national cohort default rates (FY2003-FY2005) to take into account variations in cohort default rates over time. For one-year repayment rates, I include the two-year rolling average of FY2006 and FY2007 cohorts and FY2007 and FY2008 cohorts as predictors. Due to the lack of data, I cannot match on pre-establishment three-year cohort default rates. Next, I include the proportion of borrowers who attended for-profit institutions and the proportion of borrowers who attended two-year or less than two-year institutions in 2006-2008 (average) as predictors. The remaining predictors are state unemployment rates in 2006, 2007, and 2008.

Once synthetic Tennessee is determined, synthetic control estimates are computed as the gap in post-treatment outcomes between Tennessee and synthetic Tennessee. I also test the statistical significance of synthetic control estimates on two-year cohort default rates using a placebo test based on artificial reassignments of the treatment to each state in the donor pool, suggested by Abadie, Diamond, and Hainmueller (2010) and Abadie, Diamond, and Hainmueller (2015). The test compares the ratio of root mean square prediction errors in post-treatment period to root mean square prediction errors in pre-treatment period (post/pre-treatment RMSPE ratio) among states in the donor pool. If Tennessee's ratio is located at an extreme of the distribution of the post/pre-treatment RMSPE ratio, it is reasonable to conclude that the program had systematic effects on post-treatment outcomes in Tennessee.

1.4.4 Potential Identification Issues

There may be several concerns about the identification of this study using a cross-state comparison before and after the establishment of the License Review program. The first concern would be the possibility of borrowers leaving Tennessee to avoid the program. However, for borrowers struggling to repay student loans, it would be costly to move another state. If they move, they might have to spend re-licensing costs of training, exam obligations or licensing fees as well as regular costs of relocation across states (Johnson and Kleiner 2017). Moreover, they might not be able to take advantage of reciprocal licensing agreements available for some licenses among some states. It is because Tennessee licensing boards, upon request from the TSAC, suspended Tennessee licenses of out-of-state residents as well as in-state residents. This means that Tennessee licensees who were in default or would make a default on student loans could avoid license suspension by simply moving to the other state. Hence, the possibility of migration from Tennessee to the other state is not a big threat to the study's identification.

The second concern would be that if Tennessee changed other default-prevention efforts or scholarship programs, the effects of the License Review program could be confounded by the effects of them. However, there are no noticeable changes in the TSAC's campus visit or financial aid counseling around the establishment or expansion of the License Review program. Also, there have been no significant changes in Tennessee's state aid to college students except in 2004 and 2015.[19] Therefore, other policies for default-prevention in Tennessee may not undermine the study's identification using the License Review program.

Third, one may raise concerns about changes in federal student loan programs around 2010. Federal student loan programs have transitioned from FFEL loans to Direct loans in 2009 and 2010, but the License Review program applied to both types of loans for the whole program period. Next, Income-Based Repayment (IBR) plan was introduced in 2009 and the number of enrollees on the plan rapidly increased

[19] Tennessee introduced Tennessee Lottery Scholarship program (also called as Tennessee HOPE program) in 2004, which is a scholarship programs for a broad range of college students, and Tennessee Promise program in 2015, which is a free-tuition program for community colleges.

in the early 2010s (Herbst 2018, Mueller and Yannelis 2019). However, there is no reason or empirical evidence that borrowers in Tennessee more likely to adopt the IBR plan than those in other states. In sum, contemporaneous federal-level policy changes should not hamper the study's identification.

1.5 Results

1.5.1 Difference-in-Differences Estimates

Effects on Default Rates

Figure 1.4 shows that Tennessee and other states have almost parallel trends in outcomes before the establishment of the License Review program. For all cohorts preceding the FY2009 cohort, two-year cohort default rates of Tennessee were persistently higher than those of other states. After the program was established, however, Tennessee's cohort default rates peaked for the FY2009 cohort and then declined while other states' cohort default rates continued to increase. As a result, cohort default rates of Tennessee and other states became almost the same level for the FY2011 cohort. Similarly, three-year cohort default rates of Tennessee were higher than those of other states for FY2009 cohort, but they converged for the FY 2011 cohort. After the program expanded in 2013, Tennessee's three-year cohort default rates finally fell below other states' three-year cohort default rates for the FY2015 cohort.

Difference-in-differences estimation demonstrates that the License Review program was effective in reducing student loan default rates. Table 1.4 Panel A presents estimates of the program establishment's effects on two-year cohort default rates from a comparison of FY2007 and FY2008 cohorts (pre-treatment) and FY2009 to FY2011 cohorts (post-treatment). First, the estimated coefficient on Tennessee*Post in column (1) shows that the program establishment reduced two-year cohort default rates for the post-treatment cohorts in Tennessee. Next, column (2) reveals that the program establishment had little effect on cohort default rates of the FY2009 cohort, which entered repayment before the policy change. The program's effect on cohort default rates appeared for the FY2010 cohort, which entered repayment after the program was established, and became apparent for the FY2011 cohort. Lastly, column (3) confirms the program's default-prevention effect after accounting for additional control variables including the proportion of borrowers who attended for-profit institutions, the proportion of borrowers who attended two-year or less than two-year institutions, and state unemployment rates. The estimated coefficient on Tennessee*FY2011 in column (3), the study's baseline regression model, shows that the program establishment reduced two-year cohort default rates by 1.5 percentage points, which is 19.2% of the average pre-treatment outcome in Tennessee. Both columns (2) to (3) reject the null hypothesis that the policy change has no effect on two-year cohort default rates of the FY2011 cohort at the 1% significance level.

These findings are substantiated by estimation on three-year cohort default rates. Table 1.4 Panel B shows estimates of the program's effect on three-year cohort default rates from a comparison of FY2009 (pre-treatment) with FY2010 to FY2015 cohorts (post-treatment). The estimates reaffirm that the program's default-prevention effect were larger for FY2011 cohort than FY2010 cohort. The estimated coefficient on Tennessee*FY2011 in column (3) shows that the program establishment reduced three-year cohort default rates by 2.4 percentage points, which is 18% of the average pre-treatment outcome in Tennessee. Compared with the estimate on two-year cohort default rates, the estimate on three-year cohort default rates is larger in terms of change in percentage points but almost the same in terms of change in percentage. The estimates also show that the program expansion significantly reduced three-year cohort default rates. The difference between coefficients on Tennessee*FY2011 and Tennessee*FY2015 in column (3) shows that the program expansion reduced three-year cohort default rates by 1.6 percentage points, which is 12% of the average pre-treatment outcome in Tennessee. A joint hypothesis test confirms that the difference between the coefficients is statistically significance at the 1% level. Column (3) also reveals that the program expansion had little effect on cohorts entering repayment before the expansion (FY2012 and FY2013 cohorts) and increasing effects for cohorts entering repayment after the expansion (FY2014 and FY2015 cohorts), just as the program establishment did. Combining the establishment and expansion of the program, the estimated coefficient on Tennessee*FY2015 in column (3) shows that the program reduced three-year cohort default rates by 4 percentage points, which is 30% of the average pre-treatment outcome in Tennessee.

Figure 1.5 summarizes difference-in-difference estimates of the program's effect on two-year and three-year cohort default rates on the basis of FY2009 cohort. The size of point estimates on both two-year and three-year cohort default rates similarly grows for FY2010 and FY2011 cohorts. It plateaus for FY2011 and FY2013 cohorts and then expands for FY2014 and FY2015 cohorts. 99% confidence intervals marked as shaded areas are distant from the line at zero, confirming that these point estimates are statistically significant at the 1% level. From the figure, it becomes clear that both the program establishment and expansion had little effect on cohorts entering repayment before the policy change but increasing effects for cohorts entering repayment within two years after them.

There may be several reasons for this pattern of time-varying effects on cohort default rates. First, cohorts entering repayment before the program are at most partially exposed to it, but cohorts entering repayment after the program could be fully exposed. Next, even among cohorts entering repayment after the program, later cohorts are likely to be better informed of the program than earlier cohorts given that the TSAC did not publicly announce the License Review program. Lastly, cohort default rates are not affected by any repayment induced by default notices or subsequent license suspensions. As a result, cohort default rates are affected only by behavioral changes of borrowers not in default, who might learn about the program slowly than those in default. For these reasons, the program establishment in July 2009 had full effects on cohort default rates of the FY2011 cohort, and the program expansion in July 2013 did on the FY2015 cohort.

Effects on Repayment Rates

Figure 1.5 shows that one-year repayment rates of Tennessee were lower than those of other states by more than 10 percentage points for FY2007/FY2008 cohorts (plotted as a dot between 2007 and 2008). The gap narrowed to less than 10 percentage points for FY2009/FY2010 and following cohorts, as other states' repayment rates have declined faster than Tennessee's repayment rates.

Difference-in-differences estimation demonstrates that the License Review program improved student loan repayment rates. Table 1.5 presents estimation results on one-year repayment rates from a comparison of FY2007/FY2008 cohorts (pre-treatment) with FY2009/FY2010, FY2011/FY2012, and FY2013/FY2014 cohorts (post-treatment). The coefficient on Tennessee*Post in column (1) shows that the program significantly raised one-year repayment rates for the post-treatment cohorts in Tennessee. Column (2) reveals that the program's effects on repayment rates emerged promptly and increased over time. Column (3) confirms that this pattern holds after accounting for additional controls. The coefficient on Tennessee*FY2013/FY2014 in column (3) implies that the program resulted in a 4.5 percentage point reduction in one-year repayment rates for FY2013/FY2014 cohorts in Tennessee. The magnitude is equivalent to 9.3% of the pre-treatment outcome in Tennessee (48.2%).

Heterogeneity in the Program's Effects

The last set of difference-in-differences estimation results is about the potential of heterogeneous program effects. Table 1.6 Panel A collects estimates of the overall effects of the program on three-year cohort default rates using a subsample of institutions. First, the program reduced cohort default rates of all institution types. Next, borrowers who attended for-profit or public institutions experienced a larger drop in cohort default rates than those who attended private nonprofit institutions. Third, borrowers who attended two-year institutions saw the largest decline in cohort default rates. Compared with the baseline outcome, borrowers who attended public or four-year institutions were affected most by the program. Lastly, borrowers from institutions that have offered healthcare-related degree, most of whom might be treated by the program, saw a substantial large decline in default rates, 67% of the baseline outcome.[20]

Similarly, the program's effect on one-year repayment rates varies across different types of institutions. As shown in Table 1.6 Panel B, borrowers who attended public or private nonprofit institutions experienced a large improvement in one-year repayment rates. By contrast, the program did not improve the repayment of borrowers from for-profit institutions, probably due to their low ability to repay. Next, borrowers who attended four-year institutions were affected more than those who attended two-year or less than two-year institutions. Third, borrowers from institutions that have offered healthcare-related degree only for the entire panel period saw a much larger

[20] In this subsample analysis with institutions having offered healthcare-related degrees only for the entire panel period, one institution in Tennessee is included. The institution is a for-profit less than two-year school with 178 borrowers for each cohort on average.

improvement in repayment rates than borrowers from other institutions.[21]

Furthermore, the program's effect on one-year repayment rates differs across demographic subgroups. Table 1.7 compares the program's effects on borrowers grouped by family income, gender, and education program completion status. First, the program mostly affected borrowers who have not completed their education program.[22] Due to the lower baseline repayment rates, non-completers have much more room to improve their repayment rates. Next, the program had a larger effect on female borrowers more than male borrowers, probably because predominantly female occupations such as nurses and cosmetologists were severely affected by the program. Third, the program had similar effects on borrowers with different family income categories. Interestingly, borrowers from high-income families showed a substantial improvement in one-year repayment rates in spite of their high baseline repayment rates. Borrowers from low-income families also showed a large improvement despite their low ability to repay.

Discussion

These estimates from difference-in-differences estimations are broadly robust to the choice of control group. As shown in Table 1.8, including Illinois and Texas in control group makes little change in estimates. Similarly, removing states that have ever enacted license suspension laws from control group does not make a meaningful difference in estimates. But, using 11 states neighboring Tennessee as control group gives somewhat smaller estimates than baseline estimations. This discrepancy provides an additional rationale to compare difference-in-difference estimates with synthetic control estimates in the following section.

Overall, difference-in-differences estimates demonstrate that the License Review program not only reduced student loan defaults but also improved student loan repayments. A comparison of estimates in column (3) in Table 1.5 with those in Table 1.4 suggests that the program's effect on one-year repayment rates emerged relatively more quickly than those on two-year cohort default rates. It is primarily because

[21] In this subsample analysis with institutions offering healthcare-related degree, three institution in Tennessee is included: one is for-profit less than two-year institution with about 350 borrowers, another is for-profit two-year institution with about 1,800 borrowers, and the other is private four-year institution with about 450 borrowers for each combination of two consecutive cohorts.

[22] According to the CSD data, about 60% of borrowers are non-completors.

cohort default rates are not affected by any repayment of borrowers who have ever defaulted. Licensees might promptly respond to default notices by repaying their debt in order to avoid license suspension. The repayments of ever-defaulted borrowers might raise repayment rates but could not affect cohort default rates because of the definition of these measurements.

For the same reason, estimates on cohort default rates show that the program had default-prevention effect for borrowers who have never defaulted on student loans. Even though these borrowers had never received a default notice or subsequent license suspension, they were incentivized to repay student loans due to the increase in expected costs of student loan default. Conversely, estimates on one-year repayment rates shows that the program's effect on the repayment rates were positive even after accounting for the potentially negative earnings effects on borrowers whose licenses were suspended due to student loan defaults.

1.5.2 Synthetic Control Estimates

Synthetic Tennessee consists of the following 6 states with different weights stated in parentheses: Kentucky (0.457), Georgia (0.280), Alabama (0.208), South Carolina (0.028), Florida (0.024), and Nevada (0.003). Kentucky has the highest weight among them, and 4 states bordering Tennessee including Kentucky, Georgia, Alabama, and South Carolina have almost all weights (0.973).

Two-year cohort default rates of Tennessee and synthetic Tennessee are close to identical for pre-treatment (FY1995 to FY2008) cohorts, as shown in Figure 1.7. Tennessee's two-year cohort default rates stay similar to the counterfactual two-year cohort default rates for the FY2009 cohort, but they diverge down from the counterfactual for FY2010 and FY2011 cohorts. The figure also plots three-year cohort default rates of synthetic Tennessee even though three-year cohort default rates of the pre-treatment period are not matched between Tennessee and synthetic Tennessee due to the lack of data. Similar to two-year cohort default rates, three-year cohort default rates of Tennessee and synthetic Tennessee are almost the same for the FY2009 cohort; and Tennessee's three-year cohort default rates systematically deviates from the counterfactual three-year cohort default rates for later cohorts including FY2012 to FY2015 cohorts, whose two-year cohort default rates are unavailable.

Synthetic control estimation reaffirms that the License Review program reduced student loan defaults in Tennessee. As shown in Figure 1.8, synthetic control estimates show that the program establishment reduced two-year cohort default rates of the FY2011 cohort by 1.8 percentage points or 23% of the average outcome of FY2007 and FY2008 cohorts in Tennessee. The estimates also show that the program overall reduced three-year cohort default rates of the FY2015 cohort by 3.7 percentage points or 28% of the outcome of the FY2009 cohort in Tennessee.

The placebo test, suggested by Abadie, Diamond, and Hainmueller (2010) and Abadie, Diamond, and Hainmueller (2015), supports the statistical significance of synthetic control estimates on two-year cohort default rates. Figure 1.9 shows the distribution of the ratio between post- and pre-treatment root mean squared prediction errors (RMSPE). The ratio of Tennessee is the highest among 48 states and DC in the sample. This means that if the treatment would be randomly reassigned in the sample, the probability of obtaining a ratio of post- to pre-treatment RMSPE as large as the Tennessee' is 1/49=0.02. Therefore, the reduction in two-year cohort default rates in Tennessee after the program establishment is highly likely to be a systematic change in the outcome rather than a random disturbance.

Figure 1.10 shows trends in one-year repayment rates of Tennessee and synthetic Tennessee. Synthetic Tennessee's one-year repayment rates are very close, though the level differs slightly, to Tennessee's one-year repayment rates for pre-treatment (FY2006/FY2007 and FY2007/FY2008) cohorts. Figure 1.11 shows that synthetic control estimates on one-year repayment rates reach 6 percentage points for FY2013/FY2014 cohorts.

1.5.3 Discussion

Synthetic control estimates are close to the baseline difference-in-difference estimates using 47 states and DC as control group, as shown in Figure 1.12. The synthetic control estimate on two-year cohort default rates is just slightly larger than the difference-in-difference estimate, and that on three-year cohort default rates is only slightly lower. Even though synthetic Tennessee mostly consists of Tennessee's four neighboring states (Kentucky, Georgia, Alabama, and South Carolina), synthetic control estimates are much closer to the baseline difference-in-difference estimates than alternative difference-in-difference estimates using 11 states neighboring Tennessee as control group (Table 1.8). The synthetic control estimate on one-year repayment rates is somewhat higher than the baseline difference-in-differences estimates.

1.6 Conclusion

Both difference-in-differences and synthetic control estimates show that Tennessee's License Review program improved student loan repayment outcomes by a surprisingly large amount. The significant decline in cohort default rates for post-treatment cohorts in Tennessee demonstrates the program's default-prevention effect. This effect is not confounded by the reduced earnings effects on borrowers who lost their licenses due to student loan default. In addition, the prompt improvement in one-year repayment rates reveals that borrowers quickly responded to default notices or subsequent license suspensions by repaying their student loans to avoid license suspension or seek reinstatement. This reasoning is in line with the records of Tennessee Student Assistance Corporation (2013) showing that a majority of individuals reinstated their licenses that had been suspended by the program. The findings show some borrowers who default on student loans are not so liquidity-constrained that they cannot repay more. Despite existing disincentives for student loan defaults, it may be optimal for them to prioritize repayments for credit card balances or other consumer loans with higher interest rates.

I show that Tennessee's occupational license suspension program reduced three-year cohort default rates by 4 percentage points or 30% of the treatment group average before the policy. However, I estimate the program's effects on borrowers as a whole, rather than only on those who have licenses. In order to obtain the program's effects only on license holders, it is necessary to scale-up the study's estimate by considering the proportion of licensees among borrowers and the relative default rates between licensees and non-licensees in Tennessee. Given that approximately one-third of borrowers have occupational licenses and that the average default rates of licensees and non-licensees are the same, the program's default-prevention effect may be as high as 90%.[23]

[23] Of course, there is a possibility that the program's effect might spillover to non-licensees through a potentially heightened awareness of student loan repayments among Tennesseans. It is also possible

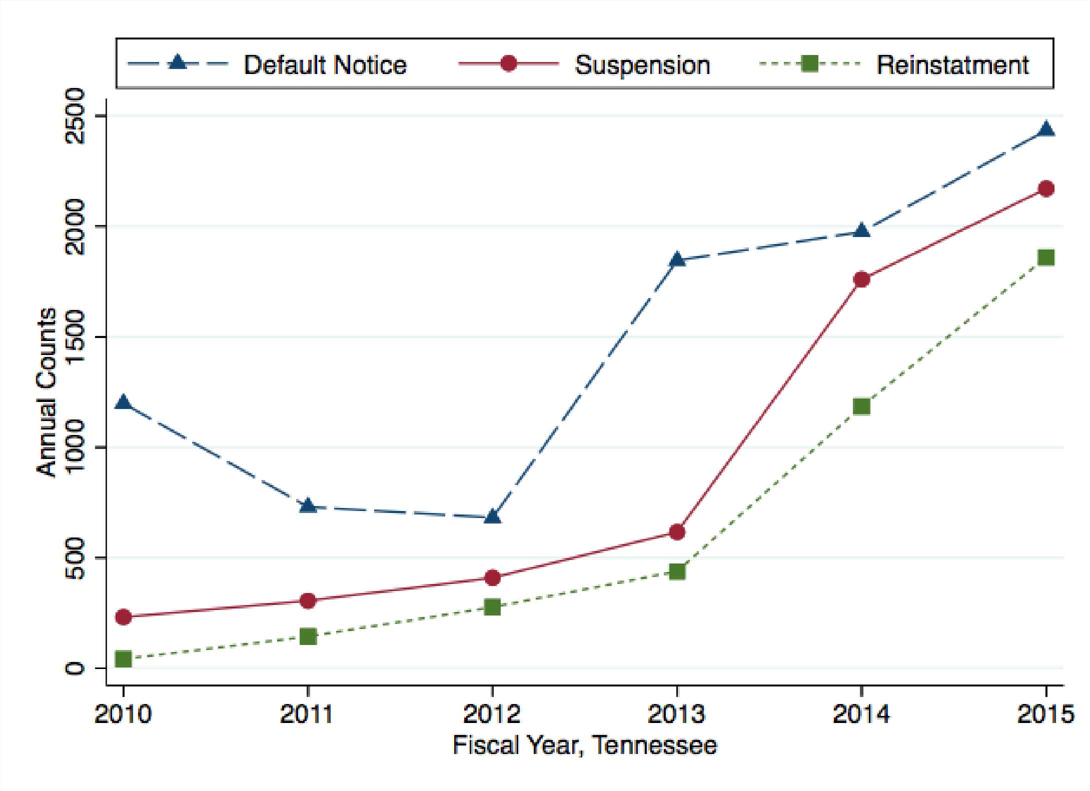
Tennessee's license suspension program is comparable to two federal-level policy measures to improve student loan repayment outcomes: wage garnishment and the removal of federal student loan bankruptcy discharge. Yannelis (2017) estimates that after the 2006 reform raising the upper limit of wage garnishment from 10% to 15% of disposable income, student loan default rates declined by 0.917 percentage points or 27.4% of the treatment group average for an additional $10,000 in income above the garnishment threshold wage level. He also estimates that as bankruptcy discharge for federal student loans became extremely difficult since 1998, student loan default rates fell by 0.262 percentage points or 18.2% of the treatment group average.

Overall, my empirical findings show that the occupational license suspension program is an effective way to improve the sustainability of the student loan system. However, the suspension program could have implications for repayment of other loans or for consumption, which I do not observe and which could possibly be negative. For example, borrowers may just replace student loans with credit card balances while holding the same level of debt as a whole, or they may be forced to cut consumption of necessities for student loan repayments. The impact of the suspension program on social welfare therefore cannot yet be assessed solely based on my study.

that licensees are more likely to default that non-licensees in Tennessee, particularly because Tennessee has reportedly required occupational licenses for more low-paying jobs compared with other states (Carpenter et al. 2012). In either case, the scaled-up estimate on licensees only should be lower than 90%.

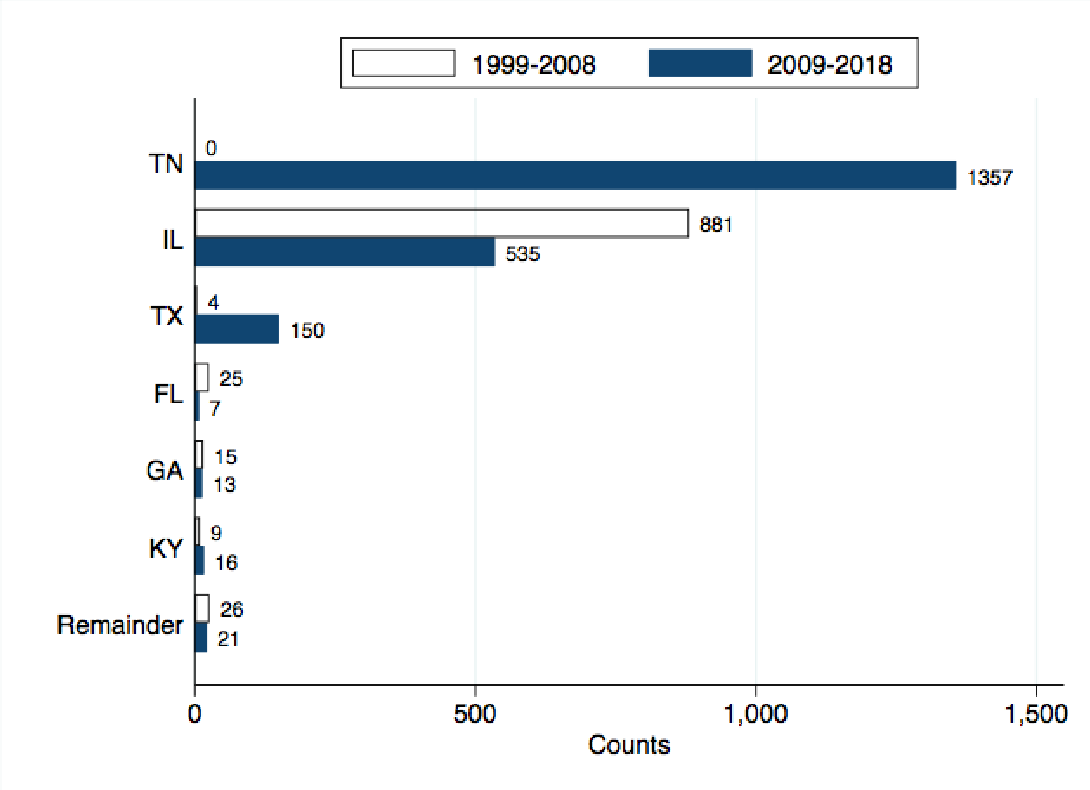
1.7 Figures and Tables

Figure 1.1: Tennessee's License Review Program



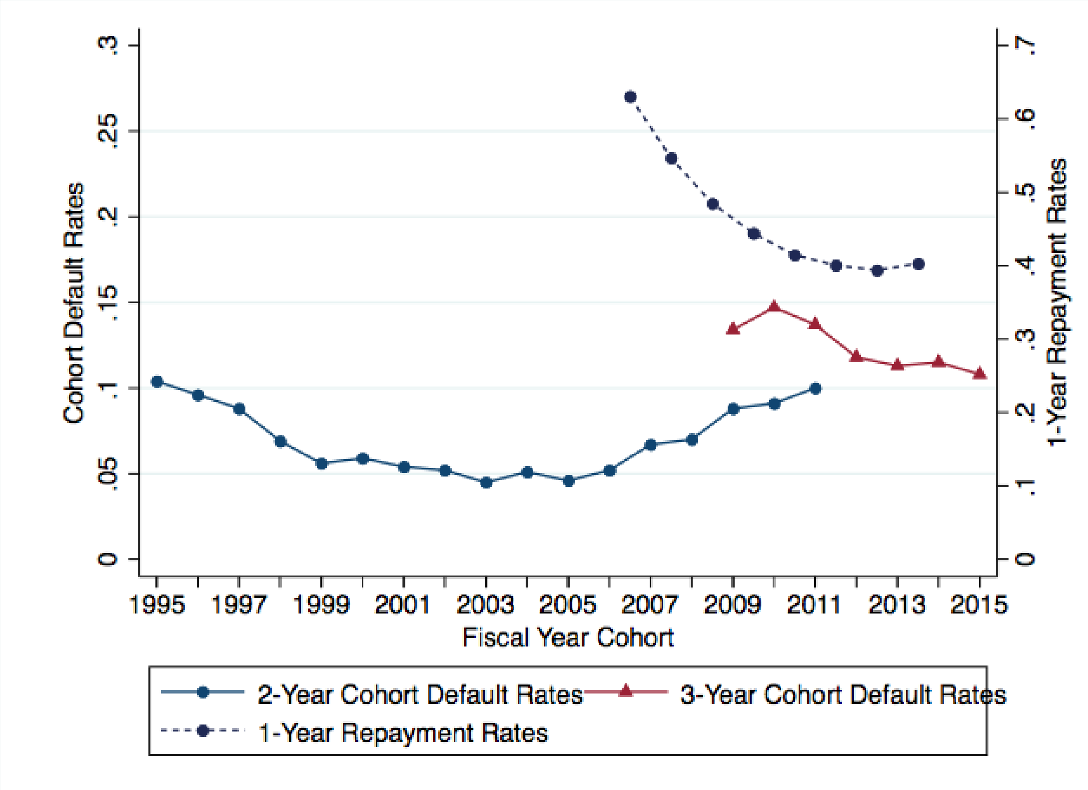
Source: Tennessee Student Assistance Corporation (2016)

Figure 1.2: Medical Practitioner License Suspension for Student Loan Default



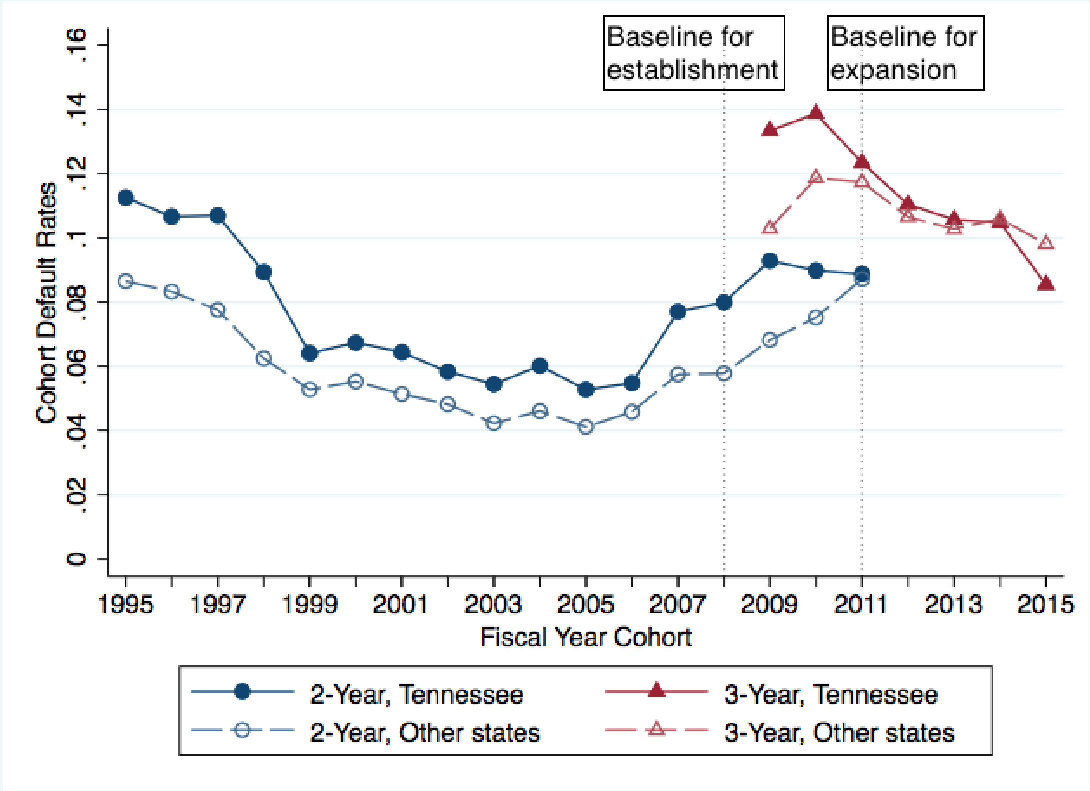
Source: National Practitioner Data Bank (2018)

Figure 1.3: National Trends in Student Loan Repayment Outcomes



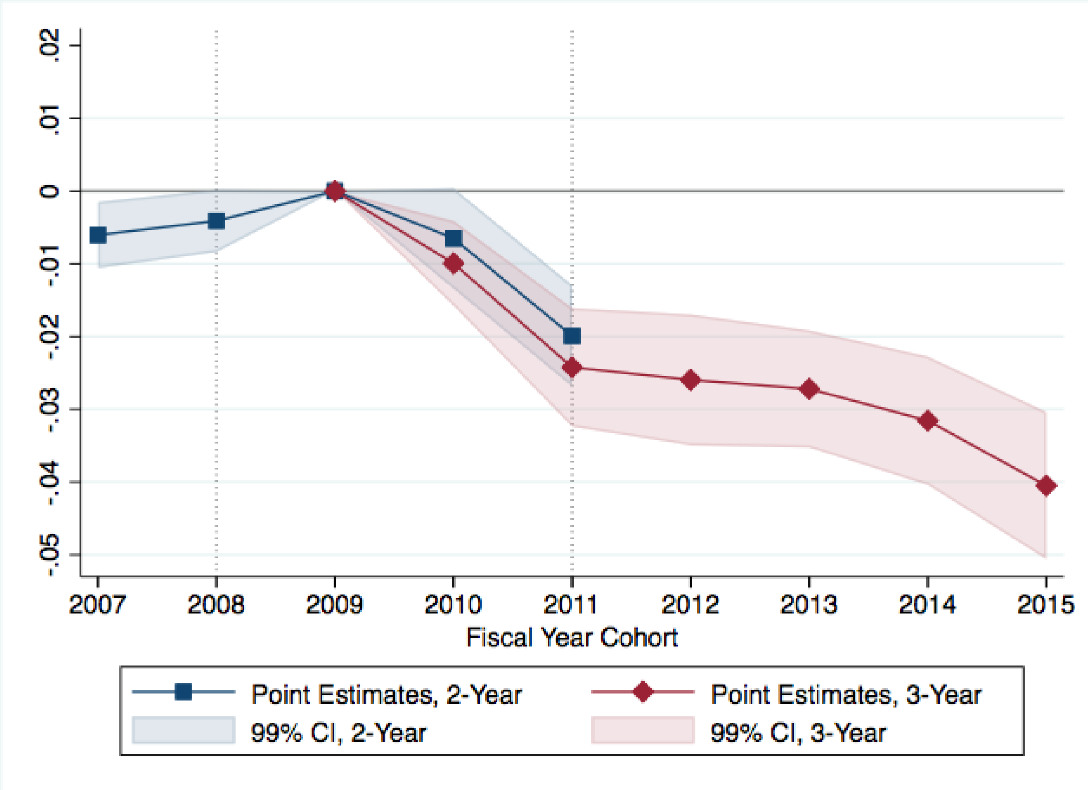
Sources: National cohort default rates are obtained from Federal Student Aid (2018) and Department of Education (2018), and national one-year repayment rates are calculated by the author using institution-level one-year repayment rates available in the College Scorecard Data. Because the dataset provides one-year repayment rates as two-year rolling averages, national one-year repayment rates are placed on the midpoint between two years in this figure.

Figure 1.4: Trends in Cohort Default Rates: Tennessee v. Other States



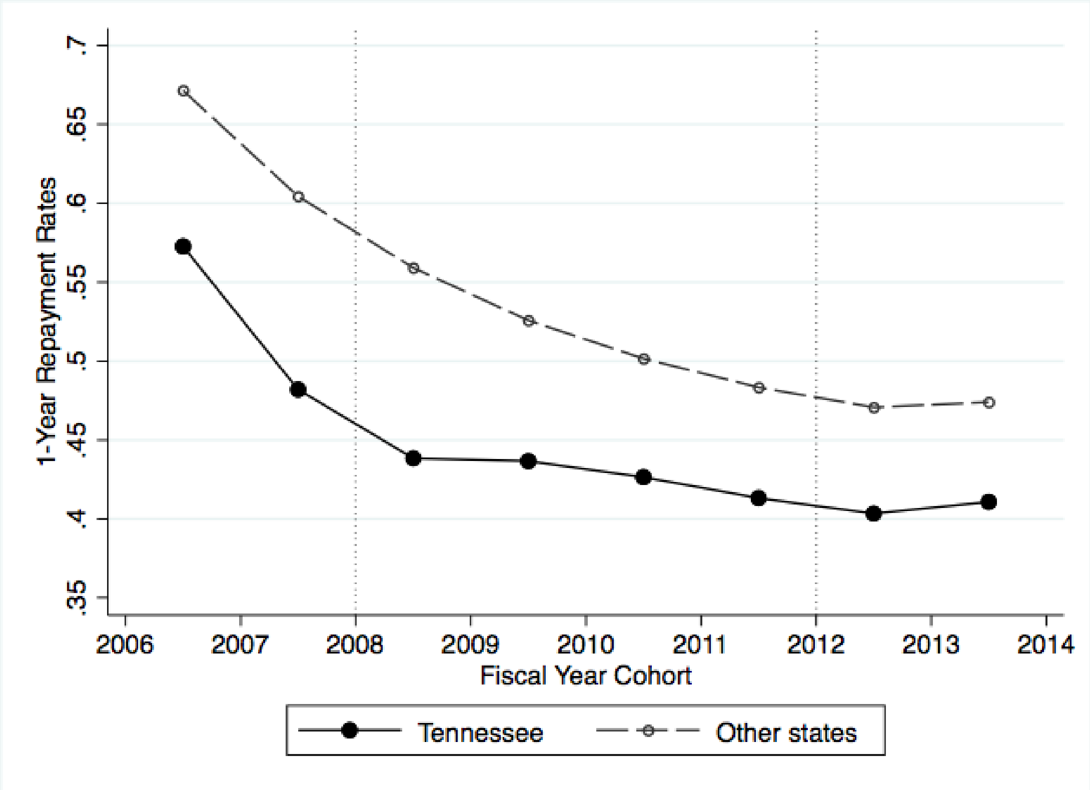
Source: Author's calculation using the College Scorecard Data.

Figure 1.5: Difference-in-Differences Estimates: Cohort Default Rates



Notes: Estimates are obtained from two separate estimations. The first estimation is on two-year cohort default rates of FY2007 to FY2011 cohorts, and the second regression is on three-year cohort default rates of FY2009 to FY2015 cohorts. Each estimation regresses cohort default rates on Tennessee*Cohort dummies (omitting one for the FY2009 cohort), cohort fixed effects, state fixed effects, the proportion of borrowers who attended for-profit institutions, the proportion of borrowers who attended two-year or less than two-year institutions, and state unemployment rates.

Figure 1.6: Trends in 1-Year Repayment Rates: Tennessee v. Other States



Notes: One-year repayment rates are provided as two-year rolling averages in the College Scorecard Data. Accordingly, each data point is placed on the midpoint of between two years in this figure.
Source: Author's calculation using the College Scorecard Data.

Figure 1.7: Trends in Cohort Default Rates: Tennessee v. Synthetic Tennessee

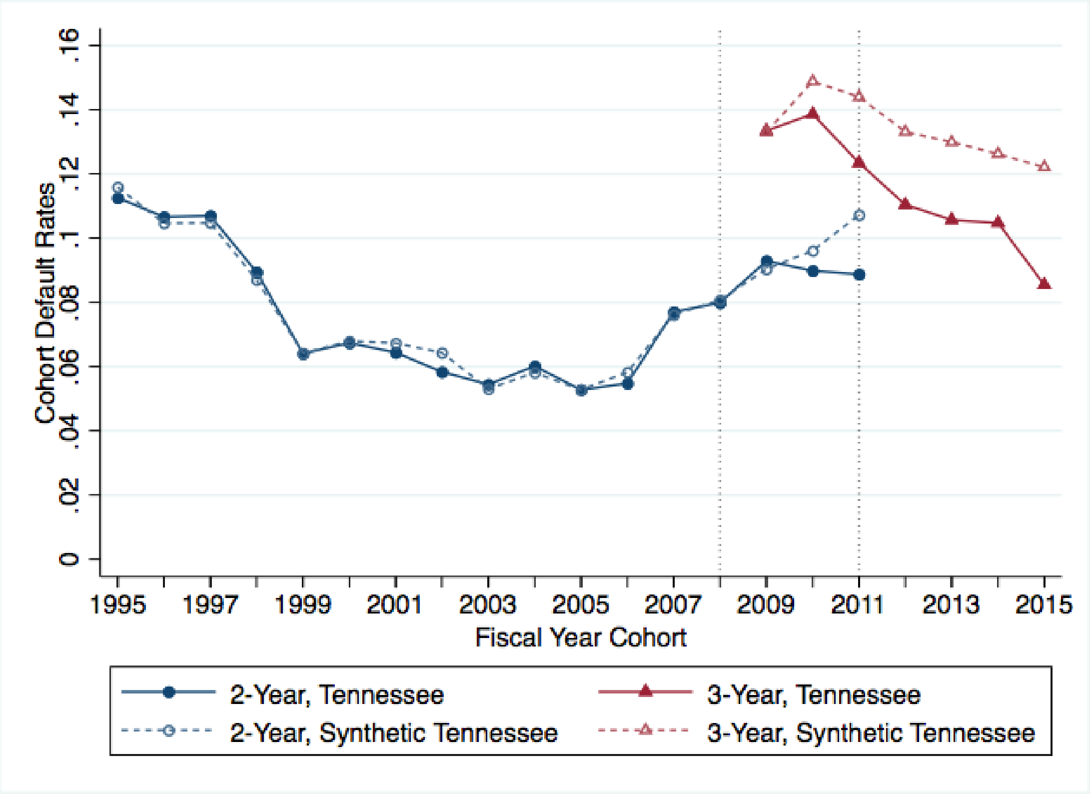


Figure 1.8: Cohort Default Rates Gap between Tennessee and Synthetic Tennessee

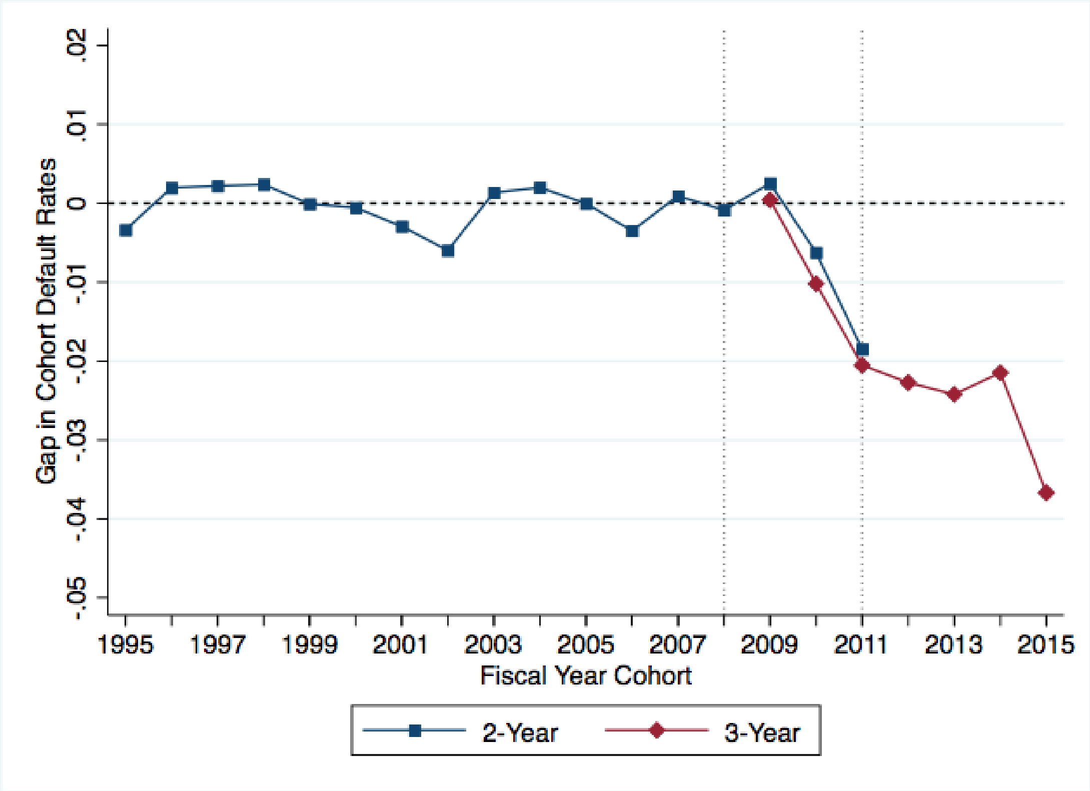
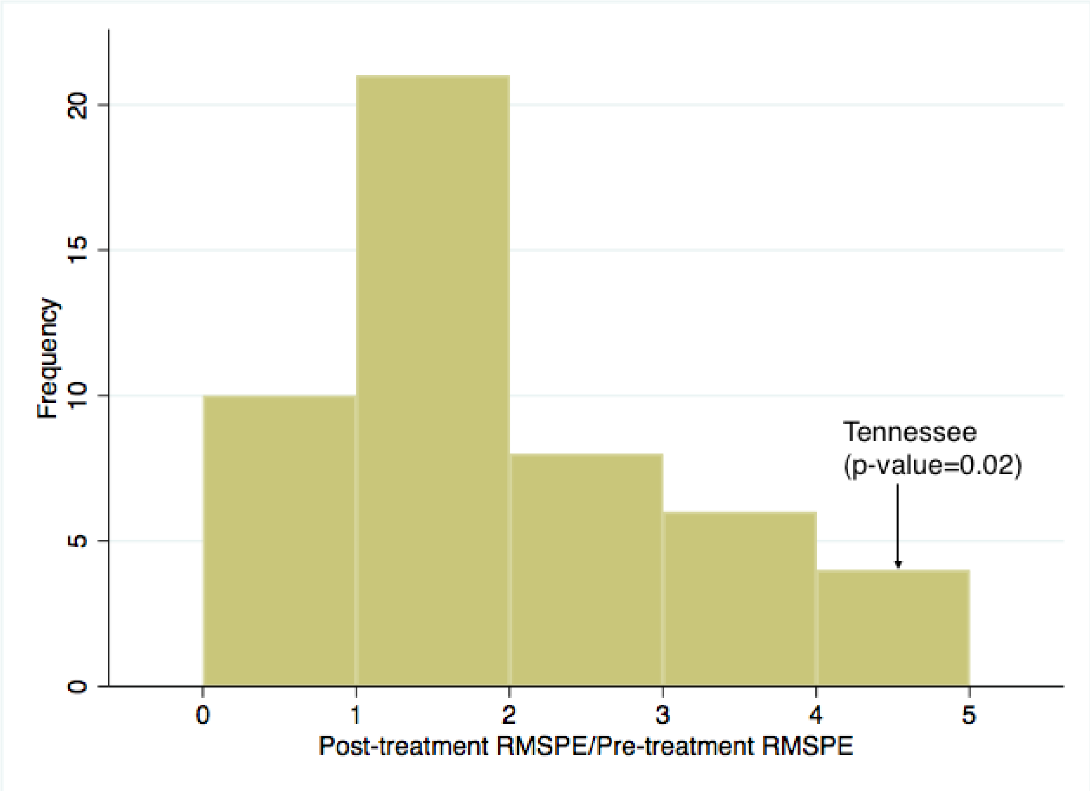
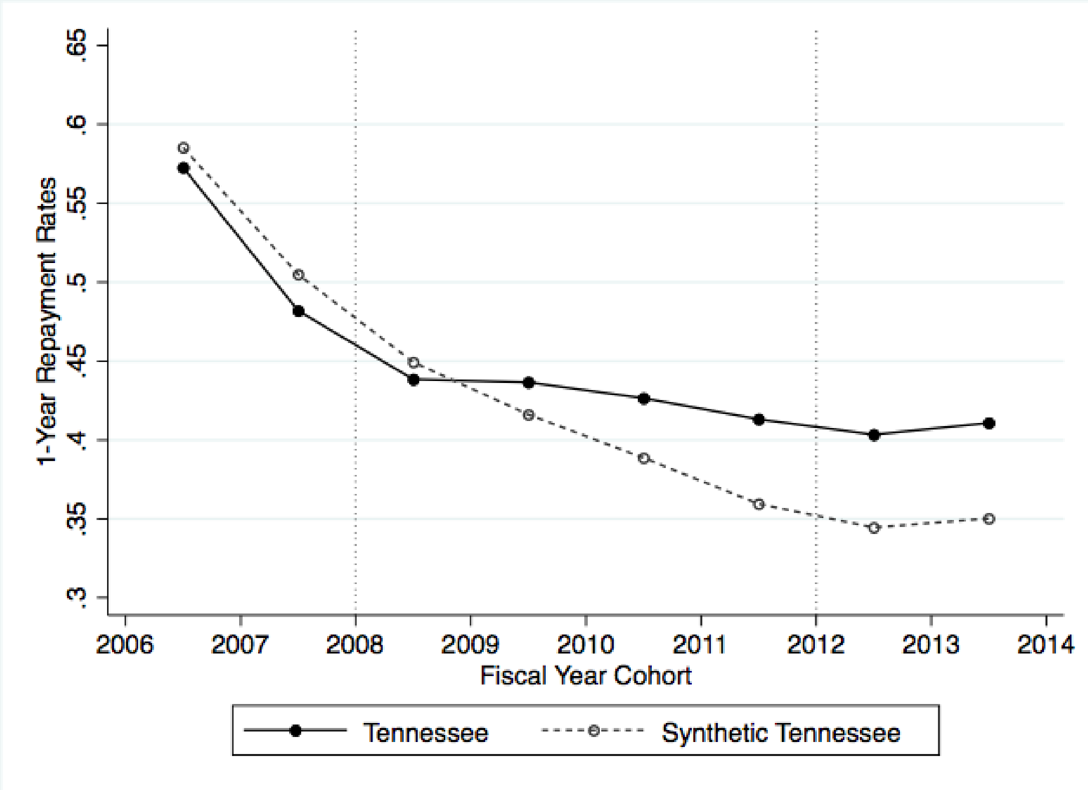


Figure 1.9: Ratio of Post-treatment RMSPE to Pre-treatment RMSPE



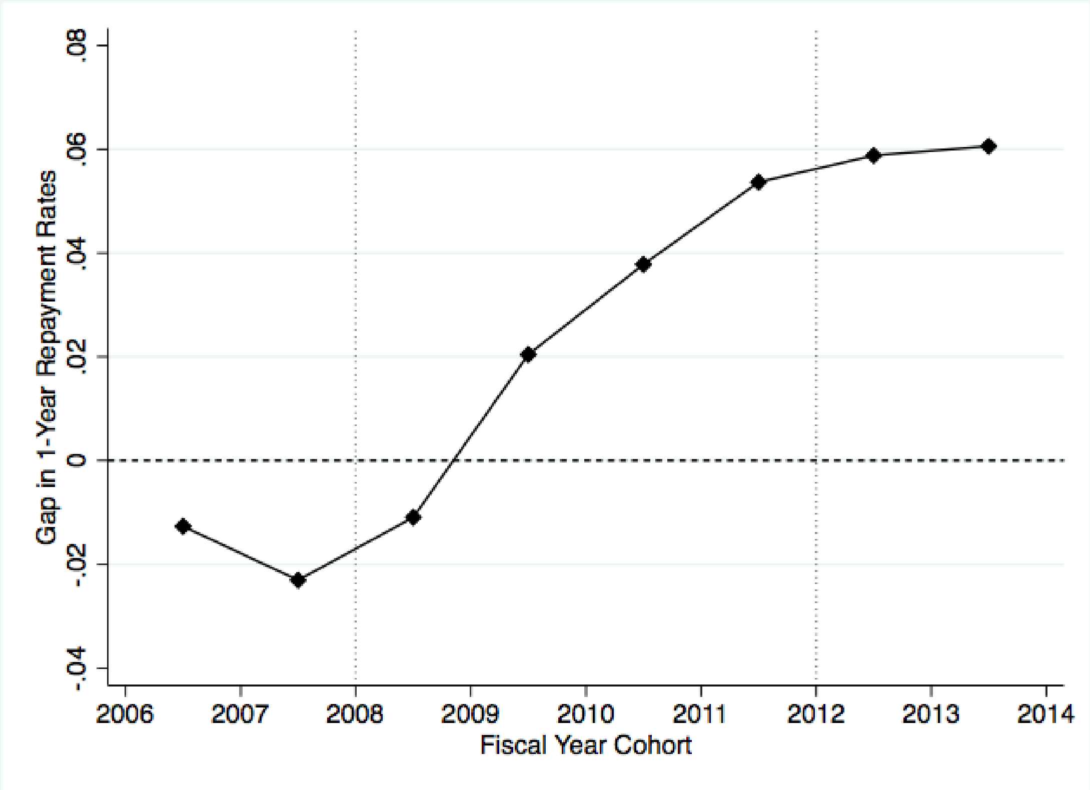
Notes: This placebo test examines the statistical significance of synthetic control estimates on two-year cohort default rates.

Figure 1.10: Trends in 1-Year Repayment Rates: Tennessee v. Synthetic Tennessee



Notes: One-year repayment rates are provided as two-year rolling averages in the College Scorecard Data. Accordingly, each data point is placed on the midpoint of between two years in this figure.

Figure 1.11: Repayment Rates Gap between Tennessee and Synthetic Tennessee



Notes: One-year repayment rates are provided as two-year rolling averages in the College Scorecard Data. Accordingly, each data point is placed on the midpoint of between two years in this figure.

Figure 1.12: Comparison of Difference-in-Differences and Synthetic Control Estimates

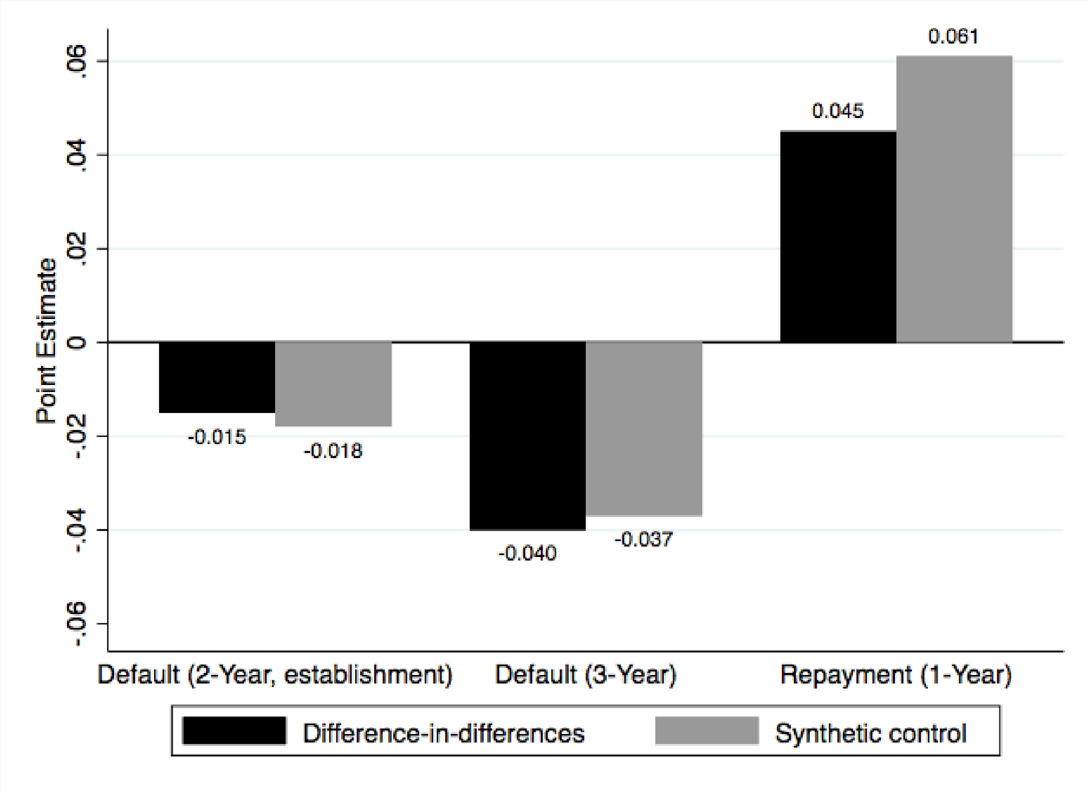


Table 1.1: Distribution of Licensees in Tennessee

Occupation (24 categories)	U.S.	Tennessee
Management, business, science, and arts occupations	0.10	0.07
Business operations specialists	0.02	0.02
Financial specialists	0.03	0.03
Computer and mathematical occupations	0.01	0.01
Architecture and engineering occupations + technicians	0.02	0.02
Life, physical, and social science occupations	0.01	0.01
Community and social service occupations	0.03	0.02
Legal occupations	0.04	0.04
Education, training, and library occupations	0.17	0.17
Arts, design, entertainment, sports, and media occupations	0.01	0.00
Healthcare practitioners and technical occupations	0.23	0.28
Healthcare support occupations	0.04	0.05
Protective service occupations	0.03	0.02
Food preparation and serving occupations	0.01	0.01
Building and ground cleaning and maintenance occupations	0.01	0.01
Personal care and service occupations	0.04	0.04
Sales and related occupations	0.06	0.08
Office and administrative support occupations	0.04	0.03
Farming, fishing, and forestry occupations	0.00	0.00
Construction and extraction occupations	0.03	0.02
Extraction workers	0.00	0.00
Installation, maintenance, and repair workers	0.02	0.02
Production occupations	0.01	0.01
Transportation and material moving occupations	0.03	0.04
Total	1.00	1.00

Notes: The table shows the distribution of workers who have a government-issued license or certificate across 24 occupation categories.
Source: IPUMS CPS Monthly Jan.-Dec. 2016.

Table 1.2: Tennessee's License Review Program: Top 25 License Types in Default Notices

License Type	Default Notices	Suspensions	Reinstatements
Cosmetology Licensee	725	408	257
Registered Nurse	534	250	195
Nurse Aide	455	210	56
Licensed Practical Nurse	432	224	180
Security guard/officer	276	138	64
Salesmen	219	106	61
Professioner Teacher	187	58	14
Apprentice Teacher	127	53	13
Armed Security Guard/Officer	127	67	35
Real Estate Agent	126	65	37
Pharmacy Technician	113	41	23
Insurance producer	85	6	1
EMS - Personnel	75	15	7
Dental Assistants	70	21	11
Master Barber	68	35	20
Massage Therapist	48	20	13
Lic. Certified Respiratory	34	14	8
Licensed Laboratory Personnel	25	10	10
Engineer	24	9	5
Certified Public Accountant	23	12	5
Medical X-ray operator	22	4	2
Advanced Practical Nurse	17	9	4
Physical Therapist Assistant	16	4	2
Licensed Master Social Worker	16	8	3
Beginning Administrator	16	4	1

Notes: The table shows the cumulative number of default notices, suspensions, and reinstatements by license types from the inception of the License Review program in July 2009 to August 2013. The 25 license types are top-ranked by the number of default notices among 105 license types that have at least one default notice record under the License Review program.
Source: Tennessee Student Assistance Corporation (2013).

Table 1.3: Descriptive Statistics

Variables	Tennessee	Other States
A. Two-year Cohort Default Rates Sample (FY2007-FY2011)		
Two-year cohort default rates	0.086	0.069
	(0.007)	(0.024)
Cohort size	59,228	57,767
	(6,693)	(58,977)
For-profit institution	0.092	0.104
	(0.016)	(0.094)
Two-year or less institution	0.242	0.305
	(0.009)	(0.145)
Unemployment rates	0.073	0.063
	(0.026)	(0.025)
Observations (state-by-year)	5	240
B. Three-year Cohort Default Rates Sample (FY2009-FY2015)		
Three-year cohort default rates	0.115	0.108
	(0.019)	(0.031)
Cohort size	75,633	69,573
	(15,672)	(68,948)
For-profit institution	0.067	0.094
	(0.010)	(0.095)
Two-year or less institution	0.234	0.314
	(0.034)	(0.155)
Unemployment rates	0.083	0.072
	(0.015)	(0.021)
Observations (state-by-year)	7	336
C. One-year Repayment Rates Sample (FY2007/FY2008-FY2013/FY2014)		
One-year repayment rates	0.436	0.522
	(0.033)	(0.104)
Cohort size	91,079	89,268
	(22,330)	(93,152)
For-profit institution	0.121	0.124
	(0.042)	(0.106)
Two-year or less institution	0.315	0.363
	(0.009)	(0.146)
Unemployment rates	0.077	0.067
	(0.019)	(0.022)
Observations (state-by-year)	4	192

Notes: Unweighted means. Standard errors are in parentheses. Other states consist of 47 states and District of Columbia except Tennessee, Illinois, and Texas. Variables for-profit institution and two-year or less institution represent the proportion of borrowers who attended for-profit institutions or two-year or less than two-year institutions, respectively. Unemployment rates are based on the calendar year at the beginning of each fiscal year cohort entering repayment (e.g. Calendar year 2008 for FY2009 cohort for Sample A and B, calendar year 2006/2007 average for FY2007/FY2008 cohorts for Sample C).

Table 1.4: Effects of the Program on Cohort Default Rates

	(1)	(2)	(3)
A. Two-year Cohort Default Rates			
Tennessee*Post	-0.007***		
	(0.002)		
Tennessee*FY2009		0.004***	0.005***
		(0.001)	(0.001)
Tennessee*FY2010		-0.006***	-0.001
		(0.002)	(0.003)
Tennessee*FY2011		-0.019***	-0.015***
		(0.003)	(0.003)
Additional controls	No	No	Yes
Observations	245	245	245
R-squared (within)	0.63	0.64	0.69
Baseline outcome	0.078	0.078	0.078
B. Three-year Cohort Default Rates			
Tennessee*Post	-0.027***		
	(0.003)		
Tennessee*FY2010		-0.011***	-0.010***
		(0.002)	(0.002)
Tennessee*FY2011		-0.024***	-0.024***
		(0.003)	(0.003)
Tennessee*FY2012		-0.027***	-0.026***
		(0.003)	(0.003)
Tennessee*FY2013		-0.028***	-0.027***
		(0.003)	(0.003)
Tennessee*FY2014		-0.032***	-0.032***
		(0.003)	(0.003)
Tennessee*FY2015		-0.043***	-0.040***
		(0.003)	(0.003)
Additional controls	No	No	Yes
Observations	343	343	343
R-squared (within)	0.33	0.34	0.39
Baseline outcome	0.133	0.133	0.133

Notes: Outcome variable is two-year cohort default rates for Panel A and three-year cohort default rates for Panel B. The coefficient estimates are from an OLS regression. The two-year cohort default rates sample consists of FY2007 to FY2011 cohorts, and three-year cohort default rates sample are FY2009 to FY2015 cohorts in Tennessee and 47 states (excluding Illinois and Texas) and DC. All regressions include cohort fixed effects and state fixed effects, whose estimates are not reported in the table. Additional control variables include the proportion of borrowers who attended for-profit institutions, the proportion of borrowers who attended two-year or less than two-year institutions, and state unemployment rates. Baseline outcome refers the average two-year cohort default rates of FY2007 and FY2008 cohorts in Tennessee for Panel A and three-year cohort default rates of FY2009 cohort in Tennessee for Panel B. Standard errors are clustered within states. Clustered standard errors are in parentheses, *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table 1.5: Effects of the Program on One-Year Repayment Rates

	(1)	(2)	(3)
Tennessee*Post	0.048***		
	(0.004)		
Tennessee*FY2009/FY2010		0.033***	0.030***
		(0.004)	(0.004)
Tennessee*FY2011/FY2012		0.052***	0.038***
		(0.005)	(0.005)
Tennessee*FY2013/FY2014		0.059***	0.045***
		(0.005)	(0.006)
Additional controls	No	No	Yes
Observations	196	196	196
R-squared (within)	0.89	0.89	0.92
Baseline outcome	0.482	0.482	0.482

Notes: Outcome variable is the two-year rolling average of one-year repayment rates. The coefficient estimates are from an OLS regression. The sample consists of combinations of FY2007/FY2008, FY2009/FY2010, FY2011/FY2012, and FY2013/FY2014 cohorts in Tennessee and 47 states (excluding Illinois and Texas) and DC. All regressions include combined cohort fixed effects and state fixed effects, whose estimates are not reported in the table. Additional control variables include the proportion of borrowers who attended for-profit institutions, the proportion of borrowers who attended two-year or less than two-year institutions, and state unemployment rates. Baseline outcome refers the two-year rolling average of one-year repayment rates of FY2007/FY2008 cohorts in Tennessee. Standard errors are clustered within states. Clustered standard errors are in parentheses, *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table 1.6: Heterogeneity by Institution Type

Sample	Point estimates	Baseline outcome
A. Three-year Cohort Default Rates		
All	-0.040***	0.133
	(0.003)	
Public	-0.051***	0.141
	(0.005)	
Private nonprofit	-0.018***	0.096
	(0.004)	
For-profit	-0.052***	0.222
	(0.009)	
4-year	-0.034***	0.109
	(0.003)	
2-year	-0.045***	0.228
	(0.006)	
Less than 2-year	-0.027**	0.180
	(0.012)	
Health only	-0.157***	0.233
	(0.011)	
B. One-year Repayment Rates		
All	0.045***	0.482
	(0.006)	
Public	0.060***	0.482
	(0.006)	
Private nonprofit	0.045***	0.575
	(0.010)	
For-profit	0.001	0.361
	(0.013)	
4-year	0.047***	0.524
	(0.006)	
2-year	0.034**	0.406
	(0.013)	
Less than 2-year	0.037***	0.326
	(0.011)	
Health only	0.055***	0.311
	(0.022)	

Notes: Outcome variable is three-year cohort default rates for Panel A and the two-year rolling average of one-year cohort default rates for Panel B. In Panel A, each cell shows the estimated coefficient on Tennessee*FY2015 from the OLS regression of the outcome variable on the Tennessee*Cohort dummies except Tennessee*FY2009, cohort fixed effect, state fixed effects, and unemployment rates using a subsample of borrowers classified into the cell. Baseline outcome refers three-year cohort default rates of FY2009 cohort in Tennessee. In Panel B, each cell shows the estimated coefficient on Tennessee*(FY2013/FY2014) from the OLS regression of the outcome variable on the Tennessee*Cohort dummies except Tennessee*(FY2007/FY2008), cohort fixed effect, state fixed effects, and unemployment rates using a subsample of borrowers classified into the cell. Baseline outcome refers the two-year rolling averages of one-year repayment rates of FY2007/FY2008 cohort in Tennessee. For both panels, institutional characteristics are also controlled for, when applicable. Standard errors are clustered within states. Clustered standard errors are in parentheses and the number of observations in brackets. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table 1.7: Heterogeneity by Demographic Subgroup: One-Year Repayment Rates

Sample	Point estimates	Baseline outcome
All	0.045***	0.482
	(0.006)	
High-income	0.051***	0.677
	(0.007)	
Middle-income	0.053***	0.585
	(0.005)	
Low-income	0.042***	0.376
	(0.008)	
Female	0.052***	0.476
	(0.007)	
Male	0.030***	0.514
	(0.009)	
Completer	-0.002	0.666
	(0.009)	
Non-completer	0.055***	0.388
	(0.006)	

Notes: Outcome variable of a column is the two-year rolling average of demographic-subgroup one-year repayment rates referenced by the column head. Each cell shows the estimated coefficient on Tennessee*(FY2013/FY2014) from the OLS regression of the outcome variable on the Tennessee*Cohort dummies except Tennessee*(FY2007/FY2008), cohort fixed effect, state fixed effects, the proportion of borrowers who attended for-profit institutions, the proportion of borrowers who attended two-year or less than two-year institutions, and unemployment rates. Baseline outcome refers the two-year rolling average of demographic-subgroup one-year repayment rates of FY2007/FY2008 cohort in Tennessee. Each subgroup is classified based on the NSLDS, and high-income means family income above $75,000; middle-income means family income between $30,000 to $70,000; and low-income means family income below $30,000 based on the Free Application for Federal Student Aid (FAFSA). Standard errors are clustered within states. Clustered standard errors are in parentheses and the number of observations in brackets. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table 1.8: Robustness: Alternative Control Group

	(1) Baseline	(2) 49 states+DC	(3) 27 states+DC	(4) 11 states
2-year cohort default rates	-0.015^{***}	-0.014^{***}	-0.014^{***}	-0.009^{*}
(FY2011)	(0.003)	(0.003)	(0.003)	(0.005)
3-year cohort default rates	-0.040^{***}	-0.039^{***}	-0.037^{***}	-0.024^{**}
(FY2015)	(0.003)	(0.004)	(0.005)	(0.010)
1-year repayment rates	0.045^{***}	0.044^{***}	0.043^{***}	0.042^{**}
(FY2013/FY2014)	(0.006)	(0.007)	(0.008)	(0.016)

Notes: Column (1) summarizes baseline estimates: the two-year cohort default rates estimate on Tennessee*FY2011 in Table 4 Panel A, the three-year cohort default rates estimate on Tennessee*FY2015 in Table 4 Panel B, and the one-year repayment rates estimate on Tennessee*FY2013/FY2014 in Table 5. Column (2) shows estimates from regressions using an alternative control group of 49 states and DC. Column (3) shows estimates from regressions using another alternative control group of 27 states and DC that have never enacted license suspension laws for student loan default. Column (4) presents estimates from regressions using another alternative control group of 11 states neighboring with Tennessee. Clustered standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

1.8 Appendix. Additional Tables

Table 1.A1: List of States Ever Enacted Occupational License Suspension Laws for Student Loan Default

State	Enacted	Repealed	Occupation Affected
Alaska	1997	2019	Any profession
Arkansas	1995	Not repealed	Physicians having used rural medical practice loan
California	2003	2017	Healing arts professions
Florida	2002	Not repealed	Healthcare practitioners
Georgia	1998	2019	Any profession
Hawaii	2002	2019	Any profession
Illinois	1996	2018	Any profession
Iowa	1998	2019	Any profession
Kentucky	2002	2019	Any profession
Louisiana	1987	2019	Any profession
Massachusetts	1990	Not repealed	Public health professions
Minnesota	1995	Not repealed	Physicians and health-related professions
Mississippi	1998	2019	Professionals having used paid educational leave
Montana	1997	2015	Any profession
New Jersey	1999	2017	Any profession
New Mexico	1993	Not repealed	Cosmetologists and barbers
North Dakota	1995	2017	Any profession
Oklahoma	1996	2017	Any profession
South Dakota	1992	Not repealed	Physicians
Tennessee	1999	Not repealed	Any profession
Texas	1989	2019	Any profession
Virginia	2003	2018	Health professions
Washington	1996	2018	Various occupations under occupation-specific statutes

Source: Author's collection of state codes as of August 2019.

Table 1.A2: Number of Medical Practitioner License Suspensions by Reason by State

	2001-2009		2010-2018	
State of License	Student Loan Default	Other reasons	Student Loan Default	Other reasons
AK	0	254	0	180
AL	0	2,076	3	2,348
AR	0	874	0	1,001
AZ	0	4,545	1	3,454
CA	0	4,597	0	17,915
CO	0	1,302	0	1,730
CT	0	266	0	297
DC	0	159	0	304
DE	0	122	0	537
FL	26	4,451	6	7,597
GA	20	522	8	633
HI	0	138	0	157
IA	0	463	1	698
ID	0	369	0	531
IL	504	2,572	526	5,426
IN	1	1,393	2	2,307
KS	0	788	2	1,595
KY	11	795	14	1,116
LA	0	2,684	0	3,751
MA	0	944	1	1,289
MD	0	1,186	0	2,861
ME	0	283	0	352
MI	0	1,728	0	2,850
MN	0	1,331	0	2,093
MO	0	2,454	0	5,992
MS	0	1,002	5	1,101
MT	0	294	0	371
NC	0	1,606	0	2,370
ND	0	206	0	394
NE	1	600	1	602
NH	0	337	0	331
NJ	1	1,974	1	3,617
NM	0	639	1	609
NV	0	920	0	1,281
NY	5	2,616	0	3,486
OH	1	4,879	0	8,494
OK	0	1,518	0	1,949
OR	1	1,378	0	1,910
PA	0	3,832	0	7,992
RI	0	179	0	222
SC	1	711	0	522
SD	0	82	2	177
TN	1	1,545	1,356	2,653
TX	6	5,526	147	7,487
UT	1	451	0	369
VA	1	2,623	0	4,478
VT	0	492	0	391
WA	4	3,536	0	4,123
WI	0	671	0	1,163
WV	0	435	0	455
WY	0	117	0	268
Aggregate	585	74,465	2,077	123,829

Source: National Practitioner Data Bank (2018)

Table 1.A3: Cohort default rates and one-year repayment rates

	Cohort default rates (CDR)	One-year repayment rates
Definition	Fraction of borrowers entering repayment in a fiscal year who defaulted by the end date of the measurement period among borrowers entering repayment in the fiscal year.	Fraction of borrowers entering repayment in a fiscal year who are not in default and who are making progress in paying them down after entering repayment among borrowers entering repayment in the fiscal year.
Measurement period	2-Year CDR: Two fiscal years 3-Year CDR: Three fiscal years	Two fiscal years
Type of loans	Undergraduate and graduate loans	Undergraduate loans only
Denominator	Borrowers who enter repayment in a fiscal year.	Borrowers who enter repayment in a fiscal year and have not received a deferment for enrollment or military duty during the measurement period.
Numerator	Among those in the denominator, borrowers who defaulted at least once by the end date of the measurement period.	Among those in the denominator, borrowers who have paid down at least $1 in the initial balance on their loans (including accrued interest) during the measurement period and are not in default as of the end date of the measurement period.
Failure of repayment	Ever in default in the measurement period.	With a balance no less than the initial balance or in default as of the end of the measurement period.
Affected by repayments after default	No	Yes
Data availability	2-Year CDR: FY1995-FY2011 3-Year CDR: FY2009-FY2015	FY2006/FY2007-FY2013/FY2014 (two-year rolling averages)
Subgroup outcomes	Not available	Available

Source: Data Documentation for College Scorecard (Version: May 21, 2019)

Chapter 2

Seeking Overdraft Fee Revenue: The Consequences of Bank Competition

2.1 Introduction

Competition is generally expected to lower prices and benefit consumers. Within the banking industry, a large body of literature has studied how competition affects interest rates.[1] However, deposit fees are more important to consumers than deposit interest rates in the current U.S. retail deposit market: Two nationally representative surveys document that consumers care much more about deposit fees than deposit interest rates when choosing a depository institution (2016 Survey of Consumer Finance), and that high deposit fees are one of three most cited reasons for unbanked households not having a deposit account (2015 FDIC National Survey of Unbanked and Underbanked Households).

Among deposit fees, overdraft fees are a particular concern in the U.S. Overdraft fees refer to deposit fees associated with non-sufficient funds (NSF) transactions that may or may not entail an extension of overdraft credits.[2] Since the roll-out of au-

[1] Degryse, Kim, and Ongena (2009) provide a survey of the literature on competition and deposit and loan rates.

[2] A non-sufficient fund (NSF) transaction occurs if a consumer attempts to pay or withdraw from a deposit account without enough balance. Banks usually deal with NSF transactions like the following: when a bank accepts an NSF transaction, it pays the debit and charges a "paid item fee" for an extension of overdraft credits. When the bank rejects the NSF transaction, it does not pay the debit and charges an "unpaid item fee", which is usually the same amount to the paid item fee. Whether the bank accepts or rejects the NSF transaction is usually under the bank's discretion based on deposit account agreements. Moreover, the NSF transaction may incur "negative balance fees" if the customer would not repay overdraft credits within a certain period of time. Consumer Financial Protection Bureau (2013) contains a detailed description of the current overdraft practices in the U.S. Melzer and Morgan (2015) provide an interesting discussion about a regulatory friction that may make almost all banks charge at least as much for unpaid items as for paid items.

tomated overdraft programs in the early 2000s, overdraft fee revenue has become a crucial source of bank revenues.[3] It reached $11.8 billion in 2016, having become three times larger than maintenance fee revenue.[4] The concern regarding overdraft fees is that they reportedly pull low-income consumers into a debt trap and push them out of the banking system (New York Times 2016). Even though the Dodd-Frank Act of 2009 introduced a strong disclosure rule on consumer overdafts, studies have commonly found evidence on suboptimal or mistaken overdrafts and subsequent checking account closures.[5] Moreover, a series of reports by financial regulators have also shown that some consumers with low deposit balances and credit constraints frequently overdraw their deposit accounts and pay a large proportion of overdraft fees.[6] Despite the importance of overdraft fees in bank business and household finance, little is known about how competition affects overdraft fees and what would be welfare implications from increased competition.

In this paper, I examine how competition affects overdraft fee revenue at the bank level in the U.S. Competition is quantified by the Herfindahl-Herschman Index (HHI), a standard market-wide competition measure in banking literature.[7] More specifically, I use deposit-weighted state HHI to measure competition varying at the bank level: a state HHI for single-state banks and a weighted average of state HHIs for multi-state banks.[8] As a result, identification comes from the variation in deposit market competition across states and the variation in banks' exposure to each state deposit

3 An automated overdraft program refers to a computer program which processes NSF transactions and charge overdraft fees. Federal Deposit Insurance Corporation (2008) and Fusaro (2009) have documented that U.S. banks rapidly adopted automated overdraft programs in the early 2000s.

4 A maintenance fee refers to a fee to have a deposit account, such as "monthly fee". Most U.S. banks nowadays provide deposit accounts for which account holders can waive monthly fees by meeting certain minimum requirements.

5 For suboptimal or mistaken overdrafts, see Stango and Zinman (2009, 2014), Liu, Montgomery, and Srinivasan (2018), Caflisch et al. (2018), Adams et al. (2018), Alan et al. (2018), and Jørring (2017). For involuntary checking account closures due to snowballed overdraft fees, see Liu, Montgomery, and Srinivasan (2018) and Campbell, Martínez-Jerez, and Tufano (2012).

6 For example, according to the Consumer Financial Protection Bureau (2017b), 9% of consumers (frequent overdrafters) pay 79% of overdraft fees, and 70% of frequent overdrafters have low daily balances and low or moderate credit scores and another 20% of frequent overdrafters have low daily balances and no credit score. Federal Deposit Insurance Corporation (2008) and Consumer Financial Protection Bureau (2013, 2014) are earlier studies that have documented similar patterns in overdraft usage and fees.

7 Degryse, Kim, and Ongena (2009), Petersen and Rajan (1995), Radecki (1998), and Park and Pennacchi (2008)

8 There are several reasons for use of state HHI rather than HHI at a finer geographic level: (1) many banks set uniform rates for both deposits and retail loans within a state (Radecki 1998), (2) market concentration at the state level has more clear relationship with deposit rates than market concentration at a finer level, and (3) overdraft prices do not vary within a state at least for the largest banks.

market. The study's primary outcome variable is overdraft fee revenue divided by the number of deposit accounts. I utilize newly available overdraft fee revenue data in recent Call Reports. Per-account overdraft fee revenue enables a comparison of the bank's fee-seeking activity using the overdraft program among banks with similar business strategies and customer bases.

I first regress per-account overdraft fee revenue on the deposit-weighted state HHI ("competition index"), controlling for bank business and customer characteristics using the ordinary least squares (OLS). But still, there is a potential endogeneity issue that both the contemporaneous competition index and overdraft fee revenue have been affected by an unobservable factor that is not accounted by the OLS method. A particular concern is related to recent changes in market environment such as the roll-out of automated overdraft programs and the interstate banking deregulation since the mid-1990s. For example, if some banks are better at adapting to changing circumstances, which is unobservable to researchers, the banks may take more advantage of new business opportunities from both interstate banking and automated overdraft programs since the mid-1990s. This high adaptability may have lowered the competition they face and raised their per-account overdraft fee revenue at the same time. The omitted unobservable factor would bias OLS estimates. To address this issue, I use a historical competition index as an instrument for the contemporaneous competition index. The historical competition index measures the competition at a time before the interstate banking deregulation and the roll-out of automated overdraft programs.

My empirical findings from both OLS and IV estimation demonstrate the positive causal relationship between competition and overdraft fee revenue. Banks facing higher competition make more per-account overdraft fee revenue than banks with similar business models and customer bases that face lower competition. Conversely, this causality does not hold for other deposit fees such as maintenance and ATM fees. These findings suggest that competition may drive banks to exploit overdraft programs more aggressively to generate fee revenues. My empirical findings are consistent with a theory of bank risk-taking, developed by Marcus (1984) and Keeley (1990): an increase in competition reduces bank charter value, encouraging the bank to take more risk.[9] In my study's context, the increased risk-taking involves supplying

[9] Charter value is the value of a bank charter in a competitive auction. Due to entry regulation into

more overdraft credits or just charging overdraft fees more aggressively at the expense of default or legal risk.

This study is relevant to literature on deposit fees. Adams (2017) has shown that competition is positively associated with deposit fee revenue. With more detailed deposit fee revenue data than his data, my study has demonstrated that competition increases per-account overdraft fee revenue but not per-account maintenance or ATM fee revenue. In regard to the effect of competition on the level of overdraft fee, previous studies have had mixed results: Hannan (2006) and Adams (2017) have documented that competition among banks has a negative or no effect on the overdraft fee level, while Melzer and Morgan (2015) have shown that competition from payday lenders has a positive relationship with the overdraft fee level. My study implies that an increase in competition may drive banks to generate more overdraft fee revenue than before by adjusting non-price elements of overdraft programs even if increased competition has no or negative effect on the overdraft fee level.

This study is also related to literature on bank risk taking. Several studies have documented that consumer overdrafts are high-risk small loans to low-income credit-constrained consumers comparable to payday loans and deposit advance products.[10]. Marcus (1984) has hypothesized that banks with a low charter value take risks to exploit the option value of deposit insurance, while banks with a high charter value avoid risk to protect investment opportunities. Keeley (1990) has provided empirical evidence supporting that increased competition may reduce the charter value and consequently increase risk taking of banks at the margin. Conversely, Boyd and De Nicolo (2005) and Banerjee (2004) have pointed out that it can go the other way if competition makes the risk-return trade-off worse. If this is the case, increased competition reduces returns to the same level of risk taking, which may result in banks taking less risk. My empirical findings are consistent with Marcus (1984) and Keeley (1990), implying that competition may be an important contributor to the current prevalence of overdraft programs associated with high default or legal risks.

the industry, banks can take deposits and/or make loans with advantageous rates and it makes the charter valuable.

[10] Fusaro (2010), Morgan, Strain, and Seblani (2012), Melzer and Morgan (2015), Romeo (2016)

2.2 Empirical Approach

2.2.1 Econometric Model

Given the cross-sectional data, this study uses the following econometric model:

$$(2.1) \quad Y_i = \beta \cdot X_i + \gamma_1 \cdot Z_{1,i} + \gamma_2 \cdot Z_{2,i} + \epsilon_i$$

where Y_i is the per-account overdraft fee revenue, X_i is the competition index, $Z_{1,i}$ is the vector of bank characteristics, $Z_{2,i}$ is the vector of customer characteristics (including the fraction of low-income customer ratio), and ϵ_i is the error term for bank i, respectively.

This econometric model describes how per-account overdraft fee revenue is associated with competition after accounting for the bank business model, customer base, and demand for overdrafts. Two sets of control variables are included in the model: bank characteristics proxy the business model, and customer characteristics account for the customer base and demand for overdrafts. Because overdrafts are predominantly used by low-income consumers, it is particularly important to control for the fraction of low-income consumers.

The ordinary least square (OLS) regression would provide the causal effect of competition and the fraction of low-income consumers, respectively, on per-account overdraft fee revenue if the error term (ϵ_i) is uncorrelated with the X_i and $Z_i = [Z_{1,i}\ Z_{2,i}]$. Otherwise, each estimated coefficient merely shows the partial correlation between each explanatory variable and the outcome variable after accounting for other explanatory variables rather than the causal relation.

2.2.2 Potential Endogeneity Issue

It is important to address the potential endogeneity related to banks' ability to adapt to changing market environments, because the mid-1990s to the early 2000s saw two critical changes in the U.S. deposit market. First, interstate branching has been allowed nationwide since the Riegle-Neal Act of 1994. Banks have become able to acquire a branch or bank in other states with few restrictions, and consequently large bank mergers flourished in the following years (Brewer III et al. 2000).[11] Next, consumer overdrafts have been a popular business for U.S. banks since the roll-out of automated overdraft programs in the early 2000s (Federal Deposit Insurance Corporation 2008, Fusaro 2009). As a new technology, automated overdraft programs enabled banks to process consumer overdrafts more efficiently than before.[12] As electronic payments by debit cards surged in 2000s, consumer overdrafts have become a more important business. Under the turbulent market environment from the mid-1990s to the early 2000s, banks with high ability to adapt to change might take more advantage of new business opportunities from deregulation or new technology than their peers with lower ability to adopt to change.

There are two possible sources of endogeneity associated with the difference in banks' ability to adapt to changing circumstances. First, I discuss a possibility of downward bias of OLS estimation. Suppose that banks with high ability to adapt to change have been more likely to utilize automated overdraft programs and to expand to states with low competition among banks. In this case, these banks with high adaptability face lower competition now than before, relative to their peers with lower adaptability.[13] This situation can be described by decomposing the error term into two parts as the following:

$$\epsilon_i = \alpha A_i + \eta_i$$

where A_i is the ability to adapt to changing circumstances and η_i is a well-behaved error term (i.e., $E[\eta_i|X_i, Z_i] = 0$). Then, $E[X_i \cdot A_i|Z_i] < 0$ since banks with high ability of adaptation face lower competition than their peers. Also, $\alpha > 0$ because these adaptive banks are more likely to use automated overdraft programs. Then, OLS regression

[11] Inter-state branching might be motivated by potential benefits from an expanded market such as geographic portfolio diversification, economies of scale, and too-big-to-fail.

[12] Federal Deposit Insurance Corporation (2008) defines automated overdraft programs as "a computerized program by which the bank honors a customer's overdraft obligations using standard procedures or a matrix to determine whether the non-sufficient fund (NSF) occurrence qualifies for the overdraft coverage". Alternatively, Fusaro (2009) distinguishes overdraft programs between a formal program, "one which has well established criteria determining which overdrafts are paid and which are bounced", and an informal program, "one in which a bank official has the discretion to bounce or pay an overdraft." According to their definitions, the formal program of Fusaro (2009) looks similar to the automated overdraft program of Federal Deposit Insurance Corporation (2008).

[13] Banks might not directly aim to lower competition by inter-state branching. But, it was likely that states with relatively low competition provide good business opportunity, which banks might seek for.

without accounting for the unobservable ability of adaptation would underestimate the causal effect of competition on per-account overdraft fee revenue.

Next, I discuss a possibility of upward bias of OLS estimation. Suppose that banks with high ability to adapt to changing circumstances have better survived competition before the sample period than their peers with lower ability to do so. Then, these high ability banks now face on average higher competition than their surviving peers and so $E[X_i \cdot A_i|Z_i] > 0$. Also, $\alpha > 0$ because these adaptive banks are more likely to use automated overdraft programs. Then, OLS regression that does not account for the unobservable ability of adaptation would overestimate the causal effect of competition on per-account overdraft fee revenue.

In sum, OLS estimates could be biased in both directions in theory, so it is necessary to compare OLS estimates with IV estimates to figure out the direction of bias empirically. Nevertheless, previous studies have shown that large banks that initiated the adoption of automated overdraft programs were more likely to use them than small banks (Federal Deposit Insurance Corporation 2008, Fusaro 2009). These facts suggest that the possibility of downward bias is more likely than that of upward bias.

2.2.3 IV Estimation

To address the potential endogeneity issue, I use the competition in 1994, a period before both the roll-out of automated overdraft programs and nationwide interstate banking deregulation, as an exogenous instrument for the competition in 2016, the sample period of this study. First, the competition in 1994 is closely associated with the competition in 2016, since the market structure in the former period provides a historical basis for that in the latter period with nationwide interstate banking. Next, the competition in 1994 is exogenous to the per-account overdraft fee revenue in 2016. This is because the degree of competition a bank faces within a state in 1994 had been determined by federal and state banking laws and institutions up to that year, and these laws are unrelated to the bank's ability to adapt to changing circumstances.[14] Given the exogenous and relevant instrument, this study obtains IV estimates using

[14] Even if banks with high ability of adaptation had also prospered before the Riegle-Neal Act of 1994, they might face similar competition to their peers with lower ability of adaptation in the same state. Before the nationwide interstate banking was allowed, banks could not easily expand to other state markets, which is a way to be exposed to lower competition.

two-stage least square (2SLS) regression.

2.3 Data

2.3.1 Data Sources

A primary data source of this study is the Reports of Condition and Income (FFIEC31 and FFIEC41), the so-called Call Reports, of U.S. banks. Most importantly, this study employs newly available information on detailed deposit fee revenue from the Call Reports in the fourth quarter of 2016. The Call Reports have provided information on deposit fee revenues as a part of the income statement for a long time, but only about the total amount of deposit fee revenues for each bank. Since the first quarter of 2015, however, the Call Reports have begun collecting information on three subcategories of the deposit fee revenues: overdraft fee revenue, maintenance fee revenue, and ATM fee revenue. Due to the limited reporting requirement, the information on detailed deposit fee revenue is available only for banks with $1 billion or more in assets. Moreover, this study obtains a number of balance sheet items as well as information on the number of deposit accounts from the Call Reports.

The other primary data source is the Summary of Deposit (SOD) in June 2016. The SOD provides information on deposits and location, particularly at the state and ZIP Code level, of each branch of U.S. banks. This branch-level information enables the calculation of the competition index and customer characteristics at the bank level. The SOD also shows whether a bank operates in a single state or multiple states and whether a bank is controlled by a bank holding company.

Combined with the SOD, several other data sources are used to compute customer characteristics of each bank. The Internal Revenue Service (IRS) Statistics on Income (SOI) Individual Income Tax Statistics of 2015 are employed to measure the fraction of low-income consumers. The IRS SOI statistics provide the number of individual income tax returns by five income groups by ZIP Code. Next, the 2015 American Community Survey (ACS) 5-year estimates at the ZIP Code Tabulation Areas (ZCTA) level are utilized to measure customer demographics such as age, gender, race, and ethnicity.[15]

[15] ZIP Codes and ZCTA Codes are comparable by definitions and so the two codes can be used in an

2.3.2 Outcome Variables

The outcome variable is per-account overdraft fee revenue. Overdraft fee revenue is measured by the item RIADH032, which is formally described as "Consumer overdraft-related service charges levied on those transaction account and nontransaction savings account deposit products intended primarily for individuals for personal, household, or family use" in the Call Reports. The overdraft fee revenue includes fees charged for non-sufficient fund (NSF) transactions regardless of whether the NSF transaction was honored or not by the bank.[16] Next, the number of deposit accounts is the sum of four Call Report items: RCONF050, RCONF052, RCONF046, and RCONF048.[17]

2.3.3 Explanatory Variable

The explanatory variable of primary interest is how much competition a bank faces in the deposit market. In this study, the Herfindhal-Hirschman Index (HHI) measures the degree of deposit market competition (or conversely, concentration) by state. The HHI of bank i is defined as the deposit-weighted average of state HHI:

$$HHI_i = \sum_{s \in S} w_{i,s} \cdot HHI_s$$

where s refers a state, S is the set of states, $w_{i,s}$ is the share of deposits in state s among total deposits of bank i, and HHI_s is the Herfindahl-Hirschman Index (HHI) in state s. For a single-state bank, it is simply the state HHI. For a multi-state bank, it is the average of state HHI weighted by the ratio of state deposits to total deposits of the bank.[18]

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integrated way for the research.

16 In practice, banks tag different names to the fees charged for a NSF transaction. Fees for honored NSF transactions are often called "overdraft paid fee", "overdraft item fee", or "overdraft fee" while fees for unhonored NSF transactions are called "unpaid item fee", "returned item fee", or "overdraft returned fee". According to the Instructions for Preparation of Consolidated Reports and Conditions and Income Statement (FFIEC31 and FFIEC41), RIADH032 clearly includes fee revenue collected from both types of NSF transactions.

17 The four items are RCONF050 "Number of deposit accounts (excluding retirement accounts) of $250,000 or less", RCONF052 "Number of deposit accounts (excluding retirement accounts) of more than $250,000", RCONF046 "Number of retirement deposit accounts of $250,000 or less", and RCONF048 "Number of retirement deposit accounts of more than $250,000".

18 For example, suppose a bank has branches in only two states: New Jersey and North Carolina. Branches in New Jersey has $50 billion of deposits and those in North Carolina has $150 billion of deposits. The state HHI of New Jersey is .0735 and that of North Carolina is 0.2601. Then, total deposits of the bank is $200 billion and the HHI of the bank is (50/200) x .0735 + (150/200) x 0.2601.

2.3.4 Control Variables

Bank characteristics are the first set of control variables to account for the business model. Above all, the book value of assets accounts for heterogeneity by bank size. The dummy for multi-state banks controls for the effect of having branches in multiple states. The dummy for banks under high holders controls for the prospective expansion or access to the wholesale fund market. The core deposit ratio measures to what extent assets are funded by retail deposits.[19] The consumer account deposit ratio controls for what proportion of deposits is in consumer deposit accounts, on which overdraft fees and other deposit fees are levied.[20] The uninsured deposit ratio is included to control for the composition of deposit portfolio and the effect of deposit insurance. The loan-to-asset ratio controls for how much assets are allocated to loans, which are less liquid than stocks or reserves. The equity-capital-ratio reflects leverage and riskiness of assets.[21] The nonperforming loan ratio controls for loan default risk.[22]

Customer characteristics are the second set of control variables to account for the customer base and demand for overdrafts. These variables are basically defined as the deposit-weighted average of neighborhood demographics at the Zip Code level, which is the finest geographic unit available for linking information on branch deposits in the SOD and information on income and demographics in public statistics. First of all, the low-income ratio measures what fraction of individuals have income less than \$25,000 based on IRS SOI Individual Income Tax Statistics. The measurement is the average of the low-income ratio of each ZIP Code weighted by the ratio of deposits in the ZIP Code to total deposits of the bank.[23] Similarly, the young, female, Black, or Hispanic ratio measures how many individuals are young (age 18 to 25), female,

[19] Core deposits are defined as the sum of demand deposits, all NOW and ATS accounts, MMDAs, other savings deposits and time deposits under \$250,000, minus all brokered deposits under \$250,000, according to the definition in Federal Deposit Insurance Corporation (2011).

[20] Consumer account deposits are defined as the sum of deposits in transaction accounts, savings accounts, and MMDA accounts intended primarily for individuals for personal, household, or family use.

[21] Equity is defined as the sum of perpetual preferred stock, common stock, surplus, and retained earnings.

[22] Nonperforming loans are defined as the sum of gross charge-offs and past due and nonaccrual loans and leases.

[23] For example, suppose a bank has only two branches: one in ZIP Code 08854 (a part of Piscataway, NJ), one in ZIP Code 08901 (a part of New Brunswick, NJ). The branch in ZIP Code 08854 has \$90 million of deposits and the branch in ZIP Code 08901 has \$110 million of deposits. The ratio of people with adjusted gross income of \$25,000 or less in ZIP Code 08854 is 27.8% and that in ZIP Code 08901 is 51.8%. Then, total deposits of the bank is \$200 million and the low-income ratio of the bank is (90/200) x 27.8% + (110/200) x 51.8%.

Black, or Hispanic, respectively, based on ACS 5-year estimates. As a result, these variables reflect characteristics of potential customers of a bank rather than actual deposit account holders of the bank. There are two merits of using potential customer characteristics. First, doing so circumvents the difficulty in access to proprietary customer information of each bank, which is unobservable in public surveys. Moreover, it helps avoid a potential selection issue associated with actual customer characteristics, which might be affected by overdraft prices of each bank.[24]

2.3.5 Sample

The study sample is a single cross-section of 579 U.S. banks for which overdraft fee revenue in 2016 are available.[25] Due to the reporting requirement, banks with less than $1billion in assets are excluded from the sample. Banks that have most branches in U.S. territories are also excluded, and so this study focuses on the deposit market of 50 states and District of Columbia. Lastly, non-standard banks such as AMEX and Charles Schwab are excluded, since their business model is too different from that of ordinary banks in the sample.

OLS estimation uses the full study sample and IV estimation employs a subsample of 487 banks which were established before 1994. Table 2.1 shows that descriptive statistics of the full sample in column (1) and those of the subsample in column (4) are on average close to each other. This means that banks established before 1994 and banks established after 1994 are exposed to similar competition and have similar business models and customer bases in 2016.

2.4 Results

2.4.1 OLS Estimates

OLS estimation results demonstrate that competition is strongly positively correlated with per-account overdraft fee revenue. Figure 2.1 shows that the HHI is negatively

[24] For example, actual customer characteristics of a bank may be affected by overdraft prices of the bank, since low-income consumers would be more likely than high-income consumers to open a deposit account at banks charging lower overdraft fees. Hence, estimates from regressions with these actual but endogenous controls could be biased. Use of potential consumer characteristics prevent this type of bias.

[25] This study does not use panel data from 2015 and 2017. Using the short panel does not seem meaningful, since competition and banks' business model may not be changeable within one or two years.

associated with per-account overdraft fee revenue at the bank level. Table 2.2 confirms that the negative association still holds after observable characteristics are controlled for in OLS regressions. Additionally, the size of estimated coefficients in columns (1) to (3) reveal that it is important to account for the business model and customer base for this study. Without considering these factors, the effect of competition on per-account overdraft fee revenue would be overestimated. Despite this, coefficient estimates in all three columns are negative and statistically significant at the 1% level.

The coefficient estimate on the HHI in column (3), the baseline model specification, demonstrates that banks facing higher competition make more overdraft fee revenue per account than their peer banks with a similar business model and customer base that face lower competition. The coefficient implies that a 0.1 reduction in the HHI results in a $3.09 increase in per-account overdraft fee revenue.[26] This magnitude is equivalent to 13.8% of the average outcome of banks in the full sample.

2.4.2 IV Estimates

IV estimation results confirm a positive causality from competition to per-account overdraft fee revenue. Table 2.3 compares OLS estimates from the full sample (columns (1) and (4)), OLS estimates from the IV subsample (columns (2) and (5)), and 2SLS estimates from the IV subsample (columns (3) and (6)). Columns (1) to (3) show coefficient estimates from regressions without accounting for customer characteristics. Coefficient estimates on the HHI in columns (4) and (5) affirms that OLS estimates from the full sample and the subsample is quite close based on the baseline model specification. In other words, the positive association between competition and per-account overdraft fee revenue in the full sample still holds in the IV subsample. Coefficient estimates in columns (5) and (6) shows that the 2SLS estimate is larger than the OLS estimate on the IV subsample. The 2SLS estimate in column (6) is -42.4, meaning that a reduction of 0.1 in the HHI leads to an increase in per-account overdraft fee revenue of $4.24, or 17.6% of the average outcome of banks in the subsample.

The lower panel in table 2.3 presents 2SLS first stage results. The first stage co-

[26] Here is an illustrative example of an increase in the HHI by 0.1. If a market is evenly divided by ten banks, the HHI is 0.1. When the number of banks reduces to five from ten, the HHI grows to 0.2 from 0.1. Because state deposit markets usually have several large banks and many mid-sized or small banks together, the illustration has limitation.

efficient estimate in column (6) shows that the historical HHI measured in 1994 is strongly correlated with the contemporaneous HHI in 2016. Two weak identification test results show that the instrument is not weak but relevant for the 2SLS estimation.

My finding of the 2SLS estimate greater than the OLS estimate on the same subsample could be interpreted in two different ways. On the one hand, obtaining larger 2SLS estimates than OLS estimates may reflect that OLS estimates are biased downward. If so, one possible explanation would be the following: banks with high adaptability have expanded to less competitive state markets and use high-powered overdraft programs than their peers with lower adaptability. Then, OLS estimates would underestimate the effect of competition on per-account overdraft fee revenue.

Conversely, the difference between 2SLS estimates and OLS estimates may be just because the 2SLS method identifies the local average treatment effect (LATE) while the OLS method identifies the average treatment effect (ATE). Based on the LATE interpretation, the 2SLS estimate in column (6) measures the causal effect of competition on per-account overdraft fee revenue for banks that face high competition in 2016 only because of their exposure to historically high competition, which had been exogenous determined by banking laws and institutions up to 1994.

2.4.3 Comparison with Other Deposit Fees

My additional analysis reveals that other deposit fee revenues are not positively related to bank competition. Table 2.4 compares how overdraft fee revenue and other deposit fee revenues are associated with the HHI. Among three identifiable deposit fees in Call Reports, only per-account overdraft fee revenue is positively significantly correlated with deposit market competition, as shown in columns (1) and (2). Both OLS and IV estimates in columns (3) to (6) show that per-account maintenance fee revenue and ATM fee revenue are not significantly related to the HHI.

These findings suggest that banks increase overdraft fee revenue but not maintenance and ATM fee revenue as competition grows. Although the reason for this asymmetric adjustment of deposit fee revenues is not totally clear, there are at least two critical differences between overdraft fees and maintenance and ATM fees. First, contract terms on overdraft fees are far more complex than those on maintenance or ATM fees in the deposit account service agreement. Next, overdraft fees are associated with a small unsecured credit extension, and therefore they are a riskier source of revenues than maintenance or ATM fees.

The findings are consistent with the previous finding of Adams (2017) on a positive relationship between competition and deposit fee revenues. Moreover, my study reveals that overdraft fee revenue plays a key role for the increase in deposit fee revenue in response to increase competition. A corollary from my findings is that the share of overdraft fee revenue among deposit fee revenues increases as competition increases, which has happened in the U.S. deposit market over the recent decades.

2.4.4 Summary of Findings

Both IV and OLS estimates demonstrate that banks facing higher competition make significantly more per-account overdraft fee revenue than banks with similar business models and customer bases that face lower competition. These findings are consistent with Melzer and Morgan (2015), which have shown than competition from payday lenders increases overdraft prices and overdraft credit limits. Although my study uses a different source of competition from their study, both studies agree that increased competition in overdraft services leads to an unusual adjustment in the listed overdraft price and non-price elements of overdraft programs. At a glance, my empirical findings seem not fit well into previous studies showing that competition had a negative or no effect on overdraft fees (Hannan 2006, Adams 2017). When competition among firms increases and prices go down or stay the same, it appears to be unlikely for firms to earn more revenue. However, the gap between the previous studies and my study could be because of the non-price adjustments of overdraft programs, which were not taken into account by previous studies.

2.5 Discussions

2.5.1 Risk Embedded on Seeking Overdraft Fees

Risks associated with overdraft programs are the key to uncover a link between competition and overdraft fee revenue. Previous studies on overdraft fees have mostly focused on profitability of overdraft fees and largely ignored the risk associated with them. However, several risk factors are embedded in standard overdraft programs in the U.S. First, consumer overdrafts are small unsecured credit extension comparable to payday loans and deposit advance products (Fusaro 2010, Morgan, Strain, and Seblani 2012, Melzer and Morgan 2015, Romeo 2016). A series of studies by financial regulators have revealed that low-income, credit constrained consumers are far more likely to overdraw their deposit accounts (Federal Deposit Insurance Cor- poration 2008, Consumer Financial Protection Bureau 2013, 2014, 2017b).[27] This implies that overdraft credits are less likely to be repaid than ordinary consumer loans.

Next, consumer overdrafts are a complex add-on to checking account services, which consumers rarely attend to when opening their accounts or swiping debit cards. Studies have repeatedly demonstrated that some consumers overdraw by mistake or suboptimally (Stango and Zinman 2009, 2014, Liu, Montgomery, and Srinivasan 2018, Caflisch et al. 2018, Adams et al. 2018, Alan et al. 2018, Jørring 2017). Also, there is accumulating evidence that behavioral limitations in different domains tend to be closely correlated one another (Jørring 2017, Chapman et al. 2018). Taking together, overdraft credits or accumulated fees are less likely to repaid than other consumer loans, since frequent overdrafters may also be poor at managing their debts than ordinary borrowers. In a similar vein, several studies have documented involuntary checking account closures as a result of snowballed overdraft fees (Liu, Montgomery, and Srinivasan 2018, Campbell, Martínez-Jerez, and Tufano 2012).

Lastly, consumer overdrafts are exposed to legal risks potentially arising from insufficient disclosure, unfair practices, or aggressive marketing. These practices are likely to be in a grey area of financial regulation or consumer protection laws, and they may lead to legal disputes at any time. For example, many large banks have changed their policy on the posting order after court decisions against them.[28] More recently, the Consumer Financial Protection Bureau sued a bank for misleading con-

[27] For example, Consumer Financial Protection Bureau (2017b) has found that (i) overdrafters have lower median deposits than non-overdrafters and (ii) frequent overdrafters have lower credit scores and are less likely to have credit cards than others.

[28] Posting order refers the sequence of transactions processed by each bank at the end of each business day. If a bank processes debit transactions from the largest one to the smallest one, the bank may earn much more overdraft fee revenue than when processing them in chronological order. A big dispute on the posting order has been resolved in courts. California consumers sued Wells Fargo for manipulating the posting order to maximize overdraft fees in 2007. U.S. District Court found in 2010 that Wells Fargo violated unfair business practices law in California, which was upheld by higher courts in 2014 and 2016. Since the judgement in 2010, a number of overdraft settlements about the same legal issue have been following. Many banks have changed their posting order in favor of customers or disclosed it more clearly in deposit account contracts now than in the past.

sumers' opt-in decision on overdraft programs (Consumer Financial Protection Bureau 2017a).[29] In sum, overdraft programs entail potentially high default and legal risks. From this perspective, seeking overdraft fee revenue using high-powered overdraft programs is a risky business decision, just like increasing risky loans.

2.5.2 Competition and Risk Taking with Overdraft Programs

My findings are congruent with the dichotomous risk taking based on charter value (Marcus 1984 and Keeley 1990).[30] In regards to charter value, Hughes, Jagtiani, and Mester (2016) provide an important empirical relationship between bank size and charter value in the U.S. In their study, charter value is estimated based on a stochastic frontier model, and is negatively associated with bank size. Combined with Marcus (1984) and Keeley (1990), this empirical relationship implies potentially heterogeneous effects of competition by bank size groups.

Table 2.5 shows heterogeneous effects by bank size groups using OLS estimation. Column (1) replicates the baseline OLS estimate of this study. The coefficient estimate on HHI*(Multi-state bank) in Column (2) shows that competition mostly affects banks operating in multiple states to generate more overdraft fee revenue. Columns (3) and (4) decompose multi-state banks into three size groups: community banks (assets less than $10 billion), mid-sized banks (assets between $10 and $50 billion), and large banks (assets above $50 billion). Estimated coefficients on the interaction terms between the HHI and the bank size group dummies in Column (4) reveal that mid-sized multi-state banks are affected the most among all bank size groups.

These findings are consistent with the prediction of the bank risk taking theory based on charter value. Small banks, with a high charter value, are less dependent on overdraft programs regardless of the degree of competition. However, mid-sized banks, with a charter value around the threshold, adopt the dichotomous strategy for risk taking: banks in the most competitive market generate more overdraft fee revenue

[29] Since the Dodd-Frank Act of 2009, banks have been required to obtain affirmative consents from customers to charge overdraft fees from some kinds of deposit account transactions. As a result, whether a customer opts into overdraft programs or not becomes a key determinant of overdraft fee revenue. A recent litigation by the Consumer Financial Protection Bureau (CFPB) provides a piece of evidence on banks' promotion of overdraft programs. The agency sued TFC National Bank for misleading customers to opt into overdraft programs (Consumer Financial Protection Bureau 2017).

[30] A worse risk-return trade-off due to increased competition, presumed by Boyd and De Nicolo (2005) and Banerjee (2004), seems not to be a key determinant of risk taking associated with consumer overdrafts. It may be too small to reverse increased risk taking due to declines in the charter value.

than than similar banks in less competitive markets. In other words, they take more risk from consumer overdrafts in response to declines in the charter value due to increased competition. Large banks, with an even lower charter value, use overdraft programs intensively regardless of the degree of competition.[31]

Moreover, Table 2.6 shows that banks facing high competition take more risk associated with consumer overdrafts than those facing lower competition. Estimations for Table 2.6 use two dummy variables, instead of a continuous HHI, to account for potentially non-linear effects of competition: a high competition dummy assigned for banks with HHI<0.1 and a low competition dummy for those with HHI>0.18.[32] Estimated coefficients in Column (1) show that the all nonperforming loans to assets ratio (NPL ratio) is positively correlated with bank competition. But, this positive relationship between competition and the NPL ratio does not hold for consumer loans as a whole and for credit card loans and non-credit-card consumer loans, separately (columns (2) to (4)). In contrast to consumer loans, the NPL ratio associated with consumer overdrafts ("All other loans" in column (5)) are significantly positively correlated with the high competition dummy.[33] This means that banks facing high competition take more default risk of overdraft credits than their peers facing mild competition (0.1<HHI<0.18).

2.5.3 Possibility of Deceptive Innovation on Overdraft Programs

Another relevant theory for my empirical findings is the deceptive innovation hypothesis. Heidhues, Kőszegi, and Murooka (2016) have theorized that firms may invest in devising hidden fees rather than in improving product value. Moreover, their paper uses overdraft fees as a leading example of a deceptive innovation. If competition trig-

[31] From a different perspective, higher risk taking of large banks can be explained with the too-big-to-fail hypothesis. If a bank believes that its uninsured liabilities are implicitly insured under too-big-to-fail, then the option value may be higher, and the bank may take more risk from consumer overdraft.

[32] Previous studies such as Petersen and Rajan (1995) and Park and Pennacchi (2008) show that bank competition may have non-linear effects on bank pricing or credit supply. I classify banks into three groups: banks with HHI<0.1, banks with HHI between 0.1 and 0.18, and banks with HHI>0.18. This categorization follows Petersen and Rajan (1995). In estimations for Table 2.6, banks with HHI between 0.1 and 0.18 are omitted as a reference category.

[33] In Call Reports, two types of overdrafts are reported as loans: a planned overdraft and an unplanned overdraft. The unplanned overdraft refers to an ordinary overdraft that occurs when a depository institution honors a check or draft drawn against a deposit account when insufficient funds are on deposit and there is no advance contractual agreement to honor the check or draft. The planned overdraft occurs when a contractual agreement has been made in advance to allow such credit extensions. By the instruction for Call Reports, both types of overdrafts are treated and reported as a "loan" rather than a negative deposit balance. The unplanned overdraft is reported as a part of "All other loans" (RCONJ451) separated from consumer loans, while the planned overdraft is included into "other revolving credit plans" (RCONB539) under consumer loans in Call Reports.

gers the deceptive innovation on overdraft fees, banks in more competitive environment earn more overdraft fee revenue using more deceptive overdraft programs than their peers in less competitive environment. So, the deceptive innovation hypothesis has some explanatory power for my empirical findings. A limitation of applying this hypothesis to my empirical findings is that banks in less competitive markets may easily adopt the deceptive innovation on overdraft programs by other banks. Therefore, the theory of deceptive innovation alone seems not enough to explain the variations in overdraft fee revenue among banks.

2.5.4 Importance of Non-price Adjustments

Banks seeking more overdraft fees may consider both price and non-price adjustments of overdraft programs. Banks can change overdraft prices. Different banks indeed post different levels of overdraft fees. A few studies on overdraft prices have found that competition had a negative or no effect on overdraft fees (Hannan 2006, Adams 2017), and that customer characteristics have insignificant effects on overdraft fees (Adams 2017). Instead of adjusting overdraft prices, banks can change non-price elements of their overdraft programs. Consumer Financial Protection Bureau (2013) provides in-depth discussion on complex details of standard overdraft programs in the U.S. For instance, available funds, posting orders, overdraft coverage limits, and fee waiver policies are important elements of overdraft programs, but they are usually not disclosed to customers. Moreover, those elements vary greatly across banks so that a comparison of different overdraft programs is almost impossible. From the banks' perspective, however, introducing or adjusting non-price elements may be a way to generate more overdraft fee revenue without triggering price competition with other banks. In a related study, Melzer and Morgan (2015) have shown that banks adjusted overdraft credit limits as well as overdraft fees in response to the change in state payday lending bans. Banks can also promote overdraft programs more aggressively, which is another non-price adjustment for raising overdraft fee revenue. Complex overdraft programs make consumers vulnerable to potentially deceptive promotions (Consumer Financial Protection Bureau 2017a). Overall, banks may have incentives to adjust non-price details rather than the listed overdraft fee in order to seek more overdraft fee revenue.These non-price adjustment may increase the amount of overdraft credits or just raise the number of un-honored NSF transactions at the expense of default or legal risks.

2.6 Conclusion

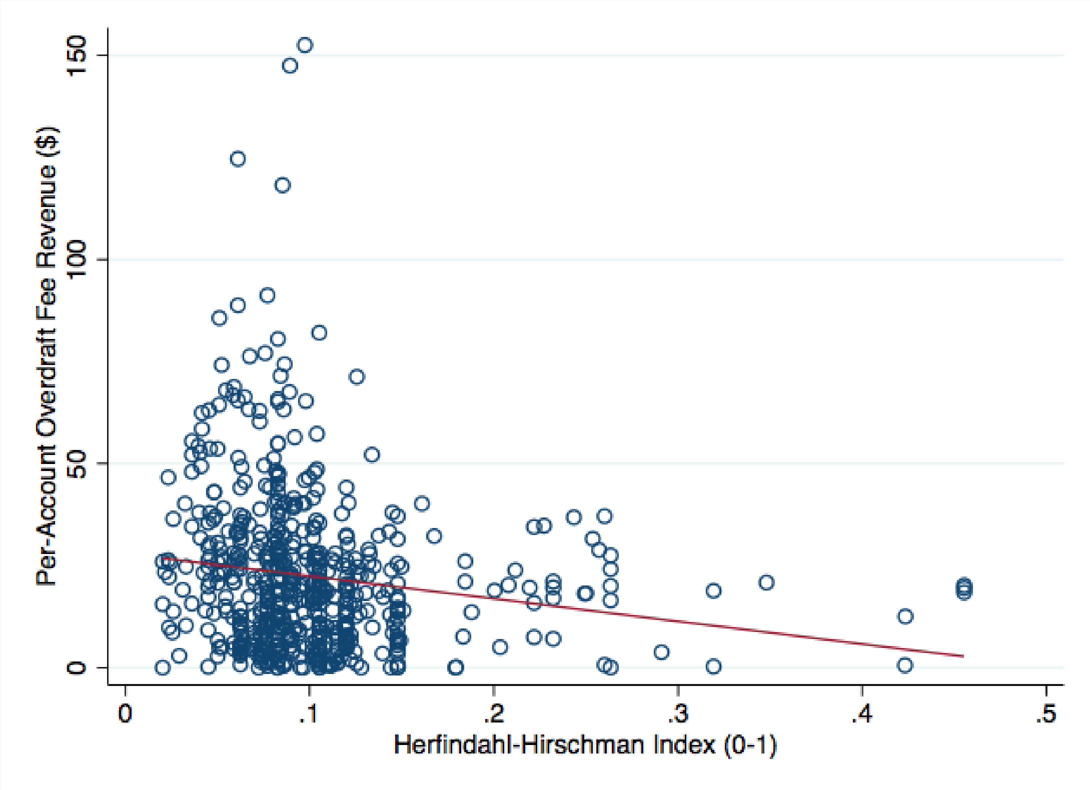
In this paper, I have demonstrated a positive causality from bank competition to overdraft fee revenue. I have also shown that this positive relationship does not hold for other deposit fees such as maintenance and ATM fees. I interpret these findings based on the two crucial differences between overdraft fees and other deposit fees: the risk associated with overdraft fees and the complexity of overdraft fees. In response to increased market competition, banks may have incentive to generate more overdraft fee revenue at the expense of default risks of overdraft credits or legal risks associated with seemingly unfair overdraft programs.

My study has several crucial policy implications. First, competition may be an important contributor to the high prevalence of overdraft fees in the U.S. Next, non-price adjustments of overdraft programs deserve additional attention from researchers and policymakers. Lastly, given that low-income consumers are disproportionately exposed to overdraft fees, increased competition may have a negative welfare effect on those financial vulnerable consumers. Therefore, my study reveals a potential trade-off between competition and financial inclusion policy. Bank regulators may need to reconsider a recurring policy proposal of separating the small dollar credit service from the deposit account service in order to prevent the apparently negative welfare effect caused by mistaken overdrafts.

Several follow-up studies would be valuable to complement this study's identification and its welfare implication. First, it would be interesting to examine how bank competition affects non-price elements of overdraft programs such as overdraft credit limits and fee waiver policies. Combined with previous studies on overdraft prices and my study on overdraft fee revenue, this type of study would provide a better understanding of overdraft fees. Next, it would be valuable to gauge the relative importance of the optimal use of overdraft credits and the suboptimal overdrafts or un-honored NSF transactions. This type of study is important to obtain a more concrete welfare implication of the current overdraft practices.

2.7 Figures and Tables

Figure 2.1: Competition and Per-Account Overdraft Fee Revenue



Note: The study sample consists of 579 banks which reported detailed deposit fee revenue including overdraft fee revenue in the Call Report of the fourth quarter of 2016.

Table 2.1: Summary Statistics

Sample	(1) S1 All	(2) S1 HHI<0.1	(3) S1 HHI>0.1	(4) S2 All
Outcome Variable				
per-account overdraft fee revenue	22.4	26.1	16.7	24.1
	(19.7)	(22.4)	(12.9)	(20.2)
Explanatory Variable				
Competition Index				
Herfindahl-Hirschman Index (HHI)	0.1004	0.0709	0.1448	0.1007
	(0.0566)	(0.0185)	(0.0651)	(0.0588)
Control Variables				
Bank Characteristics				
Assets ($1,000,000)	22,600	8,174	44,200	25,500
	(147,000)	(26,700)	(229,000)	(160,000)
Multi-state bank	0.497	0.503	0.489	0.499
Bank under higher holders	0.921	0.957	0.866	0.930
Core deposits/Assets	0.726	0.732	0.717	0.730
	(0.099)	(0.092)	(0.109)	(0.099)
Consumer accounts/Deposits	0.367	0.365	0.368	0.380
	(0.158)	(0.159)	(0.158)	(0.154)
Uninsured Deposits/Deposits	0.304	0.290	0.324	0.295
	(0.164)	(0.148)	(0.183)	(0.156)
Loans/Assets	0.698	0.699	0.696	0.690
	(0.127)	(0.123)	(0.134)	(0.124)
Equity/Assets	0.111	0.109	0.114	0.111
	(0.026)	(0.023)	(0.031)	(0.026)
Nonperforming loans/Assets	0.011	0.012	0.010	0.011
	(0.016)	(0.017)	(0.012)	(0.012)
Customer Characteristics				
Low-income ratio	0.346	0.358	0.328	0.349
	(0.064)	(0.064)	(0.060)	(0.062)
Young ratio	0.308	0.309	0.307	0.306
	(0.063)	(0.066)	(0.058)	(0.060)
Female ratio	0.512	0.512	0.513	0.513
	(0.021)	(0.023)	(0.017)	(0.016)
Black ratio	0.089	0.093	0.085	0.083
	(0.095)	(0.094)	(0.096)	(0.084)
Hispanic ratio	0.125	0.123	0.129	0.128
	(0.134)	(0.152)	(0.101)	(0.140)
N	579	348	231	487

Note: Means and standard errors (in parenthesis). Column (1) shows summary statistics of the full sample, column (2) shows those of the banks facing relatively high competition (HHI<0.1) in the full sample, column (3) shows those of the banks facing relatively low competition (HHI>0.1) in the full sample, and column (4) shows those of the subsample for the 2SLS estimation.

Table 2.2: OLS Estimation Results

Variables	(1)	(2)	(3)
HHI	-55.5***	-41.9***	-30.9***
	(10.9)	(9.4)	(9.2)
Bank Characteristics	No	Yes	Yes
Customer Demographics	No	No	Yes
R^2	0.03	0.20	0.31
Observations	579	579	579

Note: The outcome variable is overdraft fee revenue per account . The coefficient estimates are from an OLS regression. Bank characteristics include log(Book value of assets), the dummy for multi-state banks, the dummy for banks controlled by holding companies, the core deposit ratio, the consumer account deposit ratio, the uninsured deposit ratio, the loan-to-asset ratio, the equity capital ratio, and the nonperforming loan ratio. Customer demographics include the low-income, young, female, Black, and Hispanic population ratio. The sample consists of 579 banks which reported detailed deposit fee revenue including overdraft fee revenue in the Call Report of the fourth quarter of 2016. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table 2.3: IV Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation	OLS	OLS	2SLS	OLS	OLS	2SLS
Sample	S1	S2	S2	S1	S2	S2
HHI	-32.8***	-35.8***	-49.7***	-30.9***	-30.7***	-42.4**
	(8.4)	(8.6)	(17.4)	(9.2)	(9.2)	(18.4)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Customer Characteristics	No	No	No	Yes	Yes	Yes
Observations	579	487	487	579	487	487
2SLS first stage estimates						
HHI in 1994			1.141***			1.101***
(instrument)			(0.087)			(0.085)
Bank Characteristics			Yes			Yes
Customer Characteristics			No			Yes
R^2			0.37			0.37
Weak ID Test 1			260.0***			243.2***
Weak ID Test 2			162.5***			168.1***
Observations			487			487

Note: The outcome variable is overdraft fee revenue per account . The coefficient estimates in columns (3) and (6) are from an 2SLS regression. For the regression, the HHI in 2016 is instrumented by the HHI in 1994. For a comparison with OLS estimates with the full sample, columns (1) and (3) repeat columns (3) and (4) in Table 2.1, respectively. Also, columns (2) and (4) present OLS estimates with the same subsample for the 2SLS estimation. Bank characteristics include log(Book value of assets), the dummy for multi-state banks, the dummy for banks controlled by holding companies, the core deposit ratio, the consumer account deposit ratio, the uninsured deposit ratio, the loan-to-asset ratio, the equity capital ratio, and the nonperforming loan ratio. Customer demographics include the young, female, Black, and Hispanic population ratio. The full sample consists of 579 banks which reported detailed deposit fee revenue including overdraft fee revenue in the Call Report of the fourth quarter of 2016. Among them, 487 banks established before 1994 are included in the subsample for the 2SLS estimation. Weak identification tests for the first stage of 2SLS are based on Cragg-Donald Wald F statistics (Weak ID Test 1) and Kleibergen-Paap rk Wald F statistics (Weak ID Test 2). Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table 2.4: Comparison with Other Deposit Fees

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	OD	OD	Main	Main	ATM	ATM
Estimation	OLS	2SLS	OLS	2SLS	OLS	2SLS
Sample	S2	S2	S2	S2	S2	S2
HHI	-30.7***	-42.4**	-6.2	-9.7	1.7	-0.7
	(9.2)	(18.4)	(3.9)	(6.8)	(2.0)	(3.8)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Customer Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	487	487	487	487	487	487

Note: The outcome variable is per-account overdraft fee revenue for columns (1) and (2), per-account maintenance fee revenue for columns (3) and (4), and per-account ATM fee revenue for columns (5) and (6). The coefficient estimates in columns (1), (3), and (5) are from an OLS regression, while those in columns (2), (4), and (6) are from a 2SLS regression. For these regressions, the HHI in 2016 is instrumented by the HHI in 1994. Bank characteristics include log(Book value of assets), the dummy for multi-state banks, the dummy for banks controlled by holding companies, the core deposit ratio, the consumer account deposit ratio, the uninsured deposit ratio, the loan-to-asset ratio, the equity capital ratio, and the nonperforming loan ratio. Customer demographics include the young, female, Black, and Hispanic population ratio. For the consistent comparison between OLS and 2SLS estimation, all six regressions use the subsample of 487 banks established before 1994. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table 2.5: Heterogeneity by Bank Size Groups

Variables	(1)	(2)	(3)	(4)
HHI	-30.9***	-10.0	-31.0***	-9.8
	(9.2)	(10.9)	(9.2)	(10.9)
Multi-state bank	3.6**	8.2***		
	(1.8)	(2.7)		
HHI*(Multi-state bank)		-46.4***		
		(17.1)		
Multi-state, community bank			3.6**	8.1***
			(1.8)	(2.8)
Multi-state, mid-sized bank			3.2	14.4*
			(3.7)	(8.3)
Multi-state, large bank			6.2	8.7
			(5.0)	(6.0)
HHI*(Multi-state, community bank)				-44.4**
				(17.4)
HHI*(Multi-state, mid-sized bank)				-116.6*
				(68.9)
HHI*(Multi-state, large bank)				-23.5
				(43.0)
Bank Characteristics Controls	Yes	Yes	Yes	Yes
Customer Demographics Controls	Yes	Yes	Yes	Yes
R^2	0.31	0.32	0.32	0.32
Observations	579	579	579	579

Note: The outcome variable is overdraft fee revenue per account . The coefficient estimates are from an OLS regression. Bank characteristics include log(Book value of assets), the dummy for banks controlled by holding companies, the core deposit ratio, the consumer account deposit ratio, the uninsured deposit ratio, the loan-to-asset ratio, the equity capital ratio, and the nonperforming loan ratio. Customer demographics include the low-income, young, female, Black, and Hispanic population ratio. The sample consists of 579 banks which reported detailed deposit fee revenue including overdraft fee revenue in the Call Report of the fourth quarter of 2016. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table 2.6: Competition and Nonperforming Loans

Variables	(1) All Loans	(2) Consumer Loans	(3) Card Loans	(4) Non-card Loans	(5) "All Other Loans"
HHI<0.1 (dummy)	0.00271**	-0.00025	-0.00045	0.00020	0.00013***
	(0.00107)	(0.00065)	(0.00052)	(0.00038)	(0.00004)
HHI>0.18 (dummy)	-0.00023	-0.00123	-0.00101	-0.00022	0.00010
	(0.00167)	(0.00122)	(0.00117)	(0.00027)	(0.00008)
Low-income ratio	0.00003	0.00175	0.00288	-0.00114	0.00161***
	(0.01039)	(0.00458)	(0.00266)	(0.00372)	(0.00059)
Young ratio	-0.00599	0.00540	0.00578	-0.00038	0.00144***
	(0.01307)	(0.00554)	(0.00499)	(0.00206)	(0.00046)
Female ratio	-0.11416	-0.01057	-0.01144	0.00088	0.00130
	(0.09061)	(0.01384)	(0.01243)	(0.00439)	(0.00134)
Black ratio	0.03103**	-0.00183	-0.00359	0.00176	-0.00075*
	(0.01307)	(0.00387)	(0.00329)	(0.00166)	(0.00040)
Hispanic ratio	0.00751	-0.00212	-0.00319	0.00107	-0.00019
	(0.00521)	(0.00348)	(0.00287)	(0.00180)	(0.00020)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes
Customer Demographics	Yes	Yes	Yes	Yes	Yes
R^2	0.14	0.06	0.08	0.02	0.07
Observations	579	579	579	579	579

Note: Outcome variables vary by column: column (1) for all nonperforming loans to assets ratio, column (2) for nonperforming consumer loans to assets ratio, column (3) for nonperforming credit card loans to assets ratio, column (4) for nonperforming non-credit-card consumer loans (including planned overdraft as well as auto loans and any other revolving credit plans), and column (5) for nonperforming all other loans (including unplanned overdrafts) to assets ratio. The coefficient estimates are from an OLS regression. Bank characteristics include log(Book value of assets), the dummy for multi-state banks, the dummy for banks controlled by holding companies, the core deposit ratio, the consumer account deposit ratio, the uninsured deposit ratio, the loan-to-asset ratio, and the equity capital ratio. Customer demographics include the low-income, young, female, Black, and Hispanic population ratio. The sample consists of 579 banks which reported detailed deposit fee revenue including overdraft fee revenue in the Call Report of the fourth quarter of 2016. Robust standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Chapter 3

Overdraft Fees in a Spatial Model of Bank Competition

3.1 Introduction

Consumer overdrafts are a short-term small credit extension based on deposit account agreements. Although consumer overdrafts are an add-on service, U.S. banks earn much more overdraft fee revenue than general maintenance fee revenue according to the recent Call Reports. A few studies have documented that consumers overdraw their deposit account as a means of borrowing quick money similar to payday loans or deposit advance products.[1] Moreover, a series of studies by financial regulators have commonly found that low-income or credit-constrained consumers overdraw much more frequently and consistently than other consumers.[2] This stylized fact suggests the possibility that many consumers rationally use overdrafts. However, most studies on consumer overdrafts have ignored the empirical regularity while focusing on mistaken or suboptimal overdrafts.[3] To fill this gap, I develop a rational model of overdraft pricing.

To study the effect of competition on overdraft fees, I propose a spatial model of bank competition with differentiated products in the spirit of Hotelling (1929) and Salop (1979). In my model, banks charge only two types of deposit fee: the mainte-

[1] Fusaro (2010), Morgan, Strain, and Seblani (2012), Melzer and Morgan (2015), Romeo (2016).

[2] Federal Deposit Insurance Corporation (2008), Consumer Financial Protection Bureau (2013), Consumer Financial Protection Bureau (2014), Consumer Financial Protection Bureau (2017b).

[3] A number of behavioral economic theory papers have discussed overdraft fees as an example of shrouded attributes of deposit account agreement: Armstrong and Vickers (2012), Heidhues, Kőszegi, and Murooka (2016), Heidhues, Kőszegi, and Murooka (2017), Heidhues and Kőszegi (2017), Kosfeld and Schüwer (2017), Bubb and Kaufman (2013), and Ko and Williams (2017). Moreover, similarly many empirical papers are based on the behavioral economic theory: Stango and Zinman (2009), Stango and Zinman (2014), Alan et al. (2018), Caflisch et al. (2018), Adams et al. (2018), Liu, Montgomery, and Srinivasan (2018), Jørring (2017), Williams (2016), and Adams (2017).

nance fee and the overdraft fee. The maintenance fee stands for a membership fee for the generic deposit account service and the overdraft fee is an add-on usage fee for the overdraft service.[4] To account for the heterogeneity on overdraft usage by income, I divide consumers into two types: high- and low-income consumers. It is assumed that low-income consumers are more likely to use overdrafts than high-income consumers. This tendency has been well-documented by regulatory agencies with supervisory datasets on checking account transaction histories: consumers with low deposit balances and credit constraints far more frequently overdraw their deposit account than other consumers (Consumer Financial Protection Bureau 2017b).

Moreover, I assume that low-income consumers have lower travel costs than high-income consumers, which implies that low-income consumers are more sensitive to a difference in deposit fees between competing banks than high-income consumers. The distance in a spatial competition model could have two different meanings – a distance to the seller in a physical space or a distance to the ideal product in a product space – and both of them seem relevant for this study on the deposit market. According to the 2016 Survey of Consumer Finance (SCF), the deposit account market is differentiated by both location and other product attributes, such as price and quality.[5] So, the assumption of different travel costs between high- and low-income consumers could be supported by two distinct lines of reasoning. With respect to the opportunity costs of a physical trip to the branch office, low-income consumers have lower time value of the trip than high-income consumers. With respect to the disutility from a distance to the ideal product in a product space, the SCF data show that low-income consumers have a tendency to put the product price ahead of non-price product attributes (e.g., brand or quality) relative to high-income consumers.[6]

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[4] For many deposit accounts in reality, a monthly maintenance fee could be waived if the consumer meets certain requirements on minimum balances, direct deposits, or other criteria. Strictly speaking, this type of maintenance fee is not the maintenance fee in this model.

[5] The survey asks the reason why the survey respondent chooses the bank that issues his or her debit card. This multiple-choice question provides 43 available answers, each of which represents a product attribute of the bank service. Among them, the most frequent answer is "Location of their offices" chosen by 43% of respondents. This means that, the remaining 57% of consumers regards other product attributes more important than the location of branch office. The second and their most frequent answers are "Able to obtain many services at one place" (17%) and "Had the lowest fees/minimum balance requirement" (12%).

[6] Consumers with annual income above $100,000 are much less care about fees than consumers with annual income below $100,000 ("Had the lowest fees/minimum balance requirement": 8% vs 16%). Instead, these high income consumers tend to value bank-customer relationship and safety of the bank (e.g., "Offered safety and absence of risk", "Personal relationship; they know me; R/spouse or partner works there; small institution; family member works there", or "Always done business there; banked

My model predict that competition raises the equilibrium overdraft fee while lowering the equilibrium base fee. The economic logic is the following: low-income consumers are more responsive to changes in fees and are more likely to pay the overdraft fee than high-income consumers, and hence banks set the overdraft fee below the overdraft service costs in an equilibrium. As the number of banks in the market increases, each bank's revenue falls, and the banks respond by raising their overdraft fee in a new equilibrium.

This study makes several contributions to the literature. First, this study paper contributes to the literature on competition and deposit fee pricing. My study provides the new spatial model of deposit fee pricing, which is particularly relevant to the current deposit market environment in the U.S. Previous spatial models on deposit pricing predict that competition reduces deposit fees, given the assumption that deposit fees are equivalent to negative interest rates on deposits (Barros 1999, Park and Pennacchi 2008). In contrast to previous spatial models, my model considers two types of deposit fees to show that competition could raise certain types of deposit fees such as overdraft fees.[7]

Second, this study adds to the literature on consumer overdrafts. Except a few papers, most papers have studied overdraft fees as a shrouded attribute of deposit account agreements. In this vein, several empirical studies have recently found that consumers do not attend to the possibility of mistaken overdrafts and subsequent fees (Stango and Zinman 2014, Alan et al. 2018, Caflisch et al. 2018, Adams et al. 2018). These studies, however, have rarely attended to the fact that consumers with low deposit balances and credit constraints use overdrafts predominantly and repeatedly (Consumer Financial Protection Bureau 2017b). By contrast, my study integrates this aspect of overdraft demands to reveal that competition may increase overdraft fees, which contrasts with behavioral models predicting that competition reduces firms' shrouding of prices (Wenzel 2014, Heidhues, Kőszegi, and Murooka 2017). This study

there a long time; other business done there").

[7] Arping (2017) provides a potentially interesting explanation on the relationship between deposit market competition and loan interest rates. In his model, deposit market competition raises funding costs for loans and consequently lead to higher loan rates unless the loan market is competitive enough to countervail the effect of increased funding costs. If consumer overdrafts were regulated as consumer loans and were under little market competition, his theory predicts that deposit market competition raises overdraft fees. One limitation of this argument under the current regulatory framework is that consumer overdrafts have not been regulated as loans by the Truth in Lending Act but as a deposit service by the Truth in Savings Act.

shows that the rational use of consumer overdrafts deserves more attention from researchers and policymakers.

3.2 Baseline Model

3.2.1 Environment

There are n banks equally distanced on a circle of unit length. Let x_j be the location of bank j for $j = 1, 2, ..., n$. Banks provide the generic deposit account service with the overdraft service. Banks charge a fixed maintenance fee and a contingent overdraft fee. Let p_j and f_j be the maintenance fee and the overdraft fee of bank j, respectively.

Consumers are uniformly distributed on the circle. Consumers receive a value v from using the deposit account, which incurs travel costs in addition to deposit fees. I assume that v is large enough to make all consumers consume the deposit account. There are two types of consumers: low-income (type 1) consumers and high-income (type 2) consumers. Let $\lambda \in (0, 1)$ be the ratio of low-income consumers. High- and low-income consumers are different in two ways in this model. First, low-income consumers are more likely to overdraw their deposit accounts than high-income consumers. Let θ_t be the probability of type t consumers using an overdraft. Then, $\theta_1 > \theta_2$. I assume that θ_1 and θ_2 do not depend on the overdraft fee, which means that individual demands for the overdraft service is price-inelastic once they opened a deposit account.[8] Second, low-income consumers have lower travel costs than high-income consumers. Suppose that a type t consumer is located at x between bank j and bank $j + 1$. If the consumer purchases a deposit account from bank j, associated travel costs are $c_t(|x - x_j|)$ where $c_t'(\cdot) > 0$ and $c_t''(\cdot) > 0$. Then, $c_1'(z) < c_2'(z)$ and $c_1''(z) \leq c_2'(z)$ for all z.[9]

[8] The assumption is likely to be hold in reality for the following reason. Previous literature has revealed that some people utilize overdrafts with purpose and others do overdrafts by mistake. On the one hand, those who intentionally overdraw may have no choice but to use overdrafts because of urgent payment needs or credit constraints. On the other hand, those who mistakenly overdraw are not aware of their overdrafts. Therefore, both types of demands for overdrafts are likely to be inelastic to overdraft fees once they opened a deposit account. However, those who intentionally overdraw would still want to compare overdraft fees among banks when they choose a bank to open a deposit account. That is, banks compete with overdraft fees even if the demand for overdrafts are inelastic once they opened a deposit account.

[9] For example, if the travel cost function is linear in distance, $c_t(z) = k_t z$ where $k_1 < k_2$, then $c_1'(z) < c_2'(z)$ and $c_1''(z) \leq c_2'(z)$ for all z.

3.2.2 Equilibrium

I focus on a symmetric equilibrium in which all banks set the same fees and take the same market share. In a symmetric equilibrium, consumers between two banks choose one of them and there exists a cut-off point which divides one bank's customer and the other bank's customers. Let $x_t^*(j, j+1)$ be the cut-off point for type t consumers between bank j and bank $j+1$. Then,

$$(1) \quad v - p_j - \theta_t f_j - c_t(x_t^*(j,j+1) - x_j) = v - p_{j+1} - \theta_t f_{j+1} - c_t(x_{j+1} - x_t^*(j,j+1)).$$

From equation (1),

$$(2) \quad \frac{\partial x_t^*(j,j+1)}{\partial p_j} = \frac{-1}{c_t'(x_t^*(j,j+1) - x_j) + c_t'(x_{j+1} - x_t^*(j,j+1))} = -\frac{\partial x_t^*(j,j+1)}{\partial p_{j+1}}$$

and

$$(3) \quad \frac{\partial x_t^*(j,j+1)}{\partial f_j} = \frac{-\theta_t}{c_t'(x_t^*(j,j+1) - x_j) + c_t'(x_{j+1} - x_t^*(j,j+1))} = -\frac{\partial x_t^*(j,j+1)}{\partial f_{j+1}}.$$

Since the mid-point between two banks makes the cut-off point in a symmetric equilibrium,

$$(4) \quad x_t^*(j,j+1) - x_j = x_{j+1} - x_t^*(j,j+1) = \frac{1}{2n}.$$

From equations (2), (3) and (4), in a symmetric equilibrium

$$(5) \quad \frac{\partial x_t^*(j,j+1)}{\partial p_j} = \frac{-1}{2c_t'(\frac{1}{2n})} = -\frac{\partial x_t^*(j,j+1)}{\partial p_{j+1}}.$$

and

$$(6) \quad \frac{\partial x_t^*(j,j+1)}{\partial f_j} = \frac{-\theta_t}{2c_t'(\frac{1}{2n})} = -\frac{\partial x_t^*(j,j+1)}{\partial f_{j+1}}.$$

These two equations show how much the cut-off point changes when banks marginally change each fee in a symmetric equilibrium.

Given the cut-off points, bank j's market share for type 1 consumers is

$$(7)\quad n(j,1) = \lambda(x_1^*(j,j+1) - x_1^*(j-1,j))$$

and bank j's market share for type 2 consumers is

$$(8)\quad n(j,2) = (1-\lambda)(x_2^*(j,j+1) - x_2^*(j-1,j)).$$

In a symmetric equilibrium

$$(9)\quad n(j,1) = \frac{\lambda}{n}$$

and

$$(10)\quad n(j,2) = \frac{1-\lambda}{n}.$$

From equations (5), (7) and (8), in a symmetric equilibrium

$$(11)\quad \frac{n(j,1)}{\partial p_j} = \frac{-\lambda}{c_1'(\frac{1}{2n})}$$

and

$$(12)\quad \frac{n(j,2)}{\partial p_j} = \frac{-(1-\lambda)}{c_2'(\frac{1}{2n})}.$$

These two equations show how much bank j's market share for each type of consumers changes when the maintenance fee marginally increases in a symmetric equilibrium. From equations (6), (7) and (8), in a symmetric equilibrium

$$(13)\quad \frac{n(j,1)}{\partial f_j} = \frac{-\lambda\theta_1}{c_1'(\frac{1}{2n})}$$

and

$$(14)\quad \frac{n(j,2)}{\partial f_j} = \frac{-(1-\lambda)\theta_2}{c_2'(\frac{1}{2n})}.$$

These two equations show how much bank j's market share for each type of consumers changes when the overdraft fee marginally increases in a symmetric equilibrium.

Let γ be deposit account service costs and δ be overdraft service costs. Then, bank j's profit function is

$$\pi_j = n(j,1)(p_j - \gamma + \theta_1(f_j - \delta)) + n(j,2)(p_j - \gamma + \theta_2(f_j - \delta)). \tag{15}$$

The first order condition of profit optimization with respect to the maintenance fee is

$$n(j,1) + n(j,2) + \frac{\partial n(j,1)}{\partial p_j}(p_j - \gamma + \theta_1(f_j - \delta)) + \frac{\partial n(j,2)}{\partial p_j}(p_j - \gamma + \theta_2(f_j - \delta)) = 0. \tag{16}$$

From equations (9)-(12) and (16), in a symmetric equilibrium

$$\frac{\lambda}{n} + \frac{1-\lambda}{n} = \frac{\lambda}{c_1'(\frac{1}{2n})}(p_j - \gamma + \theta_1(f_j - \delta)) + \frac{(1-\lambda)}{c_2'(\frac{1}{2n})}(p_j - \gamma + \theta_2(f_j - \delta)) = 0. \tag{17}$$

The first order condition of profit optimization with respect to the overdraft fee is

$$\theta_1 n(j,1) + \theta_2 n(j,2) + \frac{\partial n(j,1)}{\partial f_j}(p_j - \gamma + \theta_1(f_j - \delta)) + \frac{\partial n(j,2)}{\partial f_j}(p_j - \gamma + \theta_2(f_j - \delta)) = 0. \tag{18}$$

From equations (9)-(10), (13)-(14) and (18), in a symmetric equilibrium

$$\frac{\lambda\theta_1}{n} + \frac{(1-\lambda)\theta_2}{n} = \frac{\lambda\theta_1}{c_1'(\frac{1}{2n})}(p_j - \gamma + \theta_1(f_j - \delta)) + \frac{(1-\lambda)\theta_2}{c_2'(\frac{1}{2n})}(p_j - \gamma + \theta_2(f_j - \delta)) = 0. \tag{19}$$

From equations (17) and (19), in a symmetric equilibrium

$$p_j - \gamma + \theta_1(f_j - \delta) = \frac{c_1'(\frac{1}{2n})}{n} \tag{20}$$

and

$$p_j - \gamma + \theta_2(f_j - \delta) = \frac{c_2'(\frac{1}{2n})}{n}. \tag{21}$$

Therefore, the equilibrium maintenance fee is

$$p_j^* = \gamma + \frac{\theta_1 c_2'(\frac{1}{2n}) - \theta_2 c_1'(\frac{1}{2n})}{n(\theta_1 - \theta_2)}$$

and the equilibrium overdraft fee is

$$f_j^* = \delta - \frac{c_2'(\frac{1}{2n}) - c_1'(\frac{1}{2n})}{n(\theta_1 - \theta_2)}.$$

Since type 1 (low-income) consumers are more sensitive to changes in fees and are more likely to overdraw than type 2 (high-income) consumers (i.e., $c_2'(\frac{1}{2n}) > c_1'(\frac{1}{2n})$ and $\theta_1 > \theta_2$), the overdraft fee is lower than the overdraft service costs in the equilibrium while the maintenance fee is higher than the deposit account service costs. This means that banks subsidize the overdraft fee to attract more low-income consumers.

Interestingly, the equilibrium fees are not affected by the composition of consumer types in this model. This is because banks use two deposit fees as an implicit price-discrimination mechanism to screen two types of consumers as if they observe the consumer type and subsequently charge a type-specific deposit fee. This analogue indeed provides an alternative way to obtain the equilibrium maintenance and overdraft fee, as will be elaborated in Appendix.

The equilibrium profit is

$$\pi_j^* = \frac{1}{n^2} \cdot \left[\lambda \cdot c_1'(\frac{1}{2n}) + (1-\lambda) \cdot c_2'(\frac{1}{2n})\right].$$

This means that profits are originated from travel costs of both types of consumers in the equilibrium. Banks' service costs and the likelihood of consumers doing an overdraft are not a determinant of the equilibrium profits.

It would also be informative to derive per-account maintenance and overdraft fee revenue and per-account deposit account service costs and overdraft service costs. Per-account maintenance fee revenue is the same to the equilibrium maintenance fee since every account holder pays the maintenance fee.

$$R_p^*(j) = \gamma + \frac{\theta_1 c_2'(\frac{1}{2n}) - \theta_2 c_1'(\frac{1}{2n})}{n(\theta_1 - \theta_2)}$$

By contrast, only a part of account holders ends up with overdrafts and as a result per-account overdraft fee revenue is

$$R_f^*(j) = (\lambda\theta_1 + (1-\lambda)\theta_2) \cdot \left[\delta - \frac{c_2'(\frac{1}{2n}) - c_1'(\frac{1}{2n})}{n(\theta_1 - \theta_2)}\right],$$

which is proportional to the expected number of overdrafts. Similarly, deposit account service costs per account is

$$C_p^*(j) = \gamma$$

and per-account overdraft service costs are

$$C_f^*(j) = (\lambda\theta_1 + (1-\lambda)\theta_2) \cdot \delta.$$

3.2.3 Comparative Statics:

This part examines how competition and the fraction of low-income consumers, respectively, affect equilibrium fees, per-account fee revenue, per-account service costs, and equilibrium profits.

Number of Banks (n)

As the number of banks increases, the equilibrium overdraft fee rises while the equilibrium maintenance fee falls. In this model, banks subsidize the overdraft fee to attract price-sensitive (low-income) consumers but this subsidization diminishes as competition becomes intense.

$$\frac{\partial p_j^*}{\partial n} = -\frac{1}{(\theta_1-\theta_2)n^2} \cdot \left[\frac{\theta_1 c_2''(\frac{1}{2n}) - \theta_2 c_1''(\frac{1}{2n})}{2n} + \theta_1 c_2'(\frac{1}{2n}) - \theta_2 c_1'(\frac{1}{2n})\right] < 0$$

$$\frac{\partial f_j^*}{\partial n} = \frac{1}{(\theta_1-\theta_2)n^2} \cdot \left[\frac{c_2''(\frac{1}{2n}) - c_1''(\frac{1}{2n})}{2n} + c_2'(\frac{1}{2n}) - c_1'(\frac{1}{2n})\right] > 0$$

Consequently, per-account overdraft fee revenue grows as the number of banks increases.

$$\frac{\partial R_f^*(j)}{\partial n} = \frac{\lambda\theta_1 + (1-\lambda)\theta_2}{(\theta_1-\theta_2)n^2} \cdot \left[\frac{c_2''(\frac{1}{2n}) - c_1''(\frac{1}{2n})}{2n} + c_2'(\frac{1}{2n}) - c_1'(\frac{1}{2n}) \right] > 0$$

However, increased competition lowers equilibrium profits, since it reduces per-account maintenance fee revenue as well as the market share of each bank.

$$\frac{\partial \pi_j^*}{\partial n} = -\frac{1}{2n^4} \cdot \left[\lambda c_1''(\frac{1}{2n}) + (1-\lambda)c_2''(\frac{1}{2n}) + 4n\left[\lambda c_1'(\frac{1}{2n}) + (1-\lambda)c_1'(\frac{1}{2n})\right] \right] < 0$$

Composition of Consumers (λ)

The fraction of low-income consumers does not affect equilibrium fees and as a result increase per-account overdraft fee revenue.

$$\frac{\partial R_f^*(j)}{\partial \lambda} = (\theta_1 - \theta_2) \cdot \left[\delta - \frac{c_2'(\frac{1}{2n}) - c_1'(\frac{1}{2n})}{n(\theta_1-\theta_2)} \right] > 0$$

However, per-account overdraft service costs grow more than per-account overdraft fee revenue.

$$\frac{\partial C_f^*(j)}{\partial \lambda} = (\theta_1 - \theta_2)\delta > 0$$

Therefore, the equilibrium profits fall as the fraction of low-income consumers increases.

$$\frac{\partial \pi_j^*}{\partial \lambda} = -\frac{1}{n^2} \cdot \left[c_2'(\frac{1}{2n}) - c_1'(\frac{1}{2n}) \right] < 0$$

3.3 Extension with Type-Specific Service Costs

This section provides an extended model considering that different types of consumers incur different service costs. Deposit account service costs and overdraft service costs can vary by the type of consumers. Let γ_t be deposit account service costs for type t consumers. It is natural to assume $\gamma_1 > \gamma_2$ since high-income consumers may deposit more to or borrow more from the bank than low-income consumers. That is, cross-selling of bank products may lower deposit account service costs for high-income consumers relative to that for low-income consumers. Next, let δ_t be overdraft service costs for type t consumers. I assume $\delta_1 > \delta_2$ because low-income consumers are more likely to fail to repay overdraft credits than high-income consumers. In other words, potentially high default rates on overdraft credits for low-income consumers may raise overdraft service costs for low-income consumers compared to that for high-income consumers.

Given different service costs by consumer types, bank j's profit function is changed to

$$n(j,1)(p_j - \gamma_1 + \theta_1(f_j - \delta_1)) + n(j,2)(p_j - \gamma_2 + \theta_2(f_j - \delta_2)).$$

As a result, the equilibrium maintenance fee is

$$p_j^* = \gamma_2 + \frac{\theta_1 c_2'(\frac{1}{2n}) - \theta_2 c_1'(\frac{1}{2n})}{n(\theta_1 - \theta_2)} - \frac{\theta_2(\gamma_1 - \gamma_2)}{\theta_1 - \theta_2} - \frac{\theta_1\theta_2(\delta_1 - \delta_2)}{\theta_1 - \theta_2}$$

and the equilibrium overdraft fee is

$$f_j^* = \delta_1 - \frac{c_2'(\frac{1}{2n}) - c_1'(\frac{1}{2n})}{n(\theta_1 - \theta_2)} + \frac{\gamma_1 - \gamma_2}{\theta_1 - \theta_2} + \frac{\theta_2(\delta_1 - \delta_2)}{\theta_1 - \theta_2}.$$

The expression for the equilibrium maintenance fee above has four components: deposit account service costs of high-income consumers (γ_2), an increment due to the difference in marginal travel costs ($\frac{\theta_1 c_2'(\frac{1}{2n}) - \theta_2 c_1'(\frac{1}{2n})}{n(\theta_1 - \theta_2)}$), a reduction caused by the difference in deposit account service costs ($\frac{\theta_2(\gamma_1 - \gamma_2)}{\theta_1 - \theta_2}$), and an additional reduction resulting from the difference in overdraft service costs ($\frac{\theta_1\theta_2(\delta_1 - \delta_2)}{\theta_1 - \theta_2}$). That is, deposit account service costs for high-income consumers, which is lower than that for low-income consumers, is the base of the equilibrium maintenance fee. Moreover, the difference in deposit account service costs and that in overdraft service costs reinforce each other to bring down the equilibrium maintenance fee.

The equilibrium overdraft fee is also represented by four elements: overdraft service costs of low-income consumers (δ_1), a reduction due to the difference in marginal travel costs ($\frac{c_2'(\frac{1}{2n}) - c_1'(\frac{1}{2n})}{n(\theta_1 - \theta_2)}$), an increment caused by the difference in deposit account service costs ($\frac{\gamma_1 - \gamma_2}{\theta_1 - \theta_2}$), and a further increment resulting from the difference in overdraft service costs ($\frac{\theta_2(\delta_1 - \delta_2)}{\theta_1 - \theta_2}$). This means that overdraft service costs for low-income consumers, which is higher than that for high-income consumers, provide a basis for the equilibrium overdraft fee. Furthermore, the difference in deposit account service costs and that in overdraft service costs combine to push up the equilibrium overdraft fee.

In sum, the difference in service costs by consumer types reduces the equilibrium maintenance fee and raises the equilibrium overdraft fee, regardless of whether it is about deposit account service costs or overdraft service costs. Therefore, cross-selling to high-income consumers and defaults on overdraft credits of low-income consumers explain at least to some extent why some consumers complain about such a high overdraft fee and at the same time many consumers use checking accounts without paying maintenance fees, conditional on minimum balance or other requirements.

Key predictions from comparative statics are robust to the difference in service costs. Most importantly, it does not depend on the difference in service costs how the number of banks (n) affects the equilibrium fees, per-account revenues, and profits. Also, the difference in service costs does not affect how the composition of consumer types (λ) on per-account overdraft fee revenue and equilibrium profits.

3.4 Conclusion

This study provides a spatial competition model in which competing banks provide a deposit account service and an overdraft service to high- and low-income consumers. Under the assumption that low-income consumers are more sensitive to deposit fees and use overdrafts more than high-income consumers, the spatial model predicts that bank competition raises the overdraft fee in the symmetric equilibrium. This study has several implications for the current U.S. deposit market with the prevalence of overdraft fees. First, bank competition may be a factor having contributed to the high overdraft fee in the U.S. Moreover, given that consumers' income is negatively correlated the overdraft frequency, bank competition may reallocate resources from low-income consumers to high-income consumers in the deposit market.

3.5 Appendix. Alternative Solution Method

In the appendix, I show an alternative way to obtain the equilibrium two-part tariff in the original model developed in section 3.2 via a "modified model" of an explicit price-discrimination. The "modified model" considers an environment in which banks observe the consumer type and charge a type-specific deposit fee. In this case, banks optimize for profits from each type of consumer separately. Let $q(j,t)$ and $\eta(j,t)$ be bank j's price and service costs, respectively, for type t consumers. Also, let λ_t be the fraction of type t consumers. For simplicity, I assume a linear travel cost function in this "modified model": $c_t(z) = c_t z$ where $c_1 < c_2$ (with a slight abuse of notation c_t). Then, bank j's profit function from type t consumers is

$$\pi(j,t) = n(j,t)(q(j,t) - \eta(j,t)).$$

For each t, the first order conditions of optimization is

$$n(j,t) + \frac{\partial n(j,t)}{\partial q(j,t)}(q(j,t) - \eta(j,t)) = 0.$$

In a symmetric equilibrium, for each t

$$n(j,t) = \frac{\lambda_t}{n}$$

and

$$\frac{\partial n(j,t)}{\partial q(j,t)} = -\frac{\lambda_t}{c_t}.$$

Hence, the equilibrium type-specific fee is

$$q^*(j,t) = \eta(j,t) + \frac{c_t}{n}$$

and the equilibrium profit is

$$\pi_j^* = \pi(j,1) + \pi(j,2) = \frac{1}{n^2}\left[\lambda c_1 + (1-\lambda)c_2\right].$$

The equilibrium profit from this “modified model” of an explicit price-discrimination is the same to that from the original model of an implicit price-discrimination with the linear travel cost function. In other words, banks implicitly price-discriminate between high- and low-income consumers using the overdraft fee in the original model as if they observe the consumer type and charge a type-specific deposit fee. The equilibrium two-part tariff in the original model corresponding to the equilibrium type-specific fee in the “modified model” can be found from the following condition: for each t

$$p_j^* + \theta_t f_j^* = q^*(j, t)$$

where

$$q^*(j, t) = \eta(j, t) + \frac{c_t}{n} \qquad \text{and} \qquad \eta(j, t) = \gamma + \theta_t \delta.$$

And so the equilibrium maintenance fee is

$$p_j^* = \gamma + \frac{\theta_1 c_2 - \theta_2 c_1}{n(\theta_1 - \theta_2)}$$

and the equilibrium overdraft fee is

$$f_j^* = \delta - \frac{c_2 - c_1}{n(\theta_1 - \theta_2)}.$$

This two-part tariff is the same to the equilibrium two-part tariff derived from the original model as shown in section 3.2.

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