THE EFFECT OF MARIJUANA LEGALIZATION ON SMALL BANK COMPETITIVE ADVANTAGES

by

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DEDICATION

This thesis is dedicated to Leo and Cessna Refsland, for teaching me to live with humor and tenacity.

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GLOSSARY

DEA – Data Envelopment Analysis
DDEA – Directional Data Envelopment Analysis
DMU – Decision Making Unit
FDIC – Federal Deposit Insurance Corporation
FFIEC – Federal Financial Institutions Examination Counsel
FinCEN – Financial Crimes Enforcement Network
LP – Linear Programming
MSA – Metropolitan Statistical Area
OLS – Ordinary Least Squares

ABSTRACT

Federal regulation requires that banks have specialized and sophisticated tools to prevent, identify, and record money laundering. Cash generated in states where recreational marijuana is legalized qualifies as illicit at the federal level. As such, the increase of marijuana cash in the market represents an increase in money laundering risk, to which banks must respond according to regulatory expectations. Because of scale advantages and the relationship-based nature of their transactions, small community banks may face greater constraints in responding to this risk relative to medium-to-large banks. To test this, I observe 105 banks over 12 years during a time when recreational marijuana legalization occurred in four states. I estimate bank performance with a non-parametric linear programming approach of data envelopment analysis. With marijuana legalization and bank size regressed on these measures of performance, and controlling for bank and year fixed effects, I find that small community banks in marijuana states are, on average, further from the best practice frontier relative to medium-to-large banks.

INTRODUCTION

The stated purpose of banking regulation is to ensure the safe and sound operation of banks and savings associations, protection for consumers, and compliance with applicable laws. A significant proportion of these laws pertain to the Bank Secrecy Act and anti-money laundering regulation, which assign responsibility to banks for preventing, identifying, recording, and reporting money laundering. However, recreational marijuana legalization results in cash that is simultaneously considered legal by state-level governments and illicit by the federal government, leaving banks at risk of violating the federal anti-money laundering laws. The ambiguity in regulatory response to potential marijuana banking requires banks to navigate a complex framework of regulation amidst the risk of civil money penalties for non-compliance. These penalties can be significant; the United States Government Accountability Office reports that, between 2009 and 2016, federal agencies assessed about $5.2 billion in fines for Bank Secrecy Act and anti-money laundering violations. Furthermore, compliance with anti-money laundering regulation requires certain investments in technology and human capital that small community banks may be more constrained in implementing.

While existing research indicates an overall ambiguous relationship between firm size and firm response to regulation, this relationship in the banking industry has not been significantly revisited since the Great Recession and subsequent extensive changes to the financial regulatory environment. The number of Federal Deposit Insurance Corporation (FDIC) insured community banks has declined consistently for the past three decades, with most mergers and failures occurring in banks with total asset size less than $250 million. New charters for banks have declined sharply since 2010, the year that the massive Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) was signed into law. From 2012 to 2016, the FDIC reported that there were only five new charters (see figure 1). According to the FDIC Historical Trends Report, the largest banks continue to grow in asset size while small community banks exit the market completely. The Dodd-Frank Act significantly increased regulation for all nationally regulated banks, and these changes in regulatory structure may affect the relationship between firm size, competitive advantages, and regulation.

While community banks navigate the dynamic environment of post-recovery regulation, state-level marijuana legalization continues to expand. Since 2012, nine states and Washington D.C. have voted to legalize recreational marijuana to some extent, including Colorado, Washington, Oregon, Alaska, California, Maine, Massachusetts, Nevada and Vermont. Nationwide usage rates continue to increase, and states like Arkansas, Florida, Montana, and North Dakota voted to approve or expand medical marijuana in 2016. National consumption has increased steadily year over year, with consumer spending on legal cannabis products in 2016 up 34 percent from 2015 (Chang 2017). Until there is a decisive response from the federal government, banks and regulators will be required to continue to address Bank Secrecy Act/anti-money laundering regulation issues related to the burgeoning marijuana industry.

In this research I attempt to address the relationship between recreational marijuana legalization, bank size, and regulation. With detailed financial data from 105 banks from 2005 through 2016, I observe banks of every size category before and after recreational marijuana legalization in four states: Colorado and Washington, legalizing in 2012, and Alaska and Oregon, legalizing in 2014. In this first attempt to quantify the effect of marijuana legalization on bank performance, and one of only a handful of attempts to identify the differential effects of anti-money laundering regulation on banks of different sizes, I attempt to identify whether small community banks experience a decrease in performance relative to medium-to-large banks post-legalization. I estimate performance with the non-parametric linear programming approach of data envelopment analysis (DEA). In a regression of marijuana legalization and bank size on DEA scores, and controlling for bank and year fixed effects as well as time-varying bank characteristics, the estimation suggests that small community banks move significantly further from the best practice frontier relative to medium-to-large sized banks post-legalization.

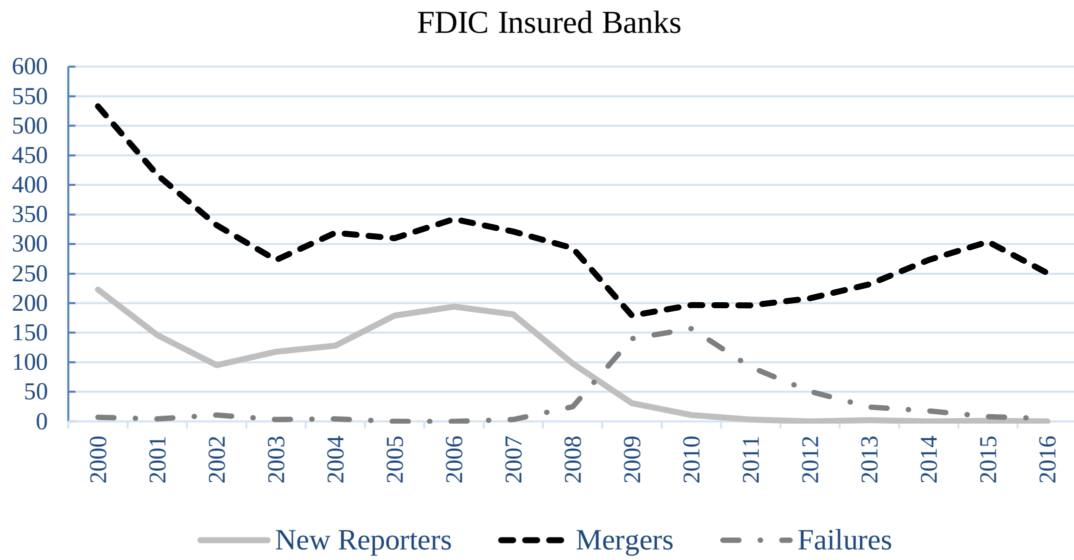

Figure 1: Bank Charters over Time. FDIC insured bank charters initiated ("New Reporters"), absorbed by another bank ("Mergers"), or failed ("Failures") from 2000-2016. Data obtained from the FDIC Historical Trends Report as of June 30, 2017

BACKGROUND

Regulatory Framework

Bank regulation in the United States emphasizes prudence; that is, safe and sound business practices that contribute to financial stability and the protection of borrowers and investors (Murphy 2015). Various state- and federal-level agencies oversee banks and savings associations, with different regulatory agencies often responsible for different products or elements of the same bank. Murphy discusses this at the federal level:

> [T]here are federal regulatory overlaps in which one agency can oversee a firm because of the firm's charter, a second agency regulates some of the activities that the firm is engaging in, but a third agency controls a government initiative to resolve or alleviate a problem related to the firm or its activities.

Four federal agencies are relevant in the context of this paper: Office of the Comptroller of the Currency, Federal Deposit Insurance Corporation, Federal Reserve Board, and Consumer Financial Protection Bureau. These agencies focus on monitoring and regulating risk (at both a system and bank-specific level) as well as the information exchange between consumers and the banks. The Federal Financial Institutions Examinations Council provides a coordinating forum that facilitates communication among member agencies (Murphy 2015). The Comptroller of the Currency, Federal Deposit Insurance Corporation, and the Federal Reserve Board each examine banks and savings associations based on their charter type, product mix, and asset size. [1]

[1] For the purposes of this research, savings associations are treated as equivalent to banks.

Bank regulation addresses economic policy problems—particularly the competing interests of bank managers and depositors—but it also addresses issues of crime. In 1970, the Currency and Foreign Transactions Reporting Act (known as the Bank Secrecy Act) established bank responsibility for record keeping regarding the "source, volume, and movement of currency and other monetary instruments transported or transmitted into or out of the United States or deposited in financial institutions" (FFIEC 2014). [2] The Money Laundering Control Act of 1986 added terms that impose "criminal liability on a person or *financial institution* that knowingly assists in the laundering of money, or that structures transactions to avoid reporting them" (FFIEC 2014) to existing Federal Deposit Insurance Act and the Federal Credit Union Act requirements. The 1986 Act also required banks to establish reporting and recordkeeping procedures, such that, as of January 27, 1987, all federally regulated banking agencies came under Bank Secrecy Act/anti-money laundering regulation. Various acts between 1992 and 2001 strengthened and developed the Bank Secrecy Act/anti-money laundering framework, resulting in a significant set of regulatory requirements applied to all banks related to the prevention of money laundering and terrorist financing. [3,4]

The most significant of these was the USA PATRIOT Act of 2001, which, according to the Federal Financial Institutions Examinations Council,

> …strengthen[ed] customer identification procedures; prohibit[ed] financial institutions from engaging in business with foreign shell banks; require[ed]

[2] 31 USC 5311 *et seq.*, 12 USC 1829b, and 1951-1959, 12 USC 1818 and 12 USC 1786(q).
[3] The Annuzio-Wylie Anti-Money Laundering Act (1992) further developed the role of the U.S. Treasury and added sanctions for violations; the Money Laundering Suppression Act (1994) elaborated on the Treasury's role in money laundering issues; The Uniting and Strengthening America by Providing Appropriate Tools Required to Intercept and Obstruct Terrorism Act (US PATRIOT Act 2001)
[4] As defined by the BSA, "bank" refers to agents, agencies, branches, and offices of U.S. commercial banks, savings and loan associations, thrift institutions, and credit unions.

> financial institutions to have due diligence procedures…and…enhanced due diligence procedures for foreign correspondent and private banking accounts; and improving information sharing between financial institutions and the U.S. government.[5]

Some researchers, including Hetzer (2003), criticize the extent to which financial markets have been subjected to additional regulatory intensity in the form of the USA PATRIOT Act. He notes that the responsibility placed on domestic institutions for indirect regulation of international terrorist financing includes significant penalties for noncompliance (Preston 2003).

Banks can incur criminal and civil liability for violating Bank Secrecy Act/anti-money laundering laws, but the laws also require investment in certain mandatory components.[6] From the FFIEC Examination Manual (updated in 2014), banks must have a written Bank Secrecy Act/anti-money laundering compliance program that includes the following components:

a. A system of internal controls to ensure ongoing compliance
b. Independent testing of Bank Secrecy Act compliance
c. A specifically designated person or persons responsible for managing Bank Secrecy Act compliance (BSA compliance officer)
d. Training for appropriate personnel

[5] The USA PATRIOT Act also increased civil money penalties and criminal penalties for money laundering, empowered the Secretary of the Treasury to impose special measures on banks that are of primary money-laundering concern, added the requirement for banks to respond to regulatory requests for BSA/Anti-money laundering related information within 120 hours, and required federal banking agencies to review anti-money laundering concerns for a bank under consideration for mergers or acquisitions.
[6] A bank violating 31 USC 5318(i) or (j) faces civil money penalties up to the maximum of $1 million or twice the transaction value.

These components comprise the "four pillars" of Bank Secrecy Act/anti-money laundering compliance, and while the specifics of each component depend on the risk profile of the bank, all are universally required in some form for every bank. The Bank Secrecy Act compliance officer has a specialized role tasked with maintaining oversight of the Bank Secrecy Act/anti-money laundering program. As Baldwin (2003) notes, tracing terrorist funds (and other forms of illicit money) is "an increasingly difficult task requiring intense and complex management." Bank Secrecy Act/anti-money laundering programs aim to provide tools to banks to distinguish between legitimate and illegitimate money, but some bank customers (especially businesses) unintentionally obtain funds from illegitimate sources (Baldwin 2003). The source of difficulty in distinguishing between legitimate and illegitimate money is the structure of money laundering: a multi-stage process that creates a bridge between the informal/illegal and formal/legal economy and includes placement, layering, and integration of funds (Hinterseer 1997). [7]

As noted in the Office of the Comptroller of the Currency's Bank Secrecy Act/anti-money laundering information page (U.S. Department of the Treasury 2015), Bank Secrecy Act/anti-money laundering compliance programs must also include customer identification programs in a written form. The customer identification program must include identity verification measures, and customer information such as address and date of birth. Other aspects of Bank Secrecy Act/anti-money laundering require Suspicious Activity Reports, which are considered a cornerstone of the BSA reporting

[7] Per Hinterseer (1997), the steps of money laundering are: placement: the infusion of criminally tainted money into private banks; layering: concealment of origins of ownership to clean the funds of illegality; and integration: "cleaned" money assimilated back into the legitimate financial system.

system and are filed through the Financial Crimes Enforcement Network following any activity that might indicate the presence of money laundering or fraud. Some aspects of the compliance program require banks to collect more detailed information regarding their customers, including occupation and sources of funds.[8] Complying with Bank Secrecy Act/anti-money laundering therefore requires significant investment in human capital, technology, and procedures. In addition, this investment must be commensurate with the present level of money-laundering risk. As such, banks in markets with higher levels of risk require more detailed or robust human capital, technology, and procedures to maintain compliance than banks in less risky markets. Considering the current regulatory environment surrounding recreational marijuana, state level legalization represents an increase in risk in those markets.

Marijuana and the Law

Recreational marijuana production, consumption, and sale has been legalized in ten states as of October 2017 but remains illegal at the federal level. As a result, funds generated from recreational marijuana sales that are legal at the state level are considered federally illicit funds and are prohibited under anti-money laundering regulation. This section defines marijuana and legalization, provides a national legalization history, and discusses the current regulatory environment surrounding marijuana banking.

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[8] This becomes relevant in discussing the differences between small and large bank products, see Literature Review: Sources of Small and Large Bank Competitive Advantages.

Marijuana Legalization

"Marijuana" refers to the plant *Cannabis sativa* along with the plant's leaves and flowers, which contain psychoactive chemicals (Caulkins, Kilmer, and Kleiman, 2016). Caulkins, Kilmer, and Kleiman (2016) note that between 125 million and 225 million people used the drug worldwide in 2015, despite laws prohibiting marijuana use in most countries, and estimate that this creates illicit markets "in the ballpark of $40 billion per year in the United States alone." Twenty million Americans self-report as current users, as in having consumed marijuana within the past month, although this is likely an underestimate (Caulkins, Kilmer, and Kleiman, 2016).

Widespread marijuana use in the United States began in the early 1900s, but was criminalized in twenty-nine states by 1931 and federally prohibited by the Boggs Act of 1952 (Caulkins, Kilmer, and Kleiman, 2016). The 1970s saw liberalization in the form of state-level decriminalization, which reduced marijuana-related penalties from criminal to civil. However, social and political pressure ended the trend of liberalization by 1979, and federal recreational marijuana laws have remained unchanged.

Marijuana legalization implies that production, distribution, sale, possession, and use of marijuana is legal for adults (Caulkins, Kilmer, and Kleiman, 2016). In 2012, Colorado and Washington became the first states to officially legalize commercial for-profit marijuana production, with the first retail sales occurring in 2014 for both states (Ingold, 2014, and Johnson, 2014). Alaska and Oregon followed in 2014 with sales beginning in 2016. While Washington, D.C., technically legalized in 2014, the additional restrictions were so great that the effect was more similar to decriminalization than legalization (Laslo 2017). California, Maine, Massachusetts, and Nevada followed suit in 2016 but recreational sales have not yet begun or began in 2018. Finally, Vermont voted to legalize in 2017. All legal recreational marijuana states had previously maintained long-standing medical marijuana programs. Now, the four states with functioning marijuana sales through 2016 (Colorado, Washington, Alaska, and Oregon) are at odds with U.S. federal law, a conflict that "creates a host of complications particular to this substance, time, and country" as federal agents can still "arrest and…prosecute those who produce, distribute or even use…marijuana" (Caulkins, Kilmer, and Kleiman, 2016).

Marijuana sales in Colorado and Washington function similarly to alcohol sales, where "regulated, for-profit companies" produce and sell marijuana (Caulkins, Kilmer, and Kleiman, 2016). Both states received about $11 million per month in marijuana tax and licensing revenue in 2015, with the volume of marijuana consumed rising over time. As more states legalize, prices (and revenues) are expected to fall in each state, with Washington particularly vulnerable to competition with Oregon-based marijuana companies. Black market sales have not disappeared completely, and there is evidence that illegal exportation from marijuana legalization states to non-legalization states occurs (Caulkins, Kilmer, and Kleiman, 2016).

Marijuana Banking

In 2009, the Justice Department's Ogden Memorandum effectively removed the threat of federal criminal prosecution. (Caulkins, Kilmer, and Kleiman, 2016). However, the conflict created by differing state and federal law is apparent in the enforcement of

Bank Secrecy Act/anti-money laundering regulation. Calukins, Kilmer, and Kleiman (2016) explain:

> [M]any marijuana businesses find it difficult to access banking services: not just loans but even checking accounts and credit-card processing. The problem seems to be more acute for retail stores than producers and processors, and it is not just the entrepreneurs who suffer. Large piles of cash tempt robbers, and the lack of banking records makes it harder for legitimate merchants to operate...

Most regulations that govern banks have been established at the federal level, including Bank Secrecy Act/anti-money laundering laws. In guidance titled "BSA Expectations Regarding Marijuana-Related Businesses," the Financial Crimes Enforcement Network ("FinCEN") sought to "enhance the availability of financial services for, and the financial transparency of, marijuana-related businesses" (FinCEN 2014). FinCEN's Marijuana Banking Update as of March 31, 2017, indicates that 368 depository institutions are actively providing banking services for marijuana businesses. In determining whether to conduct business with any particular account, banks look at multiple factors including an "evaluation of the risks associated with offering a particular product or service, and its [the bank's] capacity to manage those risks effectively" (FinCEN 2014). Risks include providing services to marijuana businesses that engage with other criminal activities along with the risk of federal civil or criminal repercussions. For marijuana businesses, FinCEN states that customer due diligence should include:

i. Verifying with the appropriate authorities whether the business is duly licensed and registered.

ii. Reviewing the license application (and related documentation) submitted by the business for obtaining a state license to operate its marijuana-related business.

iii. Requesting from state licensing and enforcement authorities available information about the business and related parties.

iv. Developing an understanding of the normal and expected activity for the business, including types of products to be sold and the type of customers to be served.

v. Ongoing monitoring of publicly available sources for adverse information about the business and related parties.

vi. Ongoing monitoring for suspicious activity, including for any of the red flags described in [FinCEN 2014] guidance.[9]

vii. Refreshing information obtained as part of customer due diligence on a periodic basis and commensurate with the present level of risk.

Per FinCEN, banks should also determine whether the marijuana business implicates any Cole Memorandum priorities.[10] These determinations must be performed

[9] Red flags include: business receives substantially more revenue than reasonably expected or than local competitors; business is depositing more cash than commensurate with revenue reported; business is unable to demonstrate revenue is derived solely from marijuana; rapid movement of funds; deposits by disconnected third parties; comingling of personal and business accounts; inconsistent financial statements; surge in third party activity; unsatisfactory documentation; unsubstantiated significant outside investments; a customer seeks to conceal involvement in marijuana activity; criminal record of related parties; and interstate activity (FinCEN 2014).

[10] The Cole Memorandum ("Cole Memo") was written in 2014 by Department of Justice Deputy Attorney General James M. Cole to all U.S.Attorneys under the Controlled Substances Act. The memo listed priorities for law enforcement to address, including the prevention of: distribution of marijuana to minors; revenue from the sale of marijuana from flowing to criminal enterprises; the diversion of marijuana from state-legal geographies to other states; state-authorized marijuana activity covering the trafficking of other illegal drugs; the use of violence in the cultivation and distribution of marijuana; drugged driving; marijuana on public lands; and marijuana possession or use on federal property (FinCEN 2014).

at the bank's expense under Bank Secrecy Act/anti-money laundering regulation, and analysis of some factors is required for banks to determine whether to do business with a customer at all. While some banks do actively provide financial services for marijuana businesses, FinCEN also received reports of 7,326 terminated accounts related directly to marijuana banking nationwide from January 2014 to March 2017 and 2,007 reports indicating an active investigation into accounts to determine the level of risk, which may end in the termination of those relationships (FinCEN 2017). Despite FinCEN's guidance, regulatory firms reportedly discourage banks from maintaining relationships with marijuana businesses (Caulkins, Kilmer, and Kleiman, 2016).

LITERATURE REVIEW

Regulation and Bank Performance

While regulation is typically targeted at economic or legal goals, regulation can produce competitive advantages, wealth redistributions, and other consequences beyond the scope of the regulation. Regulation has been found to result in asymmetrical distributions of regulatory effect among different types of firms, wherein “significant enough” competitive advantages can offset costs of regulation for the larger firms within a market (Bartel 1987). The burden of regulation can also affect firm size, with smaller firms closing in response to increased regulation (Neumann 1982). In finance, regulatory changes driven by technological, legal, and economic shocks affect competition differently for different firms, although deregulation is associated with some increases in estimated bank performance (Rose 2014).

Firm size is related to the distribution of regulatory burden across a given market, which can vary based on firm capacity to respond to regulation. As Beck (2005) finds, small firms are the most constrained. DeYoung (2001) argues that, although the number of small banks will continue to decline, well-run small banks that adjust their strategy may continue to be profitable. [11] DeYoung also emphasizes the difference in competitive strategies between large and small banks, where small banks rely on relationship-based lending and large banks utilize automation to decrease the number of inputs used to produce a given level of output.

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[11] “Small banks” and “community banks” are used interchangeably in this paper and refer to banks and savings associations with asset sizes less than $1 billion.

The U.S. PATRIOT Act (2001) increased the cost of business for banks dramatically, regardless of size, through its heightened requirements for customer identification, due diligence, and enhanced due diligence procedures. Dolar (2007) finds that, owing to scale economies in regulatory Bank Secrecy Act/anti-money laundering compliance, the burden of compliance has fallen more heavily on smaller banks. In fact, Dolar (2012) finds that the U.S. PATRIOT Act produced an intra-industry redistribution of wealth from small banks to large banks.[12]

The study of wealth redistribution across firm size in response to regulation has not addressed Bank Secrecy Act/anti-money laundering regulation in the post-Recession era or after state level marijuana legalization. While the above papers have studied changes in small and large bank performance in response to regulatory changes, most of the literature examines periods of deregulation or regulatory periods prior to the Great Recession, which was a significant event in financial regulation. From 2006 through 2011, 417 banks and thrifts failed, and the number of community bank charters continued to decline (Gilbert 2013). In fact, recovery for community banks differs in the post Great Recession era from recoveries after the 1973-1975 and 1981-1982 recessions (Morris 2014). The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 significantly increased regulation for all nationally regulated banks, and these changes in regulatory structure may affect the relationship between firm size, competitive advantages, and regulation. Therefore, this study contributes research on post Great

[12] Dolar (2012) provides a useful framework and methodology for exploring differences between large and small banks in high-risk areas; however, no research has yet addressed marijuana legalization.

Recession and Dodd-Frank Act banking performance in the transformed regulatory environment.

While prior papers have found a differential effect of BSA/anti-money laundering legislation on small and large national banks, these papers have used variation in geographic money laundering risk designation (see Dolar 2007 and 2012) and the implementation of the USA PATRIOT Act to compare changes in key financial ratios. To my knowledge no studies have explicitly examined the effect of marijuana legalization on banks.

Sources of Small and Large Bank Competitive Advantages

The mechanisms behind small versus large bank competitive advantages have been explored, and indicate that differences in product mix, scale, and corporate governance structure lead to statistical differences in certain measures of performance. Akhigbe (2005) finds that small banks with competitive advantages are typically older, operate in low default markets, function without a holding company, generate high fee income, operate in a concentrated market, or have a significant proportion of assets in loans (as opposed to securities). Small banks located in metropolitan statistical areas (MSAs) are the least profit efficient, as small banks rely on relationship development factors as a source of competitive advantage over large banks that can offer better interest rates to consumers (Akhigbe 2003). DeYoung (2004) also provides the strategic context for differences in small and large bank performance, noting that large banks use *hard* information, such as specific borrower data in an automated underwriting context, low unit costs, and standardization while small banks use *soft* information, such as knowledge of the character of a borrower, relationship development, and non-standardized loans.

Disadvantages due to scale primarily affect the smallest and largest banks, per Benston (1982), who notes that banks at scale extremes could have an operating cost disadvantage. If small banks have different sources of competitive advantages than large banks, regulation is likely to have differential effects across bank sizes. Considering this, along with the declining number of small banks (Morris 2014), it is worth discussing the role of the small bank within a local economy.

From 1985 to 2010, the number of FDIC-insured banks decreased (in net) from 18,033 to 7,658, a decline of 10,375 banks (FDIC 2012). The majority of the net decline is explained by the mergers and failures of “small community banks” under $250 million in assets. These are a subset of banks referred to as “community banks,” which are defined as banks with total assets less than $1 billion.

Large banks tend to employ a more automated or “cookie-cutter” method of loan review, while small banks offer an important alternative approach utilizing superior customer knowledge (Cole 2004). DeYoung et al. (2004) outline the ways in which competitive advantages for community banks have changed over time. In the 1970s, small banks held advantages with specialized services for small businesses. However, with technology advancement allowing for internet banking, these advantages have diminished. Alternatives to traditional checking accounts such as credit cards have also reduced the role of community banking. Larger banks benefit from the commoditization of lending such as mortgages, student loans, and other consumer loans via their automation and use of hard information, pushing community banks out of credit card, mortgage, and auto lending. As DeYoung et al. state, “[T]he size of [large bank] operations allowed them to more efficiently apply the new production technologies” that have developed rapidly in the past two decades. These technologies include advancements in underwriting, electronic payments, and risk modeling, and result in lower unit costs and a high-volume strategy for large banks that is strategically distinct from small bank operations.

MOTIVATION

The "four pillars" of Bank Secrecy Act/anti-money laundering regulation represent significant costs to banks, and after marijuana legalization these pillars must be strengthened to mitigate the increased risk of money laundering as discussed in Financial Crimes Enforcement Network guidance titled "BSA Expectations Regarding Marijuana-Related Businesses." This strengthening may be accomplished through additional training for Bank Secrecy Act (BSA) officers, strengthening and revising internal control procedures, scheduling additional internal audit reviews, enhancing customer due diligence procedures, and so on. Some of these changes will involve expanding or adjusting existing elements of a bank's compliance program, representing a one-time fixed cost. However, adjustments such as enhanced customer due diligence and reviewing accounts for ties to marijuana businesses represent an increase in variable costs, as banks must monitor, identify, and record more information per customer and account per enhanced due diligence requirements. The extent to which a bank can adapt existing policies and technological aids in these processes affects how costly they are to implement; for small community banks, these changes might represent significant adjustments – and therefore significant costs – while large banks may respond with relatively less significant measures.

I examine the effect of marijuana legalization under BSA/anti-money laundering regulation in the short run. For simplicity, consider hours of labor as the input and number of loans as the output in a single input, single output model. Also, assume there are two size categories of banks: small and large. BSA/anti-money laundering regulation requires that the number of labor hours used to produce the same number of loans should increase after marijuana legalization. Assuming that large banks can use or adapt existing production technology that small banks cannot, they would experience an increase in labor hours required that is less than or equal to the hours used by small banks. Therefore, the fixed and variable cost increases associated with marijuana legalization for large banks is less than or equal to the fixed and variable cost increases for small banks.

To investigate the viability of the assumption that large banks have access to the strategic advantage of such technology in equilibrium, I use Barney's (1991) discussion in *Firm Resources and Sustained Competitive Advantage*. According to Barney, if a strategic resource is heterogeneously distributed (endogenously or exogenously) across firms and this difference is stable over time, the resource provides a sustained competitive advantage. The definition of a sustained competitive advantage is a value-creating strategy not simultaneously being implemented by competitors such that other firms are unable to duplicate the benefits of this strategy. For example, if a single firm has access to a geographically-based resource to which other firms cannot gain access. A resource in this case is defined as a strength a firm can use to conceive of and implement strategies. To be considered a resource that could result in sustained competitive advantage, the resource must be valuable, rare, imperfectly imitable, and non-substitutable. I propose that the information technology used by large banks to identify, monitor, and prevent money laundering satisfies all four of these requirements.

A valuable resource enables firms to exploit opportunities or neutralize threats in a firm's environment. As an article on Banking Exchange (Ingber and Kherlopian, 2017) notes regarding anti-money laundering technologies:

> Banks must use advanced digital solutions to comprehensively scour worldwide public and non-public sources to ensure data quality; quickly and effectively draw out, sift through, and analyze massive amounts of structured and unstructured information to reach meaningful conclusions; and make results available in a user-friendly manner.

Anti-money laundering technologies enable banks to neutralize the threat of money laundering in ways that use fewer labor hours and limit the likelihood of costly mistakes. Technologies such as cloud computing, machine learning, predictive modelling, and advanced graphical modelling provide the opportunity for large banks to employ a strategy in anti-money laundering regulatory compliance not utilized to the same extent by other types of banks (Balooni 2017).

Rarity requires that the resource be possessed by a number of firms less than the number of firms needed for perfect competition dynamics. Small banks are the most numerous asset class size in the United States, with banks with less than $1 billion in assets representing 87.5 percent of U.S. banking institutions and banks with less than $500 million representing 75.3 percent of total banks (Klingler and Hightower, 2017). Of 5,679 banks currently in the United States, there are 757 with at least $1 billion in assets and, of these, 124 have at least $10 billion in assets (US Bank Locations, 2017). Even if all large banks hold this technology, this represents a small proportion of U.S. banks.

A resource could be imperfectly imitable for one of (or a combination of) three reasons: first, the ability for a firm to obtain it depends on unique historical conditions;

second, the link between the resource and a firm's advantage is causally ambiguous; and, third, the resource is socially complex. Information technology does not qualify under the second reason but meets the requirements of the first and third in this context. Information technology, on its own, is typically imitable; most firms could theoretically imitate the technology itself. However, how the technology is implemented can require socially complex firm resources, including the appropriate culture to implement such a strategy. As DeYoung (2004) finds, small banks after the 1970s lacked the size and the culture of automation to implement technological advancement to the same degree as large banks. This historical and social context for large banks enables an exploitation of information technology that is not feasible for small banks to the same extent.

Finally, non-substitutability requires that there are no strategically equivalent substitutes for the resource. In other words, the firm cannot be able to use a different resource as a substitute without altering their strategy. While small banks could utilize a specialized team to produce the same effect as anti-money laundering technology, this team would be unlikely to use few enough labor hours to qualify their results as strategically equivalent. The time used to perform the same analysis that anti-money laundering technologies produce would be substantial, resulting in a significantly distinct strategy and, still, much higher labor costs. Human calculation and analysis is unlikely to have the same capability to interpret and share the extensive information technologies can accumulate, analyze, and record.

Considering the value, rarity, imperfect imitability, and non-substitutability of the type of information technology large banks use, this technology is differentially distributed across banks by size and unavailable to small banks. Therefore, we can consider a model of banking where the short run equilibrium has two types of banks: small banks, which operate at zero economic profits; and large banks, which operate with economic rents earned from their capability to use information technology. Prior to legalization, large banks are already utilizing these technologies for general anti-money laundering regulation compliance. The immobility and differential distribution of such a resource as this type of information technology prevents these profits from being competed away. Small banks do not have the economies of scale to adapt to this technology or strategically equivalent resources.

As shown in figure 2, Small banks produce a small number of total loans compared to large banks, thus operating at a lower equilibrium quantity, q_S. Medium-to-large banks produce at q_L. The sustained competitive advantage of information technology is represented with a lower average total cost at q_L for large banks, reflecting the lower unit costs identified by DeYoung (2004) as core to large bank operation. Large banks experience profits from the minimum of their average total cost curve lying below $p*$, market price. The amount of profit is equal to the area between $p*$ and p to q_L.

After marijuana legalization, shown in figure 3, small banks experience an upward shift in average fixed costs and average total costs to an extent greater than the large bank increase in costs. The cost to small banks to produce q_S is p', but because banks are price takers the market price remain $p*$. For graphical simplicity, I keep large bank cost curves unchanged after legalization. While the result of these cost shifts would likely result in community banks exiting the market completely due to negative profits in the long run, I do not address this in my empirics and will focus on only short run effects. After legalization, small banks still in the market will produce a similar output as before. Increased fixed costs result in a higher quantity produced, but increased variable costs result in a lower quantity produced. These offsetting effects result in small banks continuing to produce approximately the original amount, q_S. Now, however, they sell the same quantity of loans but use higher costs to produce them. Therefore, small banks use more of their input to produce the same quantity of output, resulting in an increased competitive advantage for large banks that cannot be competed away in the short run.

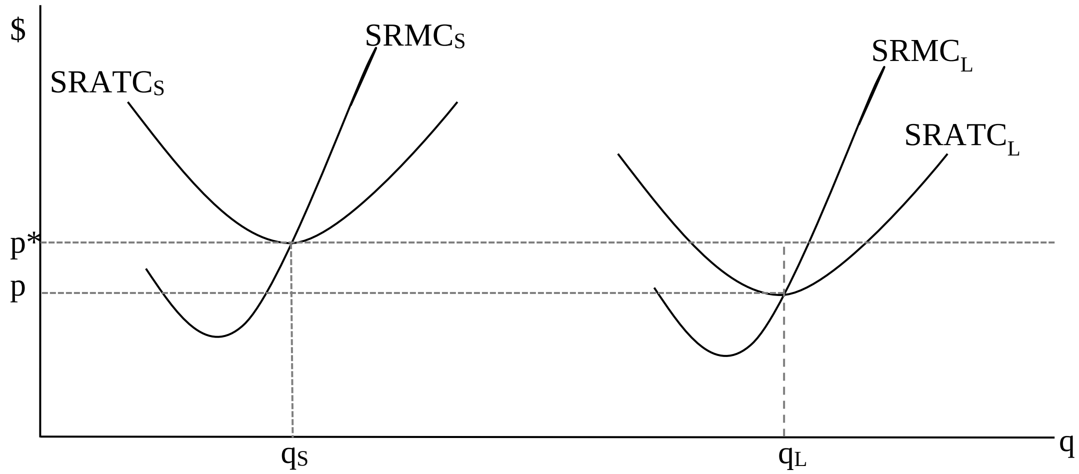

Figure 2: Equilibrium for small and large banks. *SRMC*$_S$ represents the initial short run marginal cost curve for small banks. *SRATC*$_S$ represents the short run average total cost curve for small banks. *SRMC*$_S$ intersects *SRATC*$_S$ *at* (p^*, q_S), the small community bank equilibrium. *SRMC*$_L$ represents the initial short run marginal cost curve for large banks. *SRATC*$_L$ represents the short run average total cost curve for large banks, which produce q_L.

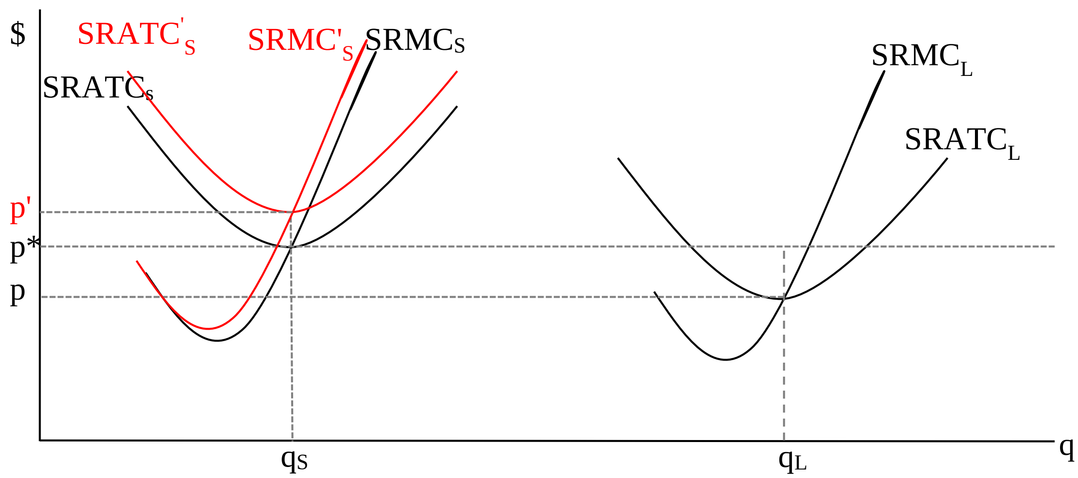

Figure 3: Short run effects of marijuana legalization for small and large banks. After legalization, increases in variable and fixed costs increase *SRATC*$_S$ to *STRATC*$_S$*'* and *SRMC*$_S$ to *SRMC*$_S$*'*. Small banks continue to produce at q_S, resulting in losses equal to the area between *p'*, the price at which *SRMC*$_S$*'* and *STRATC*$_S$*'* intersect, and p^* to q_S.

DATA

I use data from two sources, the Uniform Banking Performance Report provided by the Federal Financial Institutions Examination Council (FFIEC) and Branch Office Deposits provided by Federal Deposit Insurance Corporation (FDIC). The Uniform Banking Performance Report contains quarterly, firm-level financial information on banks in the United States, including income statement and balance sheet items and measures of lending, capital, and liquidity. Although quarterly data are available for all years, data for this study are subset to year-end data for the years 2005 through 2016, resulting in a panel data set covering twelve years and 105 banks for a total of 1,260 observations. I use annual numbers because of seasonality in inputs and outputs that does not necessarily coincide, such that quarterly Data Envelopment Analysis (DEA) scores are likely to be inaccurate. For example, banks with concentrations in agricultural lending may have steady, year-long interest expense, but a single quarter where most interest income collection occurs. This would result in artificially low DEA scores in three quarters and artificially high in the fourth.

Banks are selected for the data set based on the following criteria: (1) banks are present for the duration of the data; (2) banks are headquartered in the United States; (3) banks have positive values on inputs and outputs; (4) banks have at least $10,000 in interest expense, personnel expense, occupancy expense, other non-interest expense, net loans and leases, interest income, and non-interest income; (5) banks have at least $100,000 in total deposits; and, (6) banks have had at least 10 percent of their footprint in a marijuana state in some year between 2005 and 2016. See Appendix A for a complete list of sampled banks. [13]

A significant limitation of Uniform Banking Performance Report data is that observations are aggregated at the bank (rather than the branch) level so that it is impossible to determine the exact disaggregated amount of each balance sheet or income statement item for a selected branch. A second limitation is the inability to directly identify the costs of BSA/anti-money laundering regulation compliance. Because marijuana legalization is a state-level issue and a bank may have branches in multiple states, Uniform Banking Performance Report data alone are not sufficient to analyze the effect of legalization. While other regulatory changes could affect similar compliance costs, those regulatory changes occur at the federal level and are unlikely to be correlated with marijuana legalization.

To determine the extent to which a bank conducts business within a marijuana legalization state (a bank’s “footprint”), I use the FDIC Branch Office Deposits data. These data are provided on an annual basis and list the parent bank, regulatory agency, bank specialty, bank class, branch latitude and longitude, and branch city, state, and county, as well as an indicator of whether the branch is in a metropolitan area. Observations are available for the entire sample selected from the Uniform Banking Performance Report data (2005-2016 for 105 banks).

[13] Banks enter the data set when a new charter is enacted. Banks exit the data set when they merge, are acquired, or fail. Banks that enter or exit the data set between 2005 and 2016 are dropped from the sample. Dropping banks in this manner could introduce attenuation bias due to attrition if the decision to exit the market is correlated with recreational marijuana legalization. A discussion on bank attrition is provided in Appendix A and shows no differential attrition effects between banks before and after recreational marijuana implementation.

To determine each bank's footprint, 2010 Census Data collected by the Census Bureau are used. These population data record county-level population as of 2010. I use these data to determine how many people reside in the same county where a branch is located. Theoretically, these people represent a servable population for those branches. By aggregating county-level population to the state level and examining the percent of a bank's total servable population that resides in a legalization state, I can approximate the percent of a bank business performed in marijuana-legalized states. The calculation of this *footprint* is as follows:

$$footprint\ state_{i,t,s} = \sum_{c=1}^{m} population\ county_{i,t,c}$$

$$footprint\ national_{i,t,s} = \sum_{c=1}^{n} population\ county_{i,t,c}$$

and

$$footprint_{i,t,s} = \frac{footprint\ state_{i,t,s}}{footprint\ national_{i,t,s}}$$

with $population\ county_{i,t,c}$ equal to the population in county *c* where bank *i* has at least one branch in year *t*, *n* is the total number of counties in the United States in which a bank has at least one branch in year *t*, and *m* is the total number of counties in state *s* in which a bank has at least one branch in year *t*. Summary statistics for *footprint* are shown in table 1. Mean footprint is 0.78 with a standard deviation of 0.30 and a range from 0.01 to 1. In Colorado, mean footprint is 0.87, indicating that, on average, a bank in Colorado conducts 87.4 percent of its business in Colorado as measured by the ratio of population within the state to national population servable by that bank. In Washington, the average is 0.86 and in Oregon, the average is 0.74. Alaska only contains banks that are 100 percent contained within the state, so the mean is one. Small community banks are the most concentrated within a given state, with a mean footprint of 99 percent in Colorado, 95.5 percent in Washington, and 100 percent in both Oregon and Alaska. Similarly, medium community banks have mean footprints of 94.1 percent in Colorado, 91.8 percent in Washington, 88.7 percent in Oregon, and 100 percent in Alaska. Large community banks in Colorado are less concentrated than in other states, with a mean footprint of 60.8 percent. However, in Washington and Oregon they have a mean footprint of 94.9 and 81.1 percent, respectively, and 100 percent in Alaska. Medium-to-large banks range from being wholly contained in Alaska to having only 41.6 percent of their footprint in Oregon. In Colorado, the mean footprint for medium-to-large banks is 77.6 percent and in Washington it is 77.5 percent. Distribution of *footprint* by state is shown in figure 4, with “zoomed” versions for Colorado in figure 5, Washington in figure 6, Oregon in figure 7, and Alaska in figure 8. There is significant clustering at one given the high number of banks located entirely within a single state. See Appendix B for an example footprint calculation.

To obtain the date of initial recreational marijuana sales, I examined news releases announcing the first sale for each state. In all four states, the first sale occurred two years after legalization passed. Legalization and sales timelines are noted in table 2. Recreational marijuana rules governing sale and consumption vary widely by state. In

Colorado, availability depends on local community decision-making, while Oregon legalization is county-based. Even after state-level legalization, marijuana sales are banned in nearly every county in the eastern half of Oregon but allowed in nearly every county in the western half. Washington has the strictest rules regarding marijuana consumption, sale, and storage out of all legalization states, and Alaska maintains significant fines restricting consumption locations and methods.

Table 1: Summary Statistics of Footprint by State and Bank Size

	Mean	Std. Deviation	Minimum	Maximum
Footprint	0.777	0.297	0.007	1
Footprint in Colorado	0.874	0.213	0.054	1
Small Community Banks	0.990	0.066	0.465	1
Medium Community Banks	0.941	0.158	0.216	1
Large Community Banks	0.608	0.325	0.073	1
Medium-to-large Banks	0.776	0.217	0.054	1
Footprint in Washington	0.862	0.208	0.107	1
Small Community Banks	0.955	0.133	0.472	1
Medium Community Banks	0.918	0.192	0.139	1
Large Community Banks	0.949	0.162	0.131	1
Medium-to-large Banks	0.775	0.213	0.107	1
Footprint in Oregon	0.736	0.314	0.013	1
Small Community Banks	1	0	1	1
Medium Community Banks	0.887	0.155	0.181	1
Large Community Banks	0.811	0.329	0.058	1
Medium-to-large Banks	0.416	0.222	0.013	0.81
Footprint in Alaska	1	0	1	1
Small Community Banks	1	0	1	1
Medium Community Banks	1	0	1	1
Large Community Banks	1	0	1	1
Medium-to-large Banks	1	0	1	1

Source: U.S. Census 2010 population by county, Federal Deposit Insurance Corporation bank branch report as of 2016. Footprint is the sum of the population in each county in which a bank has a branch within a state divided by the sum of the population in each county in which has a branch total.

Table 2: Year of Recreational Marijuana Legalization & First Sale

State	Legalization Year	First Retail Sale
Colorado	2012	2014
Washington	2012	2014
Alaska	2014	2016
Oregon	2014	2016
Washington, DC[14]	2014	--
Nevada	2016	2017
California	2016	2018
Maine	2016	--
Massachusetts	2016	--
Vermont	2017	--

Date of initial retail sale obtained from newspaper articles. Legalization years obtained from "American High: State-by-State Guide to Legal Pot" by Laslo (2017). Legalization year is the year of legalization by state government, first retail sale is the first year that a legal sale of a recreational marijuana good occurs.

[14] Washington, DC laws are restrictive enough that many consider it to have only decriminalized marijuana.

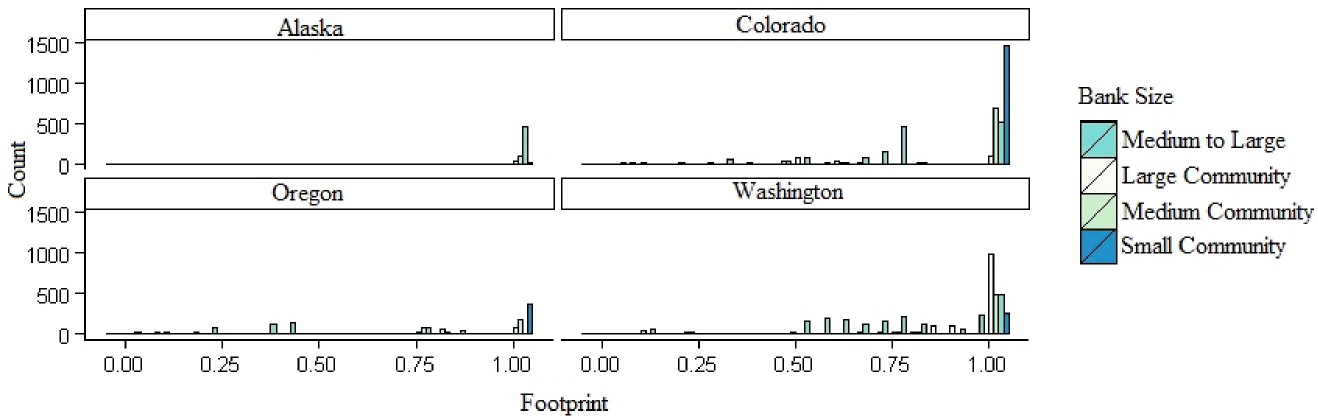

Figure 4: Distribution of footprint by state.

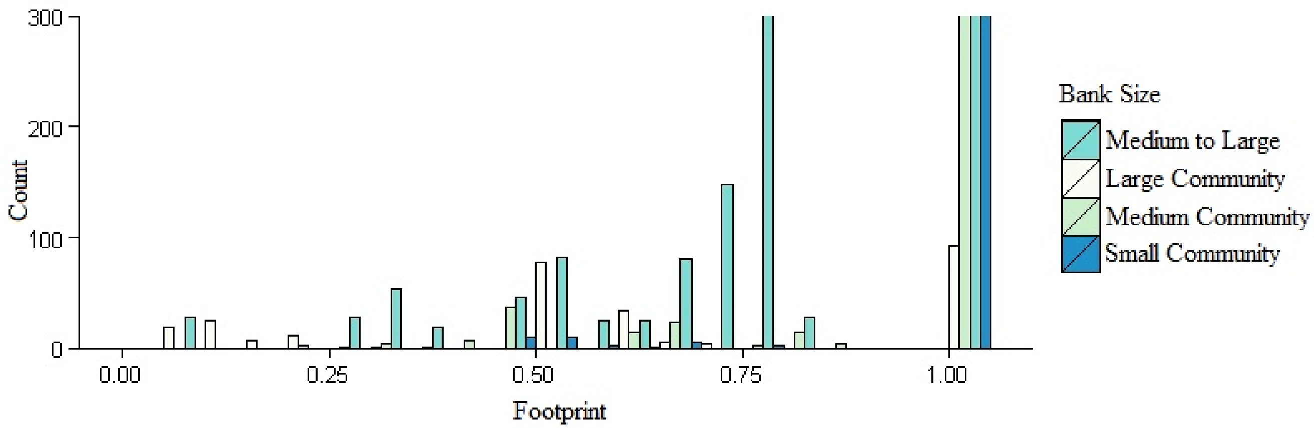

Figure 5: Distribution of footprint in Colorado. Zoomed to counts below 300.

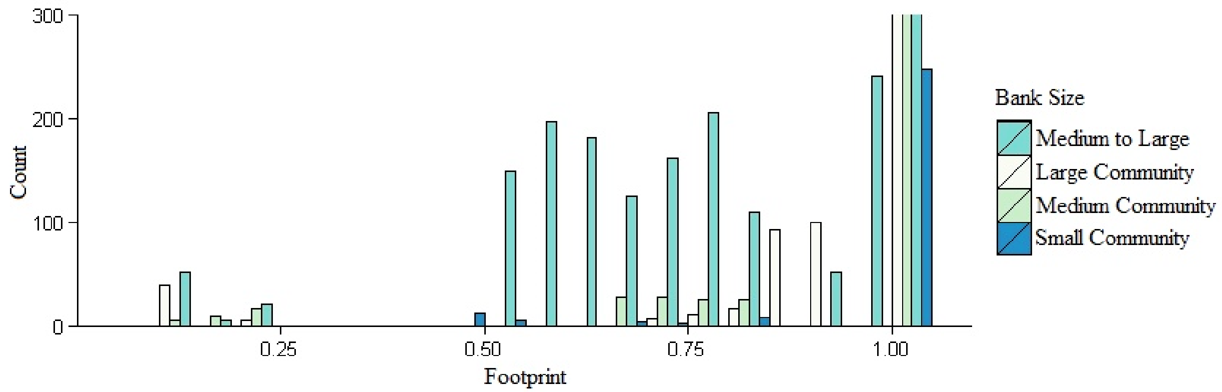

Figure 6: Distribution of footprint in Washington. Zoomed to counts below 300.

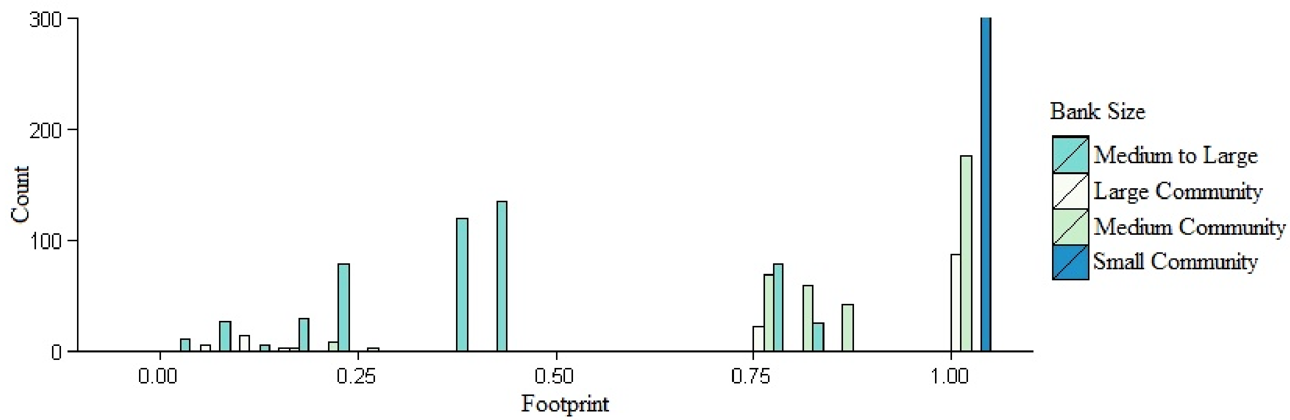

Figure 7: Distribution of footprint in Oregon. Zoomed to counts below 300.

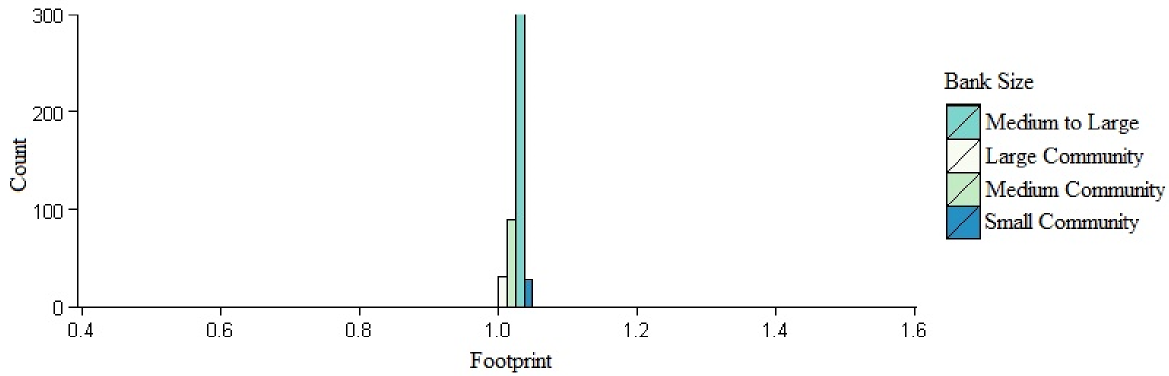

Figure 8: Distribution of footprint in Alaska. Zoomed to counts below 300.

MEASURING RELATIVE FIRM PERFORMANCE

Motivation

Differences in relative performance measurement method and bank, market, and regulatory characteristics contribute to disagreement in the literature regarding bank industry competitive advantages (Berger 1997). This section follows Cook and Seiford (2009) and Atwood and Shaik's discussion in *Quantile DEA: Estimating qDEA-α Efficiency Estimates with Conventional Linear Programming* (2018). As Farrell (1957) discussed in his seminal paper on productive efficiency, the failure to develop an adequate measure is due to an inability to combine multiple inputs that is general enough to apply to all levels of production. To address this, Charnes, Cooper, and Rhodes (1978) introduced data envelopment analysis (DEA). The concept provided a methodology for identifying which decision-making units (DMUs) perform according to "best practices" relative to their peers. These best practice DMUs form a best practice frontier, and DEA allows an analyst to identify best practice input/output combinations to compare DMUs that are not on the frontier to best practice DMUs.

One way to interpret DEA measures is in terms of distance, that is, distance of a given DMU from the production possibility frontier as constructed with peer data. Here, "peers" are a group of DMUs whose input and output data are being used to estimate "available" or attainable input/output combinations. DEA does not assume that, in the short run, a given DMU can reach the frontier, but computes the distance from the frontier. DEA also assumes that convex combinations of observed inputs and outputs are feasible. This model has the benefit of not requiring assumptions with respect to DMU-level specific production functions.

Data Envelopment Analysis

Data envelopment analysis assumes that a decision-making unit (DMU) represents an entity that maps inputs to outputs. The DMU of current interest is a bank, but DEA allows for DMUs to represent individuals, branches, or firms. The inputs and outputs are commonly assumed to be goods in the sense that DMUs and the market prefer more to fewer of the input and output levels being available to society. The assumption that inputs and outputs are goods implies that input/output combinations with fewer inputs for the same outputs or more outputs using the same inputs are preferred. These preferred combinations are closer to the best practice frontier relative to any other observed input/output combinations. Because production functions are unobservable, likely to be specific to each DMU, and market price information on some inputs or outputs may be unavailable, DEA uses observed input/output data to identify feasible combinations of inputs/outputs rather than constructing a cost or profit function. This data can either be in the form of quantities or expenditures/revenues used as a proxy for quantity.

Inputs and outputs are selected by the individual performing data envelopment analysis depending on the problem under consideration. In the case of a bank responding to anti-money laundering regulation, the most applicable definition of a bank is that of a lending institution that takes customer deposits and generates loans. Because banks are considered price takers, expenses and revenues directly correspond to quantities. Here, *interest expense* and *noninterest expense* are the observable inputs relevant to the lending process, used as proxies for traditional inputs such as labor hours. *Noninterest expense* is the likely source of most Bank Secrecy Act/Anti-Money Laundering related costs, where expenses associated with audit and internal control responsibilities would increase under the heightened scrutiny of customers introduced by marijuana legalization. Personnel expense, which is included in *noninterest expense*, may be a source of fixed cost increases, with more qualified and trained individuals needed to perform higher-complexity analysis. For outputs, I have selected *net loans and leases* and *income* as measures of lending volume produced and revenue generated. Although more detailed components of these inputs and outputs are available in the data, there are high levels of collinearity between specific inputs and outputs. High collinearity can bias DEA scores. To reduce this effect, expenses and income are aggregated into the broader categories above, which are not collinear when aggregated.

DEA can be applied to time-series, cross-sectional, or panel data. The sample selected is complete for all inputs and outputs. To differentiate preferred combinations of input/outputs, DEA fits a hull around the observed set of combinations and estimates the distance of a given DMU’s in-out combination to the surface of the hull. This distance is converted into a cardinal, unitless score, such that larger in magnitude implies an input/output combination that is closer to the best practice hull and more preferred than a combination with a lower score. DEA can accommodate various assumptions with respect to the production hull including the free disposal hull model, constant returns to scale in the long run, increasing and decreasing returns in the short run, and so on.[15] This study assumes constant returns to scale. The inputs I selected are available in dollars (*noninterest expense* and *interest expense)*. Similarly, outputs also fall under volume in dollars (*net loans and leases*) and revenues (*income*).

Conventional Data Envelopment Analysis

Implementing DEA requires the specification of a potential movement "direction" and the ability to construct a hull that encompasses observed input-output observations from the DMU "reference set." While the more recent directional DEA models (Chambers et. al) can accommodate movements in any user specified direction, the classical DEA model uses one of three directions to estimate relative performance, including input contraction and output expansion (shown in figure 9) and the in-out model (shown in figure12).

Input contraction assumes that outputs are held constant and examines input use by each DMU. Assuming that x_1, x_2 represent two inputs and y_1, y_2 represent two outputs, DMUs that use less of, without loss of generality, x_1 and holding all else equal are preferred. DMUs that use more of both x_1 and x_2 are not preferred over the comparison DMU, while DMUs using combinations of more or fewer of x_1 or x_2 have DEA scores that must be determined proportionally. See figure 10 for an example of input contraction.

[15]Free disposal implies that inputs and outputs cannot have a negative price; there is not a cost of disposing excess inputs or outputs.

As shown in figure 11, output expansion assumes that inputs are fixed at the starting level and allows output amounts to vary. Producing more of y_1 or y_2 all else equal results in a DMU that is preferred over the DMU at (3,3), while producing less of either results in a less preferred combination. Again, ambiguity is introduced when the proportion of y_1 and y_2 changes. This research focuses on input contraction from conventional DEA, called *input orientation*, as well as the Directional DEA metric, called *in-out orientation*.

Directional Data Envelopment Analysis

Directional DEA (DDEA) allows simultaneous changes in the input/output mix, representing a more general version of conventional DEA. With the assumption of constant returns to scale, the primal DDEA model can be written as:

$$
\begin{gathered}
\textit{Maximize } \phi \\
\textit{s.t. } y_0 + \phi\, d_y \leq \mathrm{Y}'\underline{z} \\
x_0 - \phi\, d_x \geq \mathrm{X}'\underline{z} \\
d_y,\, d_x,\, z,\, \phi \geq 0
\end{gathered}
$$

where $\underline{z}$ represents a vector of weights, $\mathrm{Y}'\underline{z}$ represents the production possibility frontier, $\mathrm{X}'\underline{z}$ represents the input possibility frontier, and y_0, x_0 can be either scalars or vectors to represent the observed outputs and inputs, respectively.[16] ϕ is the computed distance between the DMU and the frontier. In figure 12 , ϕ represents the normalized distance of each DMU from the best practice frontier. This distance represents how close the DMU's

[16] DDEA can be transformed into conventional input or output orientation DEA under the following assumptions:
for input contraction, $d_x = x_0$ and $d_y = 0$
for output expansion, $d_y = y_0$ and $d_x = 0$

combination of inputs and outputs is to the best practice frontier, with a higher distance implying that DMU is further from the best practice frontier and therefore less preferred than if the distance were lower. If $(d_x, d_y) = (0, y_0)$, $(x_0, 0)$ or (x_0, y_0), ϕ can be shown to be the proportion of outputs that could be added holding inputs constant, the proportions of inputs that could be saved holding outputs constant, or the proportions of both inputs and outputs that could be saved if the DMU were to move closer to the frontier. A graphical example is discussed below. Because we associate larger values with better performance, DEA scores are written as 1- ϕ. A ϕ of zero indicates that the DMU is already on the best practice frontier and cannot use fewer inputs for the same level of output or produce more output at the same level of inputs according to the production possibility frontier. Therefore, that DMU would be considered a reference or best practice bank. Its associated DEA score would therefore be 1- ϕ = 1-0 = 1. If y_0 and x_0 are in dollar units, then ϕ will also be in dollars and can be discussed in terms of, for example, cost savings.

To discuss a further economic interpretation of ϕ, we rearrange the model, rewrite in matrix notation, and transform to the dual problem. Rearranging the primal problem, we obtain:

$$\begin{gathered} \textit{Maximize } \phi \\ \textit{s.t. } Y'\underline{z} - \phi\, d_y \geq y_0 \\ X'\underline{z} + \phi\, d_x \geq x_0 \\ d_y, d_x, z, \phi \geq 0 \end{gathered}$$

The DDEA model uses linear programming (LP) to solve this maximization problem, so we can rewrite the primal LP in matrix form:

$$\textit{Maximize } [\underline{0}'\ 1]$$

$$s.t. \begin{bmatrix} Y' & -d_y \\ X' & d_x \end{bmatrix} \begin{bmatrix} \underline{z} \\ \phi \end{bmatrix} \begin{pmatrix} \geq \\ \leq \end{pmatrix} \begin{bmatrix} y_0 \\ x_0 \end{bmatrix}$$
$$\underline{z}, \phi \geq 0$$

The dual to this linear programming problem is therefore:

$$Minimize\ [y_0^{'}\ x_0^{'}]$$
$$s.t. \begin{bmatrix} Y & X \\ -d_y^{'} & d_x^{'} \end{bmatrix} \begin{bmatrix} p \\ w \end{bmatrix} \begin{pmatrix} \geq \\ \geq \end{pmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$
$$p \leq 0, w \geq 0$$

In this interpretation, the DDEA model searches for a set of imputed prices that puta a DMU's bundle of inputs and outputs in the most favorable light relative to peers. The support prices are in the form of weights *p* and *w*, representing output and input price weights, respectively. However, because *p* is typically considered to be a positive number, we multiply by -1 to obtain:

$$Minimize\ [-y_0^{'}\ x_0^{'}]$$
$$s.t. \begin{bmatrix} -Y & X \\ d_y^{'} & d_x^{'} \end{bmatrix} \begin{bmatrix} p \\ w \end{bmatrix} \begin{pmatrix} \geq \\ \geq \end{pmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$
$$p, w \geq 0$$

which can also be written as:

$$Minimize\ [-y_0^{'}\ x_0^{'}]$$
$$s.t. \begin{bmatrix} Y & -X \\ d_y^{'} & d_x^{'} \end{bmatrix} \begin{bmatrix} p \\ w \end{bmatrix} \begin{pmatrix} \leq \\ \geq \end{pmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$
$$p, w \geq 0$$

Equivalently, we write:

$$Minimize\ -py_0 + wx_0$$
$$s.t.\ Y\underline{p} - X\underline{w}\ \leq 0$$
$$pd_y + wd_x \geq 1$$
$$p, w \geq 0$$

This representation now aligns with a profit maximization optimization problem because it is equivalent to:

$$Maximize\ py_0 - wx_0$$
$$s.t.\ Y\underline{p} - X\underline{w}\ \leq 0$$

$$pd_y + wd_x \geq 1$$
$$p, w \geq 0$$

In this representation, "profits" will be negative when a DMU is not on the best practice frontier and zero for DMUs on the best practice frontier. When the LP problem is feasible and bounded, the last inequality above will be binding, resulting in prices that are normalized such that a unit movement in direction (d_x , d_y) will have unit value. The primal model searches for a set of projection weights, *z*, and estimates 1-ϕ, the DEA score of DMU *j*. The dual model searches for price vectors (*p*,*w*) that maximize the DEA score of DMU *j* subject to the restriction that all DMU "profits" be less than or equal to zero. This is how the DEA model fits a hull around the observed data, subsequently constructing a distance metric that measures the proportional distance from a given DMU's in-out combination to a point on the hull.

Using an example adapted from Cooper et. al (2006), figure 12 shows the constant returns to scale best practice frontier defined by DMU B. The input in this case is *employee expenditures* and the output is *sales*. Assuming all decision-making units are price-takers, there is a direct correspondence between the dollar value of the input and the quantity used. The best practice frontier defined by DMU B, which uses 3 dollars of input to produce 4 dollars of output, is shown as a single, solid line. DMU B is shown at (3,4). DMU A, at (3,2), uses 3 dollars of input to produce 2 dollars of output. Because DMU A uses the same input quantity as DMU B to produce a lower quantity of output, DMU A's input/output combination is less preferred than DMU B's input/output combination. As such, DMU A is located away from the best practice frontier. DMU C uses 6 dollars in employee expenditures to produce 5 dollars in sales, but the best practice frontier indicates a preferred input/output combination of (6,4). Therefore, DMU C is not located on the best practice frontier, and its combination is less preferred than DMU B. The normalized distance between the best practice frontier and each DMU is ϕ, and can be measured via the input, output, or in-out orientation. Because of symmetry between input and output orientation, I only discuss input and in-out orientation here. In the input orientation, ϕ is calculated separately for each DMU as the normalized distance from the DMU's input/output combination to the best practice frontier, shown as a thick horizontal line in figure 12. Because DMU B is on the best practice frontier, it has a ϕ of 0. DMU A's ϕ is 0.5 in the input orientation, which represents the distance to the best practice frontier normalized such that all observed input/output combinations have a maximum distance of 1. For DMU C, ϕ is 0.375. To obtain input-orientation DEA scores, the ϕ calculated for each DMU is translated such that a higher score indicates that a DMU is closer to the best practice frontier, such that the input orientation DEA score for each DMU is 1- ϕ. Therefore, DMU B has an input orientation DEA score of 1, DMU A has a score of 0.5, and DMU C has a score of 0.625. In the in-out orientation, DMUs can move closer to the best practice frontier through a combination of changes in input and output quantities, shown as a thick dashed line in figure 12. For in-out orientation, DMU B still has a distance ϕ of 0 and DEA score of 1, while DMU A has an in-out orientation DEA score of 0.429 and DMU C has an in-out orientation DEA score of 0.6429.

To examine the effects of a change in policy on relative firm performance, data envelopment analysis can be performed prior to the policy and after the policy. Under this framework, as shown in figure 13, the relative change in distance between DMU A and DMU C can be compared, answering the question of whether DMU A was affected by the policy to the same extent as DMU C in relative, proportional terms. If DMU A moved further from the best practice frontier (from point a to point A) than DMU C (from point c to point C) when compared to where DMUs A and C started, and relative to DMU C's movement, then DMU A received a greater share of the burden of the policy than DMU C. DMU A would have a relatively higher increase in distance, ϕ, after the policy, which would result in lower DEA scores than for DMU C, controlling for where DMU A was prior to the policy.

Even if both distances are shifted by the same constant, for DMU A this effect is proportionally larger than for DMU C, which is reflected in an effect on the DEA score of A that is larger in magnitude. Suppose that DMU A and DMU C must increase their inputs (identically, input costs) by 0.3 each from point a and point c, respectively, resulting in 3.3 inputs used for DMU A at point A and 6.3 inputs used for DMU C at point C. Then, the input orientation DEA scores for DMU A and DMU C are 0.455 and 0.595 after the policy, respectively. Compared to their original scores of 0.5 for DMU A and 0.625 for DMU C, the difference in scores for DMU A is 0.045 after the policy and 0.03 for DMU C. DMU A therefore faces a more significant effect on its DEA score, despite an identical shift in input costs. This relative change in distance and, thus, DEA scores can be compared in terms of both input and in-out orientation. The intent is not to prescribe that DMU A should or could make similar input/output decisions as DMU C, but rather to compare the effects of the policy on both DMUs to determine if the effects were proportionally more significant for one of them than the other.

For this research, I am interested in whether the smaller DMU type, small community banks, move proportionally further from the best practice frontier on average than the larger type, medium-to-large banks, after recreational marijuana legalization, as measured in both the input and in-out orientation. The identification strategy along with bank and year fixed effects as well as time-varying bank controls accounts for changes in the frontier overall and isolates the relative distance change in question.

To perform this calculation, I use the MMLPDEA R package authored by Atwood (2017). Using my sample of 105 banks, I run the DEA function with constant returns to scale in the input and in-out orientation for every year. First, the DEA function generates a best practice frontier from the 105 observed input/output combinations within a selected year. Second, the DEA function calculates the distance ϕ of each observed combination of inputs (interest expenses and noninterest expenses) and outputs (net loans and leases and income) for the input orientation and the in-out orientation in that year. Finally, this distance is adjusted to 1- ϕ, such that higher numbers imply observations that are closer to the best practice frontier and, as such, preferred. This process is repeated for all years, 2005-2016. Every bank has an input orientation and an in-out orientation DEA score for each year based on the input/output combinations observed in that year. The DEA input and in-out orientation scores become the dependent variables in my regressions, which use econometric controls to identify the relative, proportional change in DEA scores for banks after recreational marijuana legalization by size.

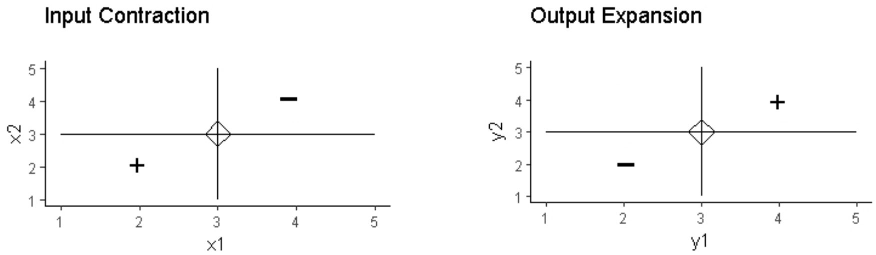

Figure 9: Conventional Data Envelopment Analysis. In input contraction, holding outputs constant while reducing x_1 or x_2 results in a preferred combination. In output expansion, holding inputs constant while increasing y_1 or y_2 results in a preferred combination.

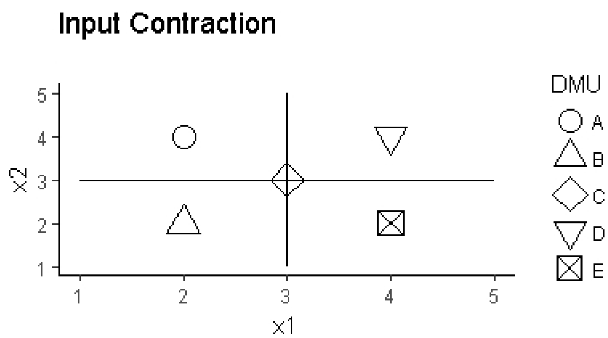

Figure 10: Input Contraction Example. DMU B is preferred over DMU C because it uses less of both x_1 and x_2 while still producing the same amount of output. DMU D is not preferred, using more of both x_1 and x_2. A and E preference depends on the proportions of x_1 and x_2 used.

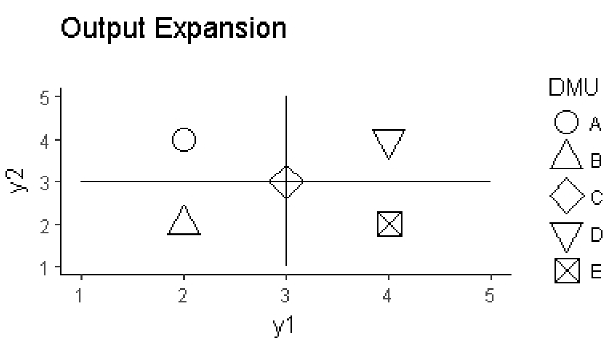

Figure 11: Output Expansion Example. Relative to DMU C, DMU D is preferred because D produces more of at least one output than C. B is not preferred because it produces less of at least one output than C. A and E preference depends on the proportions of y_1 and y_2 used. Inputs are assumed to be constant.

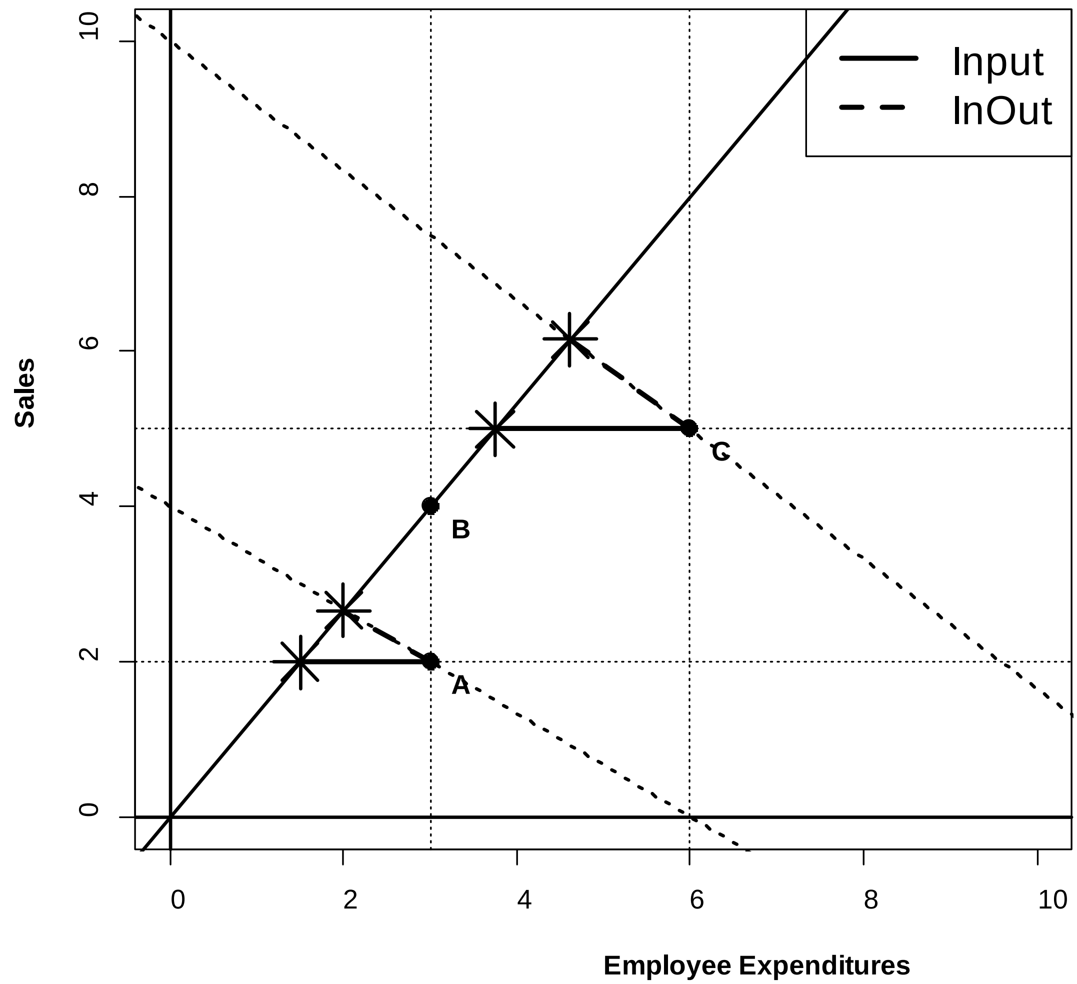

Figure 12: Input and In-out Orientation Example. DMU A represents a small firm, DMU B is the representative firm that defines the best practice frontier, and DMU C represents a large firm. The horizontal, bolded line represents how DMU A and DMU C can change their input/output combination under input orientation; the bolded and dashed line represents how DMU A and DMU C can change their input/output combination under in-out orientation.

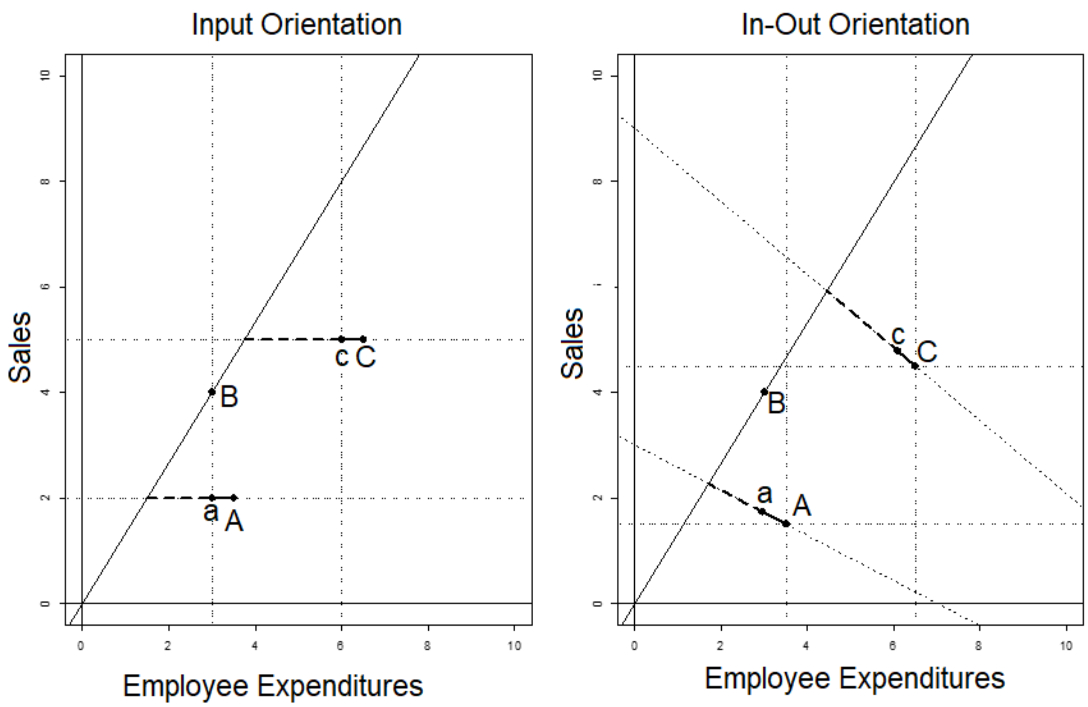

Figure 13: Input and In-out Orientation after policy change example. DMU A moves from input/output combination *a* to combination *A* and DMU C moves from input/output combination *c* to combination C, assessed under input orientation and in-out orientation. DMU B remains the reference category and remains unchanged in this example.

VARIABLES

To assess relative bank performance before and after recreational marijuana legalization, I use calculated DEA scores in the input and in-out orientation. To indicate treatment, *MJ footprint 50%* incorporates the extent to which a bank conducts business in a marijuana state and the year of observation. Bank size, an additional effect, is included to differentiate between the largest banks, including medium-to-large banks, and smallest banks, also called community banks. The community bank category is broken into the three smaller size categories of large, medium, and small community banks. Finally, I use time-varying bank controls to address sources of bank-level variation not included in bank fixed effects.

Dependent Variables

- *Input orientation* – the DEA score calculated using input-orientation (conventional DEA)
- *In-out orientation* – the DEA score calculated using in-out-orientation (directional DEA)

Treatment Variables

MJ footprint 50% represents an indicator variable equal to 1 if a bank has at least 50 percent of its *footprint* in a marijuana legalization state in the year of that states' first recreational sale. I use 50 percent because this indicates the cutoff after which banks have a majority of their business in a marijuana state, providing a divide between banks that are the most affected by marijuana legalization and those that have a majority of their business in a different state. Following Dolar's (2012) asset size indicators,

- *small community bank* - banks holding less than $250 million in assets;
- *medium community bank* - banks holding between $250 million and $500 million;
- *large community bank* - banks holding between $500 million and $1 billion; and,
- *medium-to-large bank* - banks holding between $1 billion and $10 billion.

Control Variables

Real estate lending concentration, *agricultural lending concentration*, and *commercial lending concentration* refer to lending concentrations as a percent of total risk-based capital in the areas of total real estate loans, agricultural loans, and commercial loans. [17] This is intended as a control for any major lending specialization a bank may have and varies over time. *Investments available for sale (%)* is a measure of available-for-sale investments, a common source of liquidity, as a percent of average assets. *other real estate owned ratio* is other real estate owned as a percent of average assets, which is a measure of credit quality. Nonaccrual loans (*percent of loans on nonaccrual*) controls for lending portfolio deficiencies and represents total loans and leases on nonaccrual as a percent of total loans and leases. This amount includes non-performing loans. The tier 1 leverage ratio, a measure of capital adequacy in a bank, is represented by *tier 1 leverage ratio*. This ratio represents the relationship between bank core capital and total assets,

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[17] Risk-based capital, also called "regulatory capital," is as defined in 12 CFR Part 3 for nationally-chartered banks and 12 CFR Part 217 for state-chartered banks and as reported in Call Report Schedule RC-R.

calculated by dividing Tier 1 capital by the sum of off-balance sheet exposures and average consolidated assets. *Percent of branches in MSAs* records the percent of branches each bank has in a metropolitan statistical area.

Summary Statistics

Summary statistics are reported in table 3 below. There are 105 banks observed over 12 years, resulting in 1260 bank-years.[18] The average *input orientation* DEA score is 0.63, while the average *in-out orientation* DEA score is slightly higher at 0.76. Figures 14 and 15 show the distribution of *input orientation* and *in-out orientation*, respectively. Figure 16 shows the distribution of input orientation by bank size category. All bank sizes have some clustering at one, but small community bank is the only category containing scores less than 0.25. Input orientation observations are centered between 0.50 and 0.75 for every size category. Figure 17 shows the distribution of in-out orientation by bank size. In-out orientation is more negatively skewed than input orientation, but also demonstrates some clustering at one.

Around 20 percent (or 259) of bank-years occur with at least 50 percent of their business in a marijuana state after marijuana legalization, or 98 banks. As shown in figure 18, small community banks are the most numerous for *MJ footprint 50%* = 0 and for *MJ footprint 50% = 1*, followed by medium community banks, medium-to-large banks, and large community banks. The distributions of DEA scores by treatment status for input orientation and in-out orientation are shown in figure 19 and figure 20. Across bank-

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[18] By "bank-year," I mean an observation of a bank in a given year. In discussing means across the sample, I am discussing averages for twelve years of all banks, so that each bank is observed across twelve years.

years, observations were split across sizes at 58.7 percent *small community banks*, 16.3 percent *medium community banks*, 11.4 percent *large community banks*, and 13.2 percent *medium-to-large banks*. As shown in table 4, on average 4.9 banks change size categories from the previous year. Over half (58.5 percent) of branches in the sample were in MSAs with an average *percent of branches in MSAs*. Metropolitan banks are more likely to have a higher risk of money laundering.

Concentrations of credit can be thought of as a single large exposure to credit risk (U.S. Department of the Treasury 2011), and the standard threshold for heightened risk management practices occurs at a lending concentration of 300 percent of capital (Federal Deposit Insurance Corporation 2006). *Real estate lending concentration*, *commercial lending concentration*, and *agricultural lending concentration* represent the net loans and leases of a given category (real estate, commercial, or agricultural) as a percent of total risk-based capital in the bank. The average *real estate lending concentration* is 441.9 percent of capital, representing the most significant concentration between the three types included. *Commercial lending concentration* is the next highest concentration on average at 82.5 percent. *Agricultural lending concentration* averages 40.5 percent of capital. Concentrations also provide information on lending specialties of a given bank.

Investments available for sale as a percent of average assets represents a potential source of liquidity and income for banks and indicates to what extent a bank emphasizes investing. On average, *investments available for sale* represents 18 percent of assets averaged over the year. The *other real estate owned ratio* averages 70 percent of average assets, which is about the U.S. average for community banks in 2009. National increases in other real estate owned began in 2007 and continued through 2011, peaking in 2011 at over 1 percent of average assets for community banks nationwide. The highest recorded *other real estate owned ratio* in this sample is 14.7 percent, which represents a significant degradation of real estate credit quality. *Percent of loans on nonaccrual* is a broader measure of credit quality than the *other real estate owned ratio*, with an average of 1.73 percent of total loans on nonaccrual, and a maximum of 35 percent. A higher percent of loans on nonaccrual indicates a lower level of credit quality. The *tier 1 leverage ratio*, an important measure of capital adequacy, averages 10.4 percent. A bank is considered "well-capitalized" if it has a tier 1 leverage ratio of at least 5 percent (FDIC 2014); however, this is a basic threshold for safety. Leverage ratios greater than 9 percent are commonly expected, but expectations vary according to risk. The minimum ratio observed, at 2.8 percent, would be cause for supervisory concern.

Table 5 contrasts small community banks with medium-to-large banks. Medium-to-large banks are statistically significantly closer to the best practice hull by both orientations at 0.695 compared to 0.600 and 0.736 compared to 0.808. Proportionally, medium-to-large banks have more treated observations, with 23.50 percent of medium-to-large bank observations with *MJ footprint 50%* equal to one to small community banks' 19.20 percent, but this difference is not statistically significant. Medium-to-large banks holding average *real estate lending concentrations* 30 percentage points higher than small community banks, and both above the population average of 414 at 424 and 476 percent. Small community banks held a higher average *agricultural lending concentration*, at 48.6 percent, while medium-to-large banks had a mean concentration of

12.1 percent. Similarly, medium-to-large banks had a higher average *commercial lending concentration* at 101.72 percent compared to 76.7 percent at small community banks. The difference in mean lending concentrations between the two groups are statistically significant for all specialties. The *other real estate owned ratio* is similar between two groups at 0.7 percent, and the *tier 1 leverage ratio* is also similar at 10.3 percent, with neither measure statistically significantly different. *Percent of loans on nonaccrual* is slightly higher at medium-to-large banks with a mean of 2.0 percent while small community banks average 1.6 percent, but this difference is not statistically significant. Medium-to-large banks are also more metropolitan, with a mean of 72.9 percent of branches in MSAs relative to a mean of 52 percent at small community banks; this difference is statistically significant.

Differences between small community banks and medium-to-large banks are similar between treated and untreated observations. As shown in table 6, mean DEA scores are statistically significantly different between the two size categories. For untreated observations, the commercial lending concentration and the other real estate owned ratio are not statistically different. For treated observations, the statistically similar means are investments available for sale and the tier 1 leverage ratio. Otherwise, mean financial measures are different between the two size categories.

I graph average annual DEA scores for medium-to-large banks and small community banks from 2005 to 2015 in figure 21 for input orientation and in figure 22 for in-out orientation. Mean input orientation for both bank size categories is higher in marijuana states after marijuana legalization compared to non-marijuana states in the same period. However, the gap in performance between banks of the two sizes is significantly larger in legalization states than in non-legalization states. The trends for medium-to-large banks and small community banks are similar in the pre-period, as are the trends for control versus treated banks. The control trends indicate that, after 2014, the gap between small community banks and medium-to-large banks is closing. The trends are nearly identical for in-out orientation.

Table 3: Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
Input orientation DEA score	0.632	0.170	0.083	1
In-out orientation DEA score	0.761	0.131	0.153	1
MJ footprint 50%	0.206	0.404	0	1
Small community bank	0.587	0.386	0	1
Medium community bank	0.163	0.493	0	1
Large community bank	0.114	0.374	0	1
Medium-to-large bank	0.132	0.317	0	1
Percent of branches in MSAs	0.585	0.338	0	1
Real estate lend. concentration	441.897	175.541	0	1,391.991
Agricultural lend. concentration	40.480	66.923	0	497.670
Commercial lend. concentration	82.535	57.326	0	439.564
Investments available for sale	18.022	14.545	0	73.130
Other real estate owned ratio	0.697	1.277	0	14.715
Percent of loans on nonaccrual	1.733	3.032	0	37.567
Tier 1 leverage ratio	10.400	2.807	2.820	26.520

N = 1260 observations, 105 banks for all variables.

Input orientation DEA score and in-out orientation DEA score calculated via the R package MMLPDEA by Atwood (2017). Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization.

Table 4: Number of Banks that Changed Size Category from Prior Year

Years	Changed	Unchanged
2005-2006	5	100
2006-2007	4	101
2007-2008	7	98
2008-2009	3	102
2009-2010	10	95
2010-2011	4	101
2011-2012	6	99
2012-2013	3	102
2013-2014	5	100
2014-2015	6	99
2015-2016	1	104
Mean	4.9	100
Standard Deviation	3.3	3.3
Minimum	1	95
Maximum	10	104

Bank size information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016).

Table 5: Summary Statistics - Small Community Banks and Medium-to-large Banks

	Small Community	Medium-to-large	t-statistics of difference between means
Input orientation	0.600	0.695	7.336
	(0.166)	(0.167)	
In-out orientation	0.736	0.808	7.075
	(0.134)	(0.118)	
MJ footprint 50%	19.200	23.500	1.588
	(39.400)	(1.420)	
Real estate lend. concentration	424.415	475.975	3.644
	(182.520)	(178.357)	
Agricultural lend. concentration	48.604	12.065	6.879
	(76.677)	(18.495)	
Commercial lend. concentration	76.710	101.720	6.879
	(57.916)	(63.169)	
Investments available for sale	18.164	22.219	5.429
	(15.158)	(13.910)	
Other real estate owned ratio	0.737	0.733	0.029
	(1.269)	(1.877)	
Tier 1 leverage ratio	10.350	10.375	0.036
	(2.578)	(3.085)	
Percent of loans on nonaccrual	1.620	2.027	0.119
	(2.661)	(4.294)	
Percent of branches in MSAs	52.000	72.900	1.026
	(44.400)	(26.900)	
Number of Observations	739	212	
Number of Banks	73	18	

Input orientation DEA score and in-out orientation DEA score calculated via the R package MMLPDEA by Atwood (2017). Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Small community banks have assets less than $250 million and medium-to-large banks have assets between $1 and $10 billion.

Table 6: Summary Statistics – Small Community Banks and Medium-to-large Banks by Treatment Status

	No MJ Legalization (untreated)			MJ Legalization (treated)		
	Small Community	Medium-to-large	t-statistics	Small Community	Medium-to-large	t-statistics
Input orientation	0.605	0.680	4.755	0.577	0.744	5.021
	(0.161)	(0.156)		(0.182)	(0.192)	
In-out orientation	0.742	0.799	4.648	0.714	0.838	4.45
	(0.127)	(0.119)		(0.157)	(0.145)	
Real estate lend. concentration	431.54	473.06	2.253	394.44	485.48	3.371
	(187.62)	(193.11)		(156.39)	(119.80)	
Agricultural lend. concentration	48.56	11.20	5.515	48.77	14.88	2.608
	(75.85)	(18.08)		(80.35)	(19.78)	
Commercial lend. concentration	79.30	104.37	0.809	65.81	93.08	2.82
	(59.10)	(64.02)		(51.43)	(60.30)	
Investments available for sale	17.97	22.71	3.133	18.65	20.62	0.764
	(15.74)	(14.22)		(14.65)	(12.89)	
Other real estate owned ratio	0.744	0.869	0.880	0.709	0.290	2.003
	(1.267)	(2.117)		(1.288)	(0.410)	
Tier 1 leverage ratio	10.29	24.23	5.267	10.62	9.93	1.691
	(2.62)	(64.59)		(2.40)	(1.62)	
Percent of Loans on nonaccrual	1.760	2.499	2.430	1.033	0.491	2.216
	(2.617)	(4.810)		(1.511)	(0.410)	
Percent of branches in MSAs	0.525	0.718	4.705	0.500	0.765	3.563
	(0.443)	(0.278)		(0.446)	(0.239)	
Number of Observations	597	127		142	39	
Number of Banks	73	16		53	16	

Input orientation DEA score and in-out orientation DEA score calculated via the R package MMLPDEA by Atwood (2017). Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Small community banks have assets less than $250 million and medium-to-large banks have assets between $1 and $10 billion.

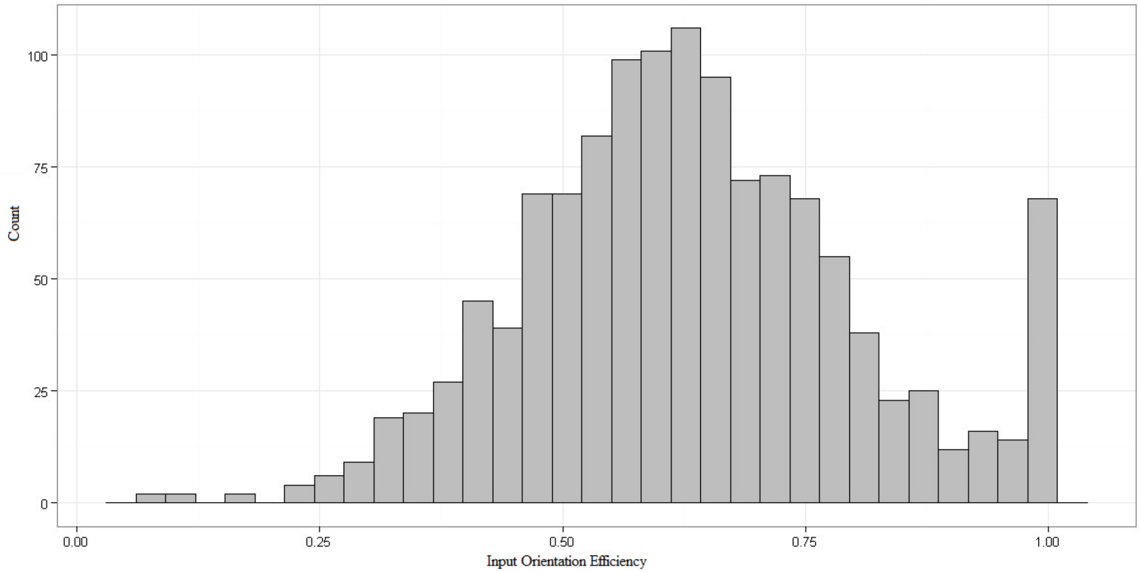

Figure 14: Histogram of *input orientation* DEA Scores

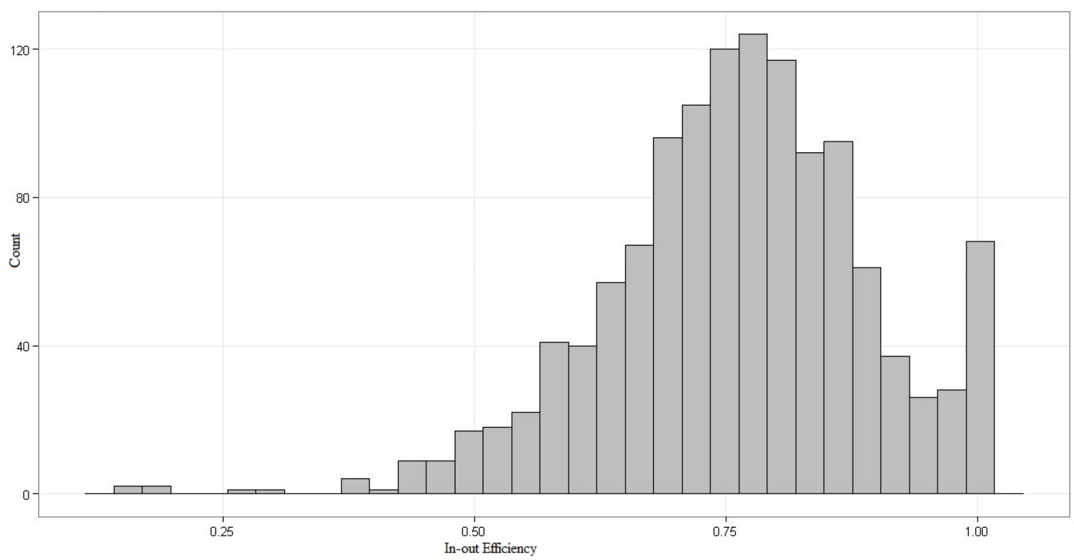

Figure 15: Histogram of *in-out orientation* DEA Scores

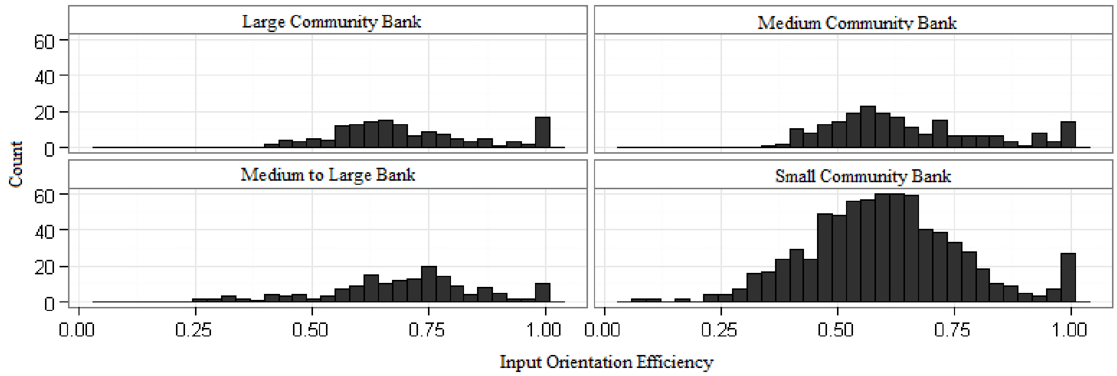

Figure 16: Histograms of *input orientation* DEA Scores by Bank Size

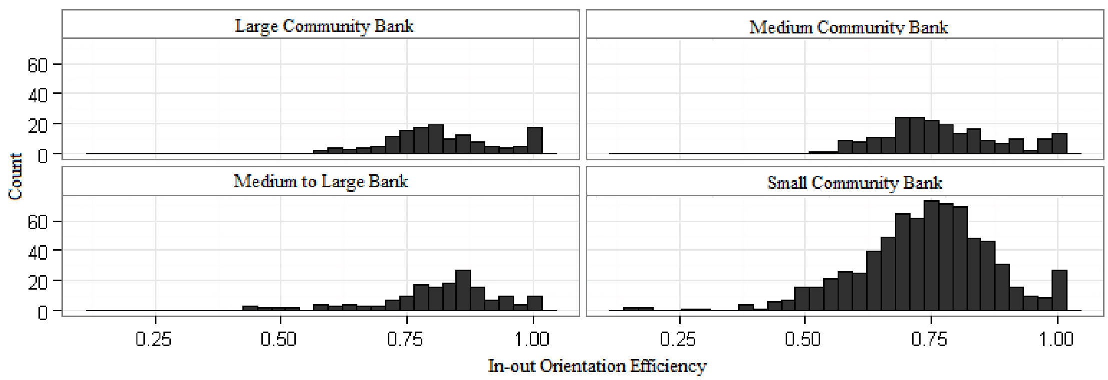

Figure 17: Histograms of *in-out orientation* DEA Scores by Bank Size

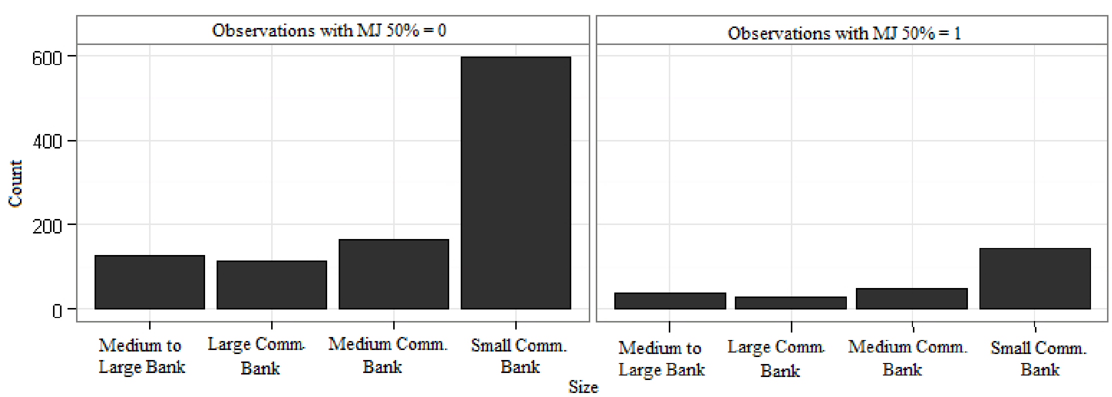

Figure 18: Histograms of Treatment Status by Bank Size

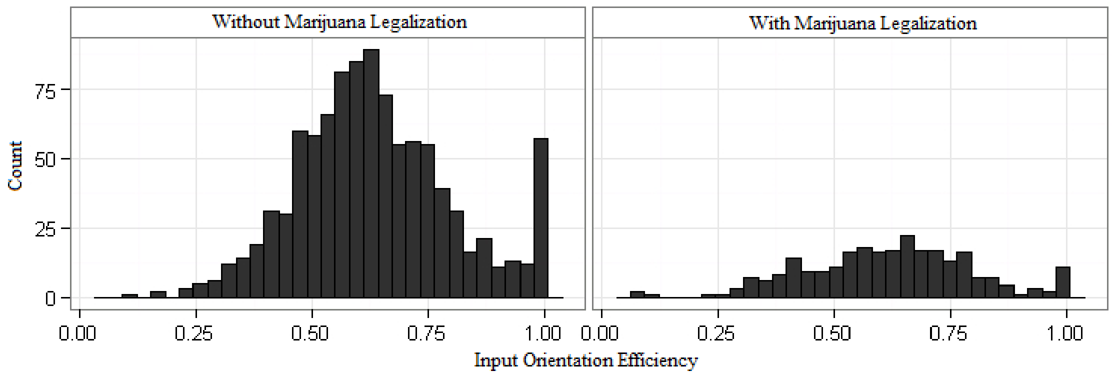

Figure 19: Histograms of *input orientation* DEA Scores by Treatment Status.

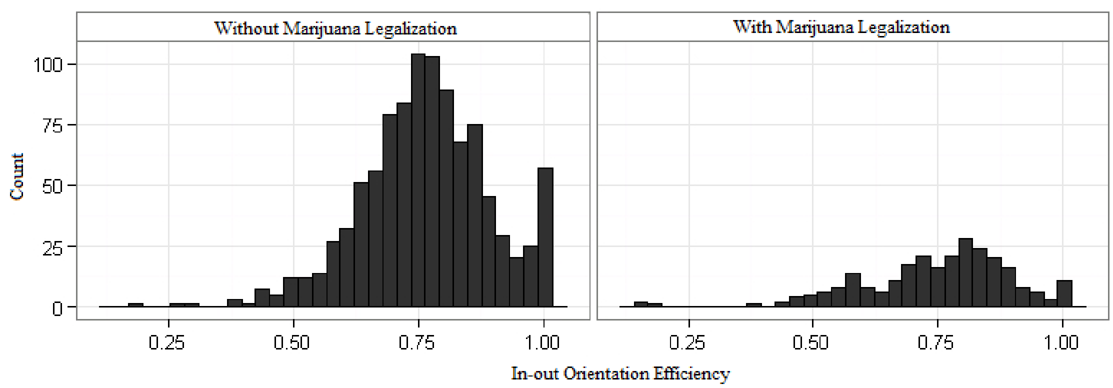

Figure 20: Histograms of *in-out orientation* DEA Scores by Treatment Status.

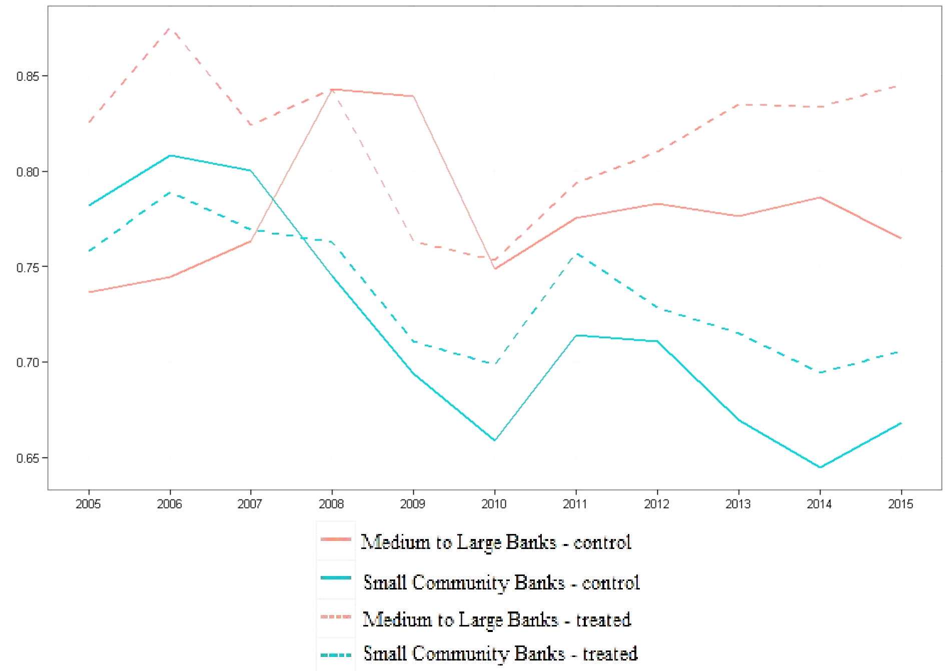

Figure 21: Mean *input orientation* by Bank Size and Treatment Status over Time.

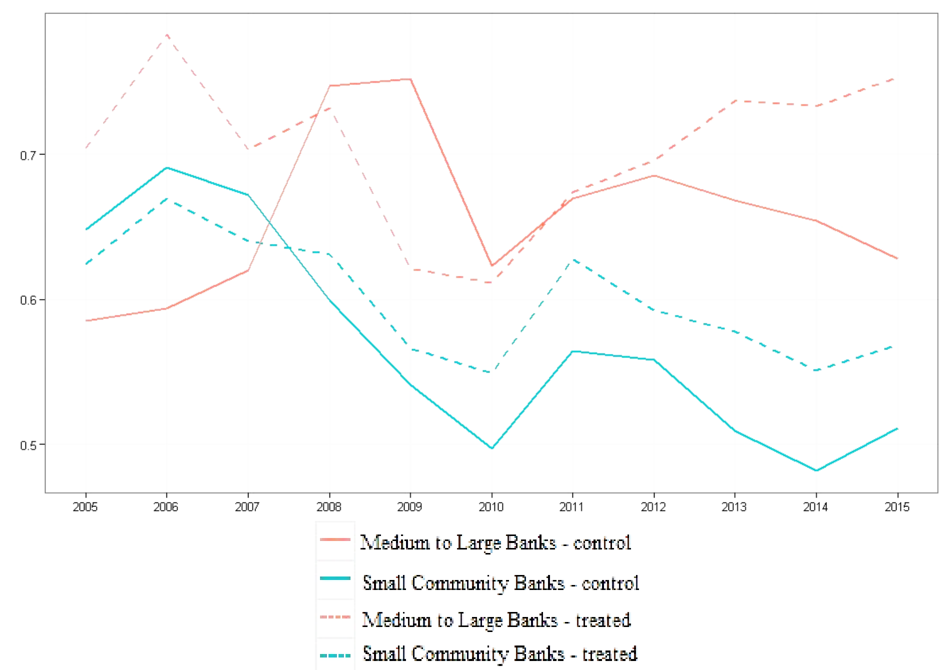

Figure 22: Mean *in-out orientation* by Bank Size and Treatment Status over Time.

EMPIRICAL METHODOLOGY

Identification Strategy and Model Specification

Because of the conflict between state and federal marijuana laws and research suggesting that increased regulation can have constraining effects on banks, there is ambiguity in predicting the effect of marijuana legalization on bank distance from the best practice hull overall. This effect could move banks closer to the hull, considering the increased business activity in legalization states. However, it could move banks further from the hull, because of the increased costs of regulatory compliance. Also, the effect may vary by how rural or metropolitan a bank is, with more metropolitan banks facing more money laundering risk. Considering the research on regulation and small bank performance, and the effect of anti-money laundering regulation on sources of community bank competitive advantages, I predict that marijuana legalization would have a negative effect on small bank DEA scores relative to larger bank scores. This study examines banks with at least 10 percent of their footprint in marijuana states at any point during the 12-year study period, and measures performance for those banks before and after legalization, while controlling for inherent bank characteristics. Variation in money laundering risk introduced exogenously by marijuana legalization in a subset of states provides the opportunity to examine a regulatory shock that is exogenous to the characteristics of the banks themselves. Additionally, I use different asset sizes to identify the differential impact of legalization due to bank size.

I use a fixed effects specification with bank and year fixed effects for several reasons. First, there is likely to be an unobserved error term associated with permanent differences across banks, so pooled OLS would result in biased and inconsistent results. Second, a random effects model is inappropriate because it is likely that the unobserved error associated with permanent differences across banks is correlated with independent variables, which are mostly financial measures. The fixed effects model accounts for both issues and includes time-varying control variables as well as permanent bank characteristics. To confirm the selection of a fixed effects model over pooled or random effects, I performed a Hausman test and the Breusch-Pagan Lagrange multiplier test. Results indicate the existence of an error term correlated with regressors and evidence of a panel effect, supporting a fixed effects specification. The fixed effects model also represents a triple difference: (1) the pre and post marijuana legalization indication is included in *MJ footprint 50%;* (2) treatment, which in this case involves the 50 percent threshold, is also included in *MJ footprint 50%*; and, (3) bank size is included in the bank size categorical indicator variables.

The model is specified as follows:

$$\textit{DEA score}_{i,t} = \beta_1 \textit{ MJ footprint } 50\%_{i,t} + \beta_2 \textit{ medium community bank}_{i,t} + \beta_3 \textit{ large community bank}_{i,t} + \beta_4 \textit{ medium-to-large bank}_{i,t} + \beta_5 \textit{ MJ footprint } 50\% \times \textit{medium community bank}_{i,t} + \beta_6 \textit{ MJ footprint } 50\% \times \textit{large community bank}_{i,t} + \beta_7 \textit{ MJ footprint } 50\% \times \textit{medium-to-large bank}_{i,t} + \delta_0 X_{i,t} + t + \alpha_i + \varepsilon_{i,t}$$

where $\textit{DEA score}_{i,t}$ is the input-orientation DEA score or the in-out orientation DEA score for bank *i* in year *t*. $\textit{MJ footprint } 50\%_{i,t}$ is the treatment indicator that is equal to one if a bank has more than 50 percent of their footprint in a marijuana state and the year is post-legalization for that state. *Medium community bank*$_{i,t}$, *large community bank*$_{i,t}$, and *medium-to-large bank*$_{i,t}$ are indicators for the size category for bank *i* in time *t*. Medium-to-large banks are the largest asset size category, larger than any community bank category in terms of asset size ranking. Although large community banks are the biggest size of community bank in terms of asset size, large community banks are smaller than medium-to-large banks. The smallest asset size category, *small community bank*$_{i,t}$, is omitted.[19] The variables of interest are *MJ* × *medium-to-large bank*$_{i,t}$, *MJ* × *large community bank*$_{i,t}$, and *MJ* × *medium community bank*$_{i,t}$ the interaction variables between bank size and the marijuana legalization treatment. I expect the coefficients on each interaction to be positive, implying that small community banks perform the worst after marijuana legalization on a relative, proportional basis. $X_{i,t}$ is a vector of time-varying bank characteristics. In particular, *real estate lending concentration, agricultural lending concentration*, and *commercial lending concentration, investments available for sale (%), other real estate owned ratio, percent of loans on nonaccrual*, and *tier 1 leverage ratio*. Finally, *t* is year fixed effects, α_i represents unobserved permanent bank characteristics (bank fixed effects), and $\varepsilon_{i,t}$ is the idiosyncratic error term. I expect all coefficients on bank controls to be positive except for the *other real estate owned ratio* and *nonaccrual loans*, because these represent declines in credit portfolio quality. Theoretically, the expected direction on *MJ footprint 50%* is ambiguous; while marijuana legalization introduces regulatory concerns, it also tends to correspond with economic growth.

[19] Note that the size category *small community bank* has the largest proportion of the observations in the sample at 58.7 percent, making it the largest category in terms of sample size.

RESULTS

Initial Regressions

To determine the extent of omitted variable bias present in an Ordinary Least Squares (OLS) model, I estimate three initial regressions prior to my preferred specification. In the first, I do not use any time-varying bank controls or bank fixed effects. In the second, I add time-varying bank controls, and in the third I add bank fixed effects. My preferred specification, discussed in the next section, uses both time-varying bank controls and bank fixed effects.

In the first OLS model with *input orientation* and *in-out orientation* as dependent variables in two separate regressions, I find an effect of 0.093 units and 0.067 units, respectively, for medium-to-large banks relative to small community banks after marijuana legalization. Results are reported in table 7. Both coefficients are statistically significant at the 5 percent level. For large community banks, which represent banks with more assets than medium community banks but fewer than medium-to-large banks, the effect is in the opposite direction. This effect is likely due to fixed effects associated with large community banks as this result does not persist in the preferred specification in table 10. The estimated coefficients on *MJ* × *large community bank* are -0.105 for *input orientation*, significant at the 1 percent level, and -0.064 for *in-out orientation*, significant at the 5 percent level. For the large community bank interaction, the coefficients represent 17.4 and 8.7 percent of mean small community bank DEA scores for input orientation and in-out orientation, respectively. I find no statistically significant effects for medium community banks relative to small community banks after legalization.

The coefficients on bank size indicators are all statistically significant at the 1 percent level for medium-to-large banks and large community banks, and at the 5 percent level for medium community banks. With *input orientation* as the dependent variable, medium-to-large banks are on average 0.074 units closer to the best practice frontier than small community banks, large community banks are 0.127 units closer, and medium community banks are 0.041 units closer. For *in-out orientation*, medium-to-large banks are 0.057 units closer, large community banks are 0.095 units closer, and medium community banks are 0.031 units closer to the best practice frontier than small community banks, on average, regardless of marijuana status. Additionally, having a footprint in a marijuana state of 50 percent or more resulted in a negative effect on both DEA scores, implying that marijuana legalization resulted in movement away from the best practice frontier for banks concentrated in marijuana states regardless of size. Banks of all sizes with over 50 percent of their footprint in marijuana states are on average 0.029 units further from the best practice frontier than those that are not, for *input orientation*, significant at the 10 percent level. For *in-out orientation*, the effect is also negative at 0.028, significant at the 5 percent level.

Coefficients in this model are likely biased due to omitted variable bias, as there are no controls in the model shown in table 7 that address bank specialization, capital ratios, or lending performance. These can be expected to affect competitive advantages and distance from the best practice frontier. Bank specialization and higher capital ratios can be expected to decrease distance to the best practice frontier, while poor lending performance would likely lead to movement away from the frontier. As reported in table 8, I add time-varying bank characteristics to the model, including real estate, agricultural, and commercial lending concentrations, the percent of loans on nonaccrual, the percent of bank branches in MSAs, the percent of investments available for sale, the other real estate owned ratio, and the tier one leverage ratio. This reduces the magnitudes of the coefficient on *MJ* × *medium-to-large bank* to 0.075 units for input orientation (significant at the 5 percent level) and by to 0.052 for in-out orientation (significant at the 10 percent level). The large community bank interaction, *MJ* × *large community bank*, remains negative, but the effect increases in magnitude to -0.119 with *input orientation* as the dependent variable and -0.071 with *in-out orientation* as the dependent variable, both statistically significant at the 1 percent significance level. This effect is likely due to bank fixed effects and time varying bank characteristics not simultaneously included in table 8. The coefficient on *MJ* × *medium community bank* remains statistically insignificant and small in magnitude.

As reported in table 8, the coefficients on asset size indicators are statistically significant, all at the 1 percent level except for the coefficient on *medium community bank* for input orientation, which is significant at the 5 percent level. With *input orientation* as the dependent variable, medium-to-large banks are on average 0.072 units closer to the best practice frontier than small community banks, large community banks are 0.093 units closer, and medium community banks are 0.034 units closer. Relative to the OLS estimates with no bank-level controls, these coefficients are smaller in magnitude by about 0.01-0.02 units. The bank size coefficients for *in-out orientation* are smaller in magnitude than the reduced OLS model, at 0.054 units for medium-to-large banks, 0.066 for large community banks, and 0.026 for medium community banks.

Banks with a footprint in a marijuana state of 50 percent experience a negative effect on both DEA scores. Banks of all sizes with over 50 percent of their footprint in marijuana states are on average 0.019 units further from the best practice frontier than those that are not, for *input orientation*, but this is not statistically significant. For *in-out orientation*, the effect is also negative at 0.018, also not statistically significant.

Another form of omitted variable bias that is likely present in the reduced form OLS regression is due to time-invariant, unobserved characteristics at the bank level. Additionally, the error terms for a bank may be serially correlated.

To address this, I run the OLS model with bank-level and year fixed effects, but without time-varying bank controls. Results are reported in table 9. Bank size and *MJ footprint 50%* interaction term coefficients are smaller in magnitude than in the original OLS regression for every size category and DEA orientation, except for *MJ* × *medium community bank* which increases by 0.01 in magnitude between the regressions. For *MJ* × *medium-to-large bank*, I find that medium-to-large banks are 0.077 units closer to the best practice frontier after marijuana legalization than small community banks on average for input orientation and 0.050 units closer for in-out orientation. Both coefficients are statistically significant at the 1 percent level. The effect for large community banks is negative, implying that large community banks are 0.051 and 0.032 units further from the best practice frontier after legalization than small community banks on average, significant at the 5 and 10 percent levels, respectively. This effect is diminished significantly in the preferred specification in table 10.

Controlling for bank-level fixed effects reduces the significance and magnitude of bank size indicators. For medium-to-large banks, the coefficients are no longer statistically significant at all. The coefficient on *large community bank* is 0.061 for input orientation and 0.044 for in-out orientation, significant at the 10 percent level, indicating that large community banks are 0.061 and 0.044 units closer to the best practice frontier than small community banks on average, for each orientation. The most statistically significant coefficient on a size indicator is on *medium community bank*, with 0.044 and 0.031 units for input and in-out orientation, respectively. Both were significant at the 1 percent level and indicate that medium community banks are closer to the frontier than small community banks. The effect of legalization changes signs from negative to positive in this model, with coefficients on *MJ footprint 50%* of 0.026 (significant at the 10 percent level) and 0.012 (not statistically significant).

Preferred Specification

Considering the possibility of omitted variable bias in the form of both fixed and time-varying bank characteristics, I run my final model with both bank and year fixed effects as well as with time-varying bank controls. Standard errors are robust to heteroscedasticity and clustered at the bank level.

Reported in Table 10, the coefficient on *MJ × medium-to-large bank* is 0.077 (significant at the 1 percent level) with *input orientation* as the dependent variable and

0.051 (significant at the 1 percent level) with *in-out orientation*. The direction is positive, as expected, in both regressions. Therefore, for banks that have at least 50 percent of their footprint in a marijuana state, medium-to-large banks are 0.077 units closer to the best practice hull based on input orientation after legalization relative to small community banks on average, and 0.051 units closer to the best practice hull in in-out orientation. Considering that the standard deviation of the input orientation DEA score for small banks across all 12 years is 0.166, this represents a relative movement away from the best practice hull of 46.4 percent of the standard deviation, or about half of a standard deviation. For in-out orientation, a coefficient of 0.051 represents 38.1 percent of the standard deviation, which is 0.134 for small community banks. This could be the result of treated small community banks moving away from the best practice hull, treated medium-to-large banks moving closer, or a combination of the two. These results indicate an economically significant difference in the relative performance when comparing small community banks and medium-to-large banks after marijuana legalization. Considering the competitive advantages experienced by medium-to-large banks in the form of technology, this conforms to the theory that small community banks should experience a relative increase in costs that is larger than the increase experienced by medium-to-large banks after marijuana legalization.

For the large community bank interaction term, the effect is reversed at -0.043 and -0.026 for *input orientation* and *in-out orientation*, respectively, but the coefficients are not statistically significant. *MJ* × *medium community bank* coefficients are not statistically significant for either measure, at -0.021 and -0.007. All *community* banks, whether small, medium, or large, experience a competitive disadvantage due to the capability of medium-to-large banks (non-community banks) to utilize, implement, and expand their information technology. Since the effect to small community banks likely comes from this relationship, it is expected that large community banks and medium community banks would respond to marijuana legalization similarly to small community banks. The estimated coefficients reflect this relationship.

Conforming to theory, the *other real estate owned ratio* has a statistically and economically significant adverse effect on performance, with coefficients of -0.026 and -0.021 for input and in-out orientation, respectively. A 1 percentage point increase in the *other real estate owned ratio* is correlated with around a 0.026 unit decrease in DEA scores. This represents a movement away from the best practice hull equal to 15.7 percent of the input orientation score standard deviation and 19.4 percent of the standard deviation of the in-out orientation score for all banks. The *tier 1 leverage ratio* is associated with movement toward the best practice frontier at 0.016 and 0.014 for input and in-out orientation, respectively, significant at the 0.1 percent level. This corresponds to 9.6 and 10.4 percent of each orientation standard deviation.

A statistically significant but economically insignificant contributor to DEA scores is real estate lending concentration at 0.001 for both input and in-out orientation, significant at the 1 percent level. Similarly, agricultural lending concentrations are associated with a 0.001 unit increase in input and in-out orientation, significant at the 1 percent level. These each represent less than one percent of the standard deviations of DEA scores in both orientations.

These results indicate a relationship between state-level marijuana legalization and small community banks moving further away from the best practice frontier relative to the performance of medium-to-large banks. However, the small total number of banks selected and low number of years post-legalization limit the robustness of these results. Using only 105 banks also limits the number of distinct inputs and outputs used to calculate DEA scores. As more time passes, this subject should be revisited with more years of financial data and a more flexible sampling methodology that allows for spillover effects across state lines or census track-level detail. However, because specific cost data related to expenses associated with anti-money laundering compliance are unavailable, the direct relationship between marijuana legalization and relative bank performance based on bank size remains unclear. This research did not incorporate the state-level variation in marijuana legalization implementation, which may also result in differential effects across a state.

Economic Costs

For input orientation, the coefficient on *MJ* × *medium-to-large banks* represents the proportion of input costs that medium-to-large banks saved in producing a given level of output relative to small community banks after marijuana legalization. In other words, it represents the relative input costs to small community banks caused by the competitive advantage experienced by medium-to-large banks after recreational marijuana legalization. This proportion is the movement of small community banks away from the best practice frontier relative to medium-to-large banks due to marijuana legalization.

For in-out orientation, the coefficient represents the combination of proportional inputs saved and additional outputs produced by the average medium-to-large bank relative to the average small community bank after marijuana legalization. This represents a relative increase in costs to small community banks. As discussed, this relative increase is likely due to the resource of information technology as it is implemented by medium-to-large banks to adapt to post-marijuana legalization regulatory expectations. This does not assume medium-to-large banks did not experience a cost increase; however, the increase in costs to medium-to-large banks was relatively smaller in magnitude than those to small community banks, the result of a sustained competitive advantage from technology.

As a result, to calculate the relative change in costs to small community banks due to marijuana legalization, I aggregate the inputs used by treated small community banks in each year and multiply them by the coefficient estimated in table 10 and do the same for inputs and outputs for the in-out model, 0.077 and 0.051, respectively. I then aggregate the estimated relatively higher costs for small community banks for each year. Results by year and in total are listed in table 11.

I find that in 2014, for the 45 small community banks with at least 50 percent of their footprint in a marijuana state after legalization have costs of $994,891 more than medium-to-large banks with at least 50 percent of their footprint in a marijuana state after legalization. For 2015, this number increases to $1,041,865 for 46 banks, and in 2016 reaches $1,378,927 for 51 banks. Across the three years, this totals $3.416 million in relatively higher input costs. Considering costs in input expenses as well as outputs using the in-out orientation coefficient, I find a cost of $831,391 in 2014, $878,128 million in 2015, and $1,154,128 in 2016. In total, small community banks faced relatively higher costs than medium-to-large banks of $2.864 million after recreational marijuana legalization. Therefore, the estimated relative cost increases to small community banks of recreational marijuana legalization with Bank Secrecy Act/anti-money laundering regulation in place are between $2.8 million and $3.4 million.

Table 7: Ordinary Least Squares Results

	OLS	
Dependent variable	Input orientation	In-out orientation
MJ × medium-to-large bank	0.093**	0.067**
	(0.037)	(0.029)
MJ × large community bank	-0.105***	-0.064**
	(0.029)	(0.029)
MJ × medium community bank	0.027	0.031
	(0.029)	(0.022)
MJ footprint 50%	-0.029*	-0.028**
	(0.007)	(0.014)
Medium-to-large bank	0.074***	0.057***
	(0.015)	(0.012)
Large community bank	0.127***	0.095***
	(0.016)	(0.011)
Medium community bank	0.041***	0.031***
	(0.015)	(0.011)
R^2	0.08	0.08
Adjusted R^2	0.07	0.07
Number of Observations	1260	1260
Number of Banks	105	105

Medium-to-large banks are between $1 and $10 billion in assets, large community banks are between $500 million and $1 billion in assets, medium community banks are between $250 and $500 million in assets, and small community banks, the excluded category, are <$250 million. MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Input orientation DEA score and in-out orientation DEA score calculated via the R package MMLPDEA by Atwood (2017). Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors clustered at the bank level are listed in parenthesis.

Table 8: Ordinary Least Squares with Bank-Level Controls Results

Dependent variable	Input orientation	In-out orientation
MJ × medium-to-large bank	0.075**	0.052*
	(0.037)	(0.029)
MJ × large community bank	-0.119***	-0.071***
	(0.029)	(0.022)
MJ × medium community bank	0.015	0.019
	(0.025)	(0.018)
MJ footprint 50%	-0.019	-0.018
	(0.014)	(0.011)
Medium-to-large bank	0.072***	0.054***
	(0.015)	(0.011)
Large community bank	0.093***	0.066***
	(0.014)	(0.010)
Medium community bank	0.034**	0.026***
	(0.014)	(0.010)
Real estate lend. concentration	0.001***	0.001***
	(0.000)	(0.000)
Agricultural lend. concentration	0.001***	0.001***
	(0.000)	(0.000)
Commercial lend. concentration	0.001***	0.001***
	(0.000)	(0.000)
Investments available for sale	-0.001	-0.003
	(0.001)	(0.004)
Other real estate owned ratio	-0.033***	-0.026***
	(0.005)	(0.004)
Tier 1 leverage ratio	0.021***	0.018***
	(0.003)	(0.002)
Percent of loans on nonaccrual	0.001	0.001
	(0.002)	(0.002)
Percent of branches in MSAs	0.006	-0.001
	(0.013)	(0.009)
R^2	0.28	0.32
Adjusted R^2	0.27	0.31
Number of Observations	1260	1260
Number of Banks	105	105

Medium-to-large banks are between \$1 and \$10 billion in assets, large community banks are between \$500 million and \$1 billion in assets, medium community banks are between \$250 and \$500 million in assets, and small community banks, the excluded category, are <\$250 million. MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Input orientation DEA score and in-out orientation DEA score calculated via the R package MMLPDEA by Atwood (2017). Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors clustered at the bank level are listed in parenthesis.

Table 9: Bank and Year Fixed Effects Results

Dependent variable	Input orientation	In-out orientation
MJ ×medium-to-large bank	0.077***	0.050***
	(0.024)	(0.019)
MJ ×large community bank	-0.051**	-0.032*
	(0.024)	(0.019)
MJ ×medium community bank	-0.04*	-0.018
	(0.019)	(0.015)
MJ footprint 50%	0.026*	0.012
	(0.015)	(0.012)
Medium-to-large bank	-0.057	-0.033
	(0.046)	(0.036)
Large community bank	0.061**	0.044**
	(0.028)	(0.021)
Medium community bank	0.044***	0.031***
	(0.028)	(0.010)
Bank Fixed Effects	Y	Y
Bank Controls	N	N
Year Fixed Effects	Y	Y
R^2	0.04	0.02
Adjusted R^2	0.03	0.02
Number of Observations	1260	1260
Number of Banks	105	105

Medium-to-large banks are between $1 and $10 billion in assets, large community banks are between $500 million and $1 billion in assets, medium community banks are between $250 and $500 million in assets, and small community banks, the excluded category, are <$250 million. MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Input orientation DEA score and in-out orientation DEA score calculated via the R package MMLPDEA by Atwood (2017). Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors clustered at the bank level are listed in parenthesis.

Table 10: Bank and Year Fixed Effects with Bank-Level Controls Results

	Input orientation	In-out orientation
MJ × medium-to-large bank	0.077***	0.051***
	(0.022)	(0.017)
MJ × large community bank	-0.043*	-0.026
	(0.025)	(0.019)
MJ × medium community bank	-0.021	-0.007
	(0.018)	(0.013)
MJ footprint 50%	0.026*	0.013
	(0.015)	(0.012)
Medium-to-large bank	-0.058	-0.038
	(0.045)	(0.036)
Large community bank	0.023	0.013
	(0.026)	(0.021)
Medium community bank	0.022	0.014
	(0.014)	(0.010)
Real estate lend. concentration	0.001***	0.001***
	(0.000)	(0.000)
Agricultural lend. concentration	0.001***	0.001***
	(0.000)	(0.000)
Commercial lend. concentration	0.000	0.000
	(0.000)	(0.000)
Investments available for sale	-0.001	0.000
	(0.001)	(0.001)
Other real estate owned ratio	-0.026***	-0.021***
	(0.005)	(0.004)
Tier 1 leverage ratio	0.016***	0.014***
	(0.004)	(0.003)
Percent of loans on nonaccrual	0.004*	0.003*
	(0.002)	(0.002)
Percent of branches in MSAs	-0.012	-0.009
	(0.037)	(0.028)
R^2	0.19	0.19
Adjusted R^2	0.17	0.17
Number of Observations	1260	1260
Number of Banks	105	105

Medium-to-large banks are between $1 and $10 billion in assets, large community banks are between $500 million and $1 billion in assets, medium community banks are between $250 and $500 million in assets, and small community banks, the excluded category, are <$250 million. MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Input orientation DEA score and in-out orientation DEA score calculated via the R package MMLPDEA by Atwood (2017). Financial information is collected from the Uniform Banking

Performance Report released by the Federal Financial Institutions Examination Council (2016). Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors clustered at the bank level are listed in parenthesis.

Table 11: Aggregate Costs of Recreational Marijuana to Small Community Banks

Input Orientation			
2014	2015	2016	Total
$994,891	$1,041,865	$1,378,927	$3,415,682
In-out Orientation			
2014	2015	2016	Total
$831,391	$878,128	$1,154,128	$2,863,647

Aggregate cost calculation for each for input orientation performed by aggregating the quantity of inputs for treated small community banks by year and multiplying by the coefficient on *MJ × Medium to Large Bank* estimated in the first column in table 10. For in-out orientation, the quantity of inputs and outputs are aggregated for treated small community banks by year and multiplying by the coefficient on *MJ × Medium to Large Bank* estimated in the second column in table 10.

ROBUSTNESS CHECKS

Difference-in-Difference Estimations by State

Marijuana laws vary by state, so I subsample my original 105 bank sample by state with a sample each for Colorado, Washington, Alaska, and Oregon. There are 63 sampled banks in Colorado (756 observations), 26 sampled banks in Washington (312 observations), 4 in Alaska (48 observations), and 12 in Oregon. I run separate difference-in-difference estimates for each state and then run the same difference-in-difference on the total sample. Results are reported in table 12 for input orientation and 13 for in-out orientation. Estimates are robust to heteroscedasticity and standard errors are clustered at the bank level. Because of the limited number of observations in each state, I use *community bank* to represent small, medium, and large community banks, while *medium-to-large bank* remains the same. *Community bank* is the omitted category, and *Post* represents a dummy variable equal to one if the year of observation is after legalization. Bank controls are identical to the preferred fixed effects specification described above. This approach only uses the footprint measure to the extent that it was used in the original sampling of 105 banks.

The difference-in-difference estimates for all 105 banks produce results in the same direction as the preferred, triple-difference fixed effects specification in table 10, but the magnitudes are different. This model does not account for the extent to which a bank is in a given state, and treats banks with a small percentage of their footprint in marijuana states as the same as those with a large percentage. The coefficient on *Post* ×

Medium-to-Large is 0.057 for input orientation (significant at the 1 percent level) and 0.038 for in-out orientation (significant at the 5 percent level). This indicates that, comparing all community banks with medium to large banks, medium to large banks are 0.057 and 0.038 units closer to the best practice frontier than community banks on average after recreational marijuana legalization. Legalization has an overall negative effect of 0.024 and 0.020 for input and in-out orientation, significant at the 1 percent level. Medium-to-large banks are estimated to be further on average from the best practice frontier than community banks, with a statistically significant coefficient on *Medium-to-Large* of negative 0.085 and negative 0.055 for input and in-out orientation, respectively.

The results in Colorado are in the same direction as the preferred specification and the combined difference-in-difference, with an input orientation coefficient of 0.105, significant at the 1 percent level. This result implies that non-community banks are 0.105 units closer to the best practice frontier after 2014 than community banks, the year of the first recreational marijuana sale in Colorado. For in-out orientation, the coefficient on *Post* × *Medium-to-Large* is 0.076, indicating that community banks are 0.076 units further from the best practice frontier after marijuana legalization than medium-to-large banks. Unlike in the preferred specification, there is a statistically significant effect of marijuana legalization on DEA scores overall, a negative effect of 0.017 for each orientation, significant at the 10 and 5 percent levels for input and in-out orientation, respectively. Furthermore, medium-to-large banks are estimated to be further from the best practice frontier on average than community banks, with a coefficient on *Medium-to-*

Large Bank of negative 0.171 units, significant at the 5 percent level for input orientation and negative 0.136 units, significant at the 5 percent level for in-out orientation.

The estimate of the coefficient on *Post* × *Medium-to-Large* in Washington is 0.072 (significant at the 5 percent level) for input orientation, but for in-out orientation, the coefficient is not statistically significant. As with Colorado, the coefficient on *Post* is negative at 0.050 for input orientation and 0.038 for in-out orientation, both significant at the 1 percent level. The coefficients on *Medium-to-Large* are not statistically significant for either orientation.

In Alaska, results are inverted, with a coefficient on *Post* × *Medium-to-Large* of negative 0.105 and negative 0.071 for input and in-out orientation, respectively (significant at the 10 percent level). With only 4 banks and one year of treated data, Alaska's results are not very informative.

Estimated coefficients on *Post* × *Medium-to-Large* return to the positive direction with 0.081 in the input orientation (significant at the 1 percent level) and 0.041 in the in-out orientation (significant at the 5 percent level). Estimates of the coefficients on *Post* and *Medium-to-Large* alone are not statistically significant.

State-level difference-in-difference estimates are generally similar to the results in the primary triple difference fixed effects specification in terms of direction, and fall between 0.072 and 0.105 in magnitude (other than Alaska), compared to 0.057 for the combined double difference in input orientation.

Table 12: Difference-in-Difference Estimation by State Results – Input Orientation

	Colorado	Washington	Alaska	Oregon	Combined
Post × Medium-to-Large Bank	0.105***	0.072**	-0.105*	0.081***	0.057***
	(0.026)	(0.036)	(0.057)	(0.028)	(0.021)
Post	-0.017*	-0.050***	-0.013	0.035	-0.024***
	(0.001)	(0.016)	(0.024)	(0.024)	(0.007)
Medium-to-Large Bank	-0.171**	-0.034	-0.0020	-0.046	-0.085***
	(0.081)	(0.037)	(0.044)	(0.056)	(0.030)
Real Estate Lend. Concentration	0.001***	0.000***	-0.001***	0.000**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Agricultural Lend. Concentration	0.001***	0.002***	0.064***	-0.0010	0.001***
	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)
Commercial Lend. Concentration	0.000**	0.000	0.001*	0.0000	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Investments Available for Sale	0.001**	-0.002	-0.005	-0.027*	0.000
	(0.001)	(0.004)	(0.003)	(0.001)	(0.000)
Other Real Estate Owned Ratio	-0.009	-0.040***	-0.0261	-0.046***	-0.023***
	(0.006)	(0.008)	(0.047)	(0.015)	(0.005)
Tier 1 Leverage Ratio	0.024***	0.002	-0.053***	0.017**	0.015***
	(0.004)	(0.007)	(0.014)	(0.007)	(0.004)
Percent of Loans on Nonaccrual	0.000	0.003	0.039***	-0.006	0.001
	(0.002)	(0.004)	(0.011)	(0.003)	(0.001)
Percent of Branches in MSAs	-0.047	0.139	0.616**	-0.134	0.011
	(0.033)	(0.124)	(0.218)	(0.341)	(0.037)
Adjusted R2	0.19	0.28	0.39	0.30	0.17
Number of Banks	63	26	4	12	105

Medium-to-large banks are between $1 and $10 billion in assets, community banks (excluded) are between $250 and $1 billion in assets. Post is equal to one if the year of observation is after recreational marijuana legalization. Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors clustered at the bank level are listed in parenthesis.

Table 13: Difference-in-Difference Estimation by State Results – In-out Orientation

Dependent variable	Colorado	Washington	Alaska	Oregon	Combined
Post × Medium-to-Large Bank	0.076***	0.046	-0.071*	0.041**	0.038**
	(0.019)	(0.028)	(0.040)	(0.020)	(0.016)
Post	-0.017**	-0.038***	-0.006	0.028	-0.020***
	(0.007)	(0.012)	(0.018)	(0.019)	(0.006)
Medium-to-Large Bank	-0.136**	-0.012	0.0071	0.007	-0.055**
	(0.068)	(0.026)	(0.028)	(0.033)	(0.024)
Real Estate Lend. Concentration	0.001***	0.000***	-0.001**	0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Agricultural Lend. Concentration	0.001***	0.001***	0.042***	0.000	0.001***
	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)
Commercial Lend. Concentration	0.000***	0.000	0.001*	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Investments Available for Sale	0.001***	-0.001	-0.003	-0.002*	0.000
	(0.000)	(0.001)	(0.002)	(0.001)	(0.000)
Other Real Estate Owned Ratio	-0.008*	-0.032***	-0.016	-0.038***	-0.019***
	(0.004)	(0.006)	(0.033)	(0.013)	(0.004)
Tier 1 Leverage Ratio	0.022***	0.002	-0.034***	0.012**	0.013***
	(0.003)	(0.005)	(0.009)	(0.006)	(0.003)
Percent of Loans on Nonaccrual	0.000	0.003	0.024***	-0.005*	0.001
	(0.002)	(0.003)	(0.007)	(0.003)	0.002
Percent of Branches in MSAs	-0.039	0.108	0.419**	-0.107	0.006
	(0.025)	(0.092)	(0.159)	(0.285)	(0.028)
Adjusted R2	0.22	0.28	0.39	0.30	0.18
Number of Banks	63	26	4	12	105

Medium-to-large banks are between $1 and $10 billion in assets, community banks (excluded) are between $250 and $1 billion in assets. Post is equal to one if the year of observation is after recreational marijuana legalization. Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors clustered at the bank level are listed in parenthesis.

Tobit Model

The ranges of *input orientation* and *in-out orientation* are both [0,1], and while there are no banks sampled for which either DEA score is zero, there are observations bunched at one for both measures. The DEA scores across all banks are restricted such that *input orientation* and *in-out orientation* are less than or equal to one; as a result, these observations are censored from above, implying that the “true” DEA score might be equal to the threshold or might be higher. An Ordinary Least Squares (OLS) regression is biased and inconsistent on the complete sample if the dependent variable is constrained and there is clustering at the constraint. To address this problem, I re-estimate my primary specification in a tobit model. The tobit model estimates a linear relationship in the presence of a censored dependent variable, acknowledging that there is an underlying latent variable subject to censoring. [20] This latent variable is unobservable and represents the true value of the censored variable when censoring is not applied.

As reported in table 14, I find that the coefficients on *MJ × medium-to-large bank* are similar to the estimated coefficients from my primary specification. Specifically, for *input orientation* I estimate an average effect of 0.078 (compared to 0.077 reported in the preferred specification in table 10) significant at the 1 percent level. For *in-out orientation*, the coefficient is 0.056 (compared to 0.051 reported in table 10), significant at the 5 percent level. Thus, the tobit model estimates for the coefficient of interest are

[20] The interpretation of tobit regression coefficients is similar to OLS regression coefficient interpretations, but the linear effect is on the uncensored latent variable rather than the observed outcome.

higher in magnitude than the fixed effects results, and of similar statistical significance.[21] For *MJ* × *large community bank*, I find effects that are larger in magnitude and more statistically significant than the fixed effects specification, with estimates of negative 0.012 and negative 0.077 significant at the 1 percent level. These results indicate that large community banks perform significantly *worse* on average than small community banks after marijuana legalization. The difference in magnitude between the fixed effects specification, at negative 0.04, and the tobit model, at negative 0.12, is substantial, indicating that the inclusion of fixed effects appropriately identifies permanent unobserved bank characteristics that account for the difference in performance between small community banks and large community banks. The coefficients on *MJ* × *medium community bank* are not statistically significantly different from zero and are small in magnitude at 0.014 and 0.019 for *input orientation* and *in-out orientation*, respectively.

Most of the estimated tobit coefficients are similar to the fixed effects specification for both dependent variables, including the coefficients on *real estate* and *agricultural lending concentration* where point estimates are within 0.001 between the two models.

The tobit model addresses the potential for positively biased coefficients due to censoring. The larger magnitudes of tobit model estimates indicate that the fixed effects model is the more conservative model.

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[21] To my knowledge, standard error clustering for right-censored data are not currently available. Results reflect original, unclustered standard errors.

Table 14: Fixed Effects Tobit Model with Bank-Level Controls Results

Dependent variable	Input orientation	In-out orientation
MJ × medium-to-large bank	0.078***	0.056**
	(0.031)	(0.023)
MJ × large community bank	-0.012***	-0.077***
	(0.034)	(0.026)
MJ × medium community bank	0.014	0.019
	(0.028)	(0.021)
MJ footprint 50%	-0.019	-0.019*
	(0.014)	(0.011)
Medium-to-large bank	0.072***	0.054***
	(0.015)	(0.015)
Large community bank	0.100***	0.072***
	(0.016)	(0.012)
Medium community bank	0.036***	0.028***
	(0.013)	(0.010)
Real estate lend. concentration	0.001***	0.000***
	(0.000)	(0.000)
Agricultural lend. concentration	0.001***	0.001***
	(0.000)	(0.000)
Commercial lend. concentration	0.001***	0.001***
	(0.000)	(0.000)
Investments available for sale	-0.001*	-0.000
	(0.000)	(0.0003)
Other real estate owned ratio	-0.034***	-0.027***
	(0.004)	(0.003)
Tier 1 leverage ratio	0.023***	0.019***
	(0.002)	(0.001)
Percent of loans on nonaccrual	0.000	0.001
	(0.002)	(0.001)
Percent of branches in MSAs	0.005	-0.000
	(0.013)	(0.010)
Right-Censored Observations	48	52
Number of Observations	1260	1260
Number of Banks	105	105

Medium-to-large banks are between $1 and $10 billion in assets, large community banks are between $500 million and $1 billion in assets, medium community banks are between $250 and $500 million in assets, and small community banks, the excluded category, are <$250 million. MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Input orientation DEA score and in-out orientation DEA score calculated via the R package MMLPDEA by Atwood (2017). Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors are listed in parenthesis.

Fixed Effects with Income and Expense Dependent Variable

To examine the direct effects of marijuana legalization and bank size on explicit income statement line items, I use logged personnel expense, occupancy expense, other non-interest expense, interest income, noninterest income, and net income as the dependent variable in six additional regressions. The independent variables and bank and year fixed effects are identical to those in my primary fixed effects specification with input and in-out orientation DEA scores as the dependent variables. I find that marijuana legalization leads to increases in expenses for medium-to-large banks compared to small community banks (see table 15) that are offset by increases in both interest income and non-interest income (see table 16). In table 17, the coefficient on *MJ × medium-to-large bank* when regressed on logged net income is 0.182, indicating that net income for medium-to-large banks after marijuana legalization is 18.2 percent higher on average than for small community banks, significant at the 1 percent level.

For specific expenses, the most direct effects of marijuana legalization would be expected in personnel expenses, due to the potential for needing more technically skilled workers or more labor hours to manage BSA/anti-money laundering regulation compliance, and other noninterest expense, due to investments in technology and audit reviews. While the coefficients on *MJ footprint 50%* are not statistically significant, the marijuana legalization term interacted with bank size is statistically significant for medium-to-large banks and large community banks. For personnel expense, medium-to-large banks have 30.7 percent higher personnel expenses after marijuana legalization compared to small community banks on average, while large community banks have 19.4

percent higher personnel expense compared to small community banks. For occupancy expense, the effects are 31.4 percent and 17.2 percent for medium-to-large and large community banks, respectively, after marijuana legalization. Bank size is correlated with higher occupancy expenses since more assets tends to imply more brick-and-mortar branches, and therefore higher rent expenses. With other noninterest expense as the left-hand side variable, the effect of marijuana legalization is estimated to be a 15.7 percent increase for medium to large banks and 11.5 percent for large community banks. There is no such effect for medium community banks.

On the income side, both interest income and noninterest income increase more for medium-to-large banks on average than small community banks after marijuana legalization. For logged interest income, the effect is 16.6 percent, significant at the 1 percent level. For logged noninterest income, the effect is 36.2 percent, significant at the 1 percent level. The effect for large community banks relative to small community banks after legalization is smaller in magnitude and significance, at 8.5 percent. However, the coefficient on *MJ × large community bank* with logged noninterest income as the dependent variable is similar to the effect for the medium-to-large bank interaction at 33.9 percent. The medium community bank interaction has no statistically significant effect for logged interest income or logged interest income.

Large community banks perform better relative to small community banks using the cost and revenue-based dependent variables than they do using the DEA scores as dependent variables. This could be due to a difference in loan production, which is used as an output in data envelopment analysis. DEA measures costs and revenues, but also incorporates output volume that is not captured in regressions with expense and income dependent variables.

Table 15: Fixed Effects with Logged Costs as Dependent Variables Results

Dependent Variable (Logged)	Personnel Expense	Occupancy Expense	Other Noninterest Expense
MJ × medium-to-large bank	0.307***	0.314***	0.157***
	(0.062)	(0.066)	(0.059)
MJ × large community bank	0.194***	0.172***	0.115**
	(0.050)	(0.065)	(0.052)
MJ × medium community bank	0.004	0.010	-0.062
	(0.039)	(0.045)	(0.040)
MJ footprint 50%	-0.023	-0.071*	0.013
	(0.034)	(0.040)	(0.039)
Medium-to-large bank	0.583***	0.649***	0.515***
	(0.075)	(0.093)	(0.086)
Large community bank	0.399***	0.455***	0.366***
	(0.051)	(0.071)	(0.061)
Medium community bank	0.200***	0.251***	0.178***
	(0.034)	(0.041)	(0.035)
Real estate lend. concentration	0.001***	0.000**	0.000
	(0.000)	(0.000)	(0.000)
Agricultural lend. concentration	0.001*	0.002***	0.001**
	(0.000)	(0.000)	(0.000)
Commercial lend. concentration	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Investments available for sale	0.001	0.000	0.002*
	(0.001)	(0.001)	(0.001)
Other real estate owned ratio	0.026**	0.017	0.046***
	(0.011)	(0.010)	(0.010)
Tier 1 leverage ratio	0.011	-0.008	-0.007
	(0.007)	(0.007)	(0.009)

Dependent Variable (Logged)	Personnel Expense	Occupancy Expense	Other Noninterest Expense
Percent of loans on nonaccrual	-0.001	0.001	0.005
	(0.004)	(0.003)	(0.003)
Percent of branches in MSAs	0.459***	0.576***	0.576**
	(0.158)	(0.223)	(0.230)
R^2	0.15	0.16	0.12
Adjusted R^2	0.14	0.14	0.10
Number of Observations	1260	1260	1260
Number of Banks	105	105	105

Medium-to-large banks are between $1 and $10 billion in assets, large community banks are between $500 million and $1 billion in assets, medium community banks are between $250 and $500 million in assets, and small community banks, the excluded category, are <$250 million. MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors clustered at the bank level are listed in parenthesis.

Table 16: Revenues as Dependent Variables Results

Dependent Variable (Logged):	Interest Income	Noninterest Income
MJ × medium-to-large bank	0.166***	0.362***
	(0.052)	(0.103)
MJ × large community bank	0.085*	0.339***
	(0.046)	(0.089)
MJ × medium community bank	-0.039	0.085
	(0.039)	(0.077)
MJ footprint 50%	0.008	-0.040
	(0.033)	(0.076)
Medium-to-large bank	0.816***	0.365***
	(0.089)	(0.130)
Large community bank	0.5314***	0.397***
	(0.059)	(0.091)
Medium community bank	0.273***	0.181***
	(0.037)	(0.060)
Real estate lend. concentration	0.001***	-0.001
	(0.000)	(0.000)
Agricultural lend. concentration	0.001**	-0.001**
	(0.000)	(0.001)
Commercial lend. concentration	-0.000	-0.001
	(0.000)	(0.001)
Investments available for sale	0.0027**	-0.005
	(0.001)	(0.003)
Other real estate owned ratio	-0.022*	0.040*
	(0.013)	(0.023)
Tier 1 leverage ratio	-0.003	-0.026*
	(0.009)	(0.018)
Percent of loans on nonaccrual	0.005	-0.003
	(0.006)	(0.007)
Percent of branches in MSAs	0.629**	0.352
	(0.282)	(0.246)
R^2	0.21	0.05
Adjusted R^2	0.19	0.04
Number of Observations	1260	1260
Number of Banks	105	105

Medium-to-large banks are between $1 and $10 billion in assets, large community banks are between $500 million and $1 billion in assets, medium community banks are between $250 and $500 million in assets, and small community banks, the excluded category, are <$250 million. MJ footprint 50% is constructed using US Census

Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors clustered at the bank level are listed in parenthesis.

Table 17: Logged Net Income as Dependent Variable Results

Dependent variable (Logged)	Net Income
MJ × medium-to-large bank	0.182***
	(0.068)
MJ × large community bank	0.017
	(0.012)
MJ × medium community bank	-0.011
	(0.017)
MJ footprint 50%	0.005
	(0.012)
Medium-to-large bank	-0.062
	(0.040)
Large community bank	0.030
	(0.032)
Medium community bank	0.037
	(0.027)
Real estate lending concentration	-0.000
	(0.000)
Agricultural lending concentration	0.000
	(0.000)
Commercial lending concentration	-0.000
	(0.000)
Investments available for sale	-0.0018
	(0.0019)
Other real estate owned ratio	0.010
	(0.017)
Tier 1 leverage ratio	-0.000
	(0.005)
Percent of loans on nonaccrual	-0.025
	(0.017)
Percent of branches in MSAs	-0.001
	(0.056)
R^2	0.09
Adjusted R^2	0.08
Number of Observations	1260
Number of Banks	105

Medium-to-large banks are between $1 and $10 billion in assets, large community banks are between $500 million and $1 billion in assets, medium community banks are between $250 and $500 million in assets, and small community banks, the excluded category, are <$250 million. MJ footprint 50% is constructed using US Census Bureau (2010) and Federal Deposit Insurance Corporation (2016) information and represents an indicator equal to 1 if a bank has 50% of its servable population in a marijuana state after recreational marijuana legalization. Financial information is collected from the Uniform Banking Performance Report released by the Federal Financial Institutions Examination Council (2016). Asterisks denote significance, ***p<0.01, **p<0.05, *p<0.1. Standard errors clustered at the bank level are listed in parenthesis.

CONCLUSION

After the legalization of marijuana, small community banks operating in the marijuana states are further from the best practice hull generated by the banks in the sample than medium-to-large banks, on average. The difference in relative performance could be driven by either small community banks moving further from the hull, medium-to-large banks moving closer, or a combination of both. Small community banks have declined significantly in number in the past decade, and additional pressure on small community bank competitive advantages resulting from differences in the use of technology, response to regulation, and approach to hard or soft information may have an adverse effect on the number of these banks that are available. Competitive advantages held by small community banks are reduced in markets where technological innovations are prominent, and medium-to-large banks benefit by utilizing technology to keep costs lower in responding to increased regulatory requirements. Additionally, marijuana legalization and the accompanying regulatory changes can be thought of as producing a transfer of wealth from small community banks to medium-to-large banks, in the form of the relative net income gains medium-to-large banks experience.

This transfer is not insignificant; the effect on small community bank distance from the best practice frontier relative to medium-to-large banks after marijuana legalization is between seven and thirteen percent of the average small community bank distance, depending on the measure of distance used. This corresponds to additional costs to small community banks in the form of additional expenses for inputs or a reduction in revenues from outputs of $2.9 million to $3.4 million from 2014 to 2016. Considering that more states are expected to legalize recreational marijuana and begin recreational marijuana sales in the coming years, and that the federal government has not indicated a change in national marijuana laws, the performance gap between small community banks and medium-to-large banks may continue to grow.

REFERENCES CITED

Akhigbe, A., and J.E. McNulty. (2005). "Profit Efficiency Sources and Differences Among Small and Large U.S. Commercial Banks." *Journal of Economics and Finance*, 29(3): 289-299.

Akhigbe, A., and J.E. McNulty. (2003). "The Profit Efficiency of Small U.S. Commercial Banks." *Journal of Banking & Finance*, 27(2): 307-325.

Aly, H., Grabowski, R., Pasurka, C., & Rangan, N. (1990). "Technical, Scale, and Allocative Efficiencies in U.S. Banking: An Empirical Investigation." *The Review of Economics and Statistics*: *72*(2): 211.

Atwood, J.A., and S. Shaik. (2016). "Quantile DEA: Estimating qDEA-α Efficiency Estimates with Conventional Linear Programming." *Staff paper.*

Atwood, J. A. (2017). MMLPDEA: FORTRAN LP interface and DEA-DDEA modeling and bootstrapping. R package version 1.07. http://www.montana.edu/atwood/rdata/MMLPDEA-manual.pdf

Atwood, J.A., and S. Shaik. (2018). Quantile DEA: Estimating qDEA-α Efficiency Estimates with Conventional Linear Programming. New York City, NY: Springer International Publishing AG.

Baldwin, F. (2003). "Money laundering countermeasures with primary focus upon terrorism and the USA Patriot Act 2001." *Journal of Money Laundering Control*, *6*(2): 105-136.

Balooni, A. (2017). "How Technology is Helping Overcome Anti-Money Laundering Challenges." *BankNXT.* Retrieved from https://banknxt.com.

Barney, J. (1991). "Firm Resources and Sustained Competitive Advantage." *Journal of Management*, 17(1): 99-120.

Bartel, A., and Thomas, L. (1987). "Predation through Regulation: The Wage and Profit Effects of the Occupational Safety and Health Administration and the Environmental Protection Agency." *The Journal of Law and Economics*, 30(2): 239-264.

Beck, T., Kunt, A., and Maksimovic, V. (2005). "Financial and legal constraints to growth: Does firm size matter?" *The Journal of Finance*, 60: 137–177.

Benston, G.J., Hanweck, G.A., Humphrey, D.B. (1982). "Scale Economies in Banking." *Journal of Money, Credit and Banking*, 14: 426-455.

Berger, A.N., Goulding, W., Rice, T. (2014). "Do Small Businesses Still Prefer Community Banks?" *Journal of Banking & Finance*, 44: 264-278.

Berger, A.N. and Mester, L.J. (1997). “Inside the black box: What explains differences in the efficiencies of financial institutions?” *Journal of Banking & Finance,* 21 (7): 895–947.

Chang, E. (2017). “Here Are the Next 6 States Likely to Legalize Recreational use of Marijuana.” *The Street*, April 23, 2017.

Charnes, A., Cooper, W.W., and Rhodes, E. (1978). “Measuring the Efficiency of Decision Making Units.” *European Journal of Operational Research,* 2: 429-444.

Cohen, B. (2015). “Marijuana Dispensaries Not Feeling So High: Financial Institutions Close Their Doors to State-Legalized Marijuana Businesses.” *Review of Banking and Financial Law,* 35: 72-78.

Cole, R.A., Goldberg, L.G., White, L.J. (2004). “Cookie Cutter vs. Character: The Micro Structure of Small Business Lending by Large and Small Banks.” *Journal of Financial and Quantitative Analysis,* 39 (2): 227-251.

Cook, W.D., and Seiford, L.M. (2009). “Data Envelopment Analysis (DEA) – Thirty Years On.” *European Journal of Operational Research,* 192 (1): 1-17.

Cooper, W.W., Seiford, L.M., and Tone, K. (2006). Introduction to Data Envelopment Analysis and Its Uses (pp. 4-5). New York, NW: Springer Science and Business Media, LLC.

DeYoung, R. and Hunter, W.C. (2001). “Deregulation, the Internet, and the Competitive Viability of Large Banks and Community Banks.” *Federal Reserve Bank of Chicago Working Paper Series* WP-2001-11: 1–37.

DeYoung, R., Hunter, W.C., Udell, G.F. (2004). “The Past, Present, and Probable Future for Community Banks.” *Journal of Financial Services Research,* 25:85.

Dolar, B. & Shughart, W. (2007). “The wealth effects of the USA Patriot Act: evidence from the banking and thrift industries.” *Journal of Money Laundering Control*, *10*(3): 300-317.

Dolar, B. & Shughart, W. (2012). “The USA Patriot Act's differential impact on large and small banks: Evidence from California's high-risk money laundering and related financial crime areas.” *Journal of Banking Regulation, 13*(2): 127-146.

Farrell, M.J. (1957). “The Measurement of Productive Efficiency.” *Journal of the Royal Statistical Society, Series A,* 120(3): 253-290.

Federal Deposit Insurance Corporation. (2006). "Concentrations in Commercial Real Estate Lending, Sound Risk Management Practices." *Press Release,* December 12, 2006.

Federal Deposit Insurance Corporation. (2012). "Community Banking by the Numbers: The FDIC Community Banking Research Project." *FDIC Future of Community Banking Conference,* February 16, 2012.

Federal Deposit Insurance Corporation. (2014). "12 CFR Part 327 Final Rule." *News,* November 18, 2014.

Federal Financial Institutions Examination Council, (2014). "Bank Secrecy Act/Anti-Money Laundering Examination Manual." Washington, D.C.

Financial Crimes Enforcement Network, (2014). "BSA Expectations Regarding Marijuana-Related Businesses." Washington, D.C.

Financial Crimes Enforcement Network, (2014). "Guidance Clarifies Expectations of Financial Institutions Serving Marijuana Businesses." Washington, D.C.

Gilbert, R.A., Meyer, A. P., & Fuchs, J.W. (2013). "The Future of Community Banks: Lessons from Banks that Thrived During the Recent Financial Crisis." *Federal Reserve Bank of St. Louis Review*, 95(2): 115-43.

Henningsen, A. (2017). censReg: Censored Regression (Tobit) Models. R package version 0.5. http://CRAN.R-Project.org/package=censReg.

Hetzer, W. (2003). "Money Laundering and Financial Markets." *European Journal of Crime, Criminal Law and Criminal Justice, 11*(3): 264-277.

Hinterseer, K. (1997). "An Economic Analysis of Money Laundering." *Journal of Money Laundering Control*: *1*(2), 154-164.

Ingber, J., and Kherlopian, A. (2017). "5 AML Technologies You Must Understand." *Banking Exchange.* Retrieved from https://www.bankingexchange.com.

Ingold, J. (2014). "World's First Legal Recreational Marijuana Sales Begin in Colorado." *The Denver Post*. Retrieved from https://www.denverpost.com.

Johnson, K. (2014). "Sales of Recreational Marijuana Begin in Washington State." *The New York Times*. Retrieved from https://www.nytimes.com.

Klingler, R., and Hightower, J. (2017). "Landscape of the U.S. Banking Industry." *Bank Bryan Cave.* Retrieved from https://www.bankbryancave.com.

Laslo, M. (2017). "American High: State-by-State Guide to Legal Pot." *Rolling Stone*. Retrieved from https://www.rollingstone.com.

Morris, C.S. and Regehr, K. (2014). "What Explains Low Net Interest Income at Community Banks?" *Economic Review: Federal Reserve Bank of Kansas City*, 2Q14:5-33.

Murphy, E. V. (2015). "Who Regulates Whom and How? An Overview of U.S. Financial Regulatory Policy for Banking and Securities Markets." *Congressional Research Service report 7-5700*.

Neumann, G.R. and Nelson, J.P. (1982) "Safety regulation and firm size: Effects of the Coal Mine Health and Safety Act of 1968." *Journal of Law and Economics*, 25 (2): 183–199.

Preston, E. (2003). "The USA PATRIOT Act: new adventures in American extraterritoriality." *Journal of Financial Crime, 10*(2): 104-116.

Rose, N. (2014). Economic Regulation and Its Reform (1st ed., pp. 485-543). Chicago, IL: The University of Chicago Press.

US Bank Locations. (2017). "Banks Ranked by Total Assets." usbanklocations.com/bank-rank/total-assets.html

U.S. Department of the Treasury. (2015). "Bank Secrecy Act: Combating Money Laundering and Terrorist Financing." Washington, D.C. Office of the Comptroller of the Currency.

U.S. Department of the Treasury. (2011). "Safety and Soundness: Concentrations of Credit." Comptroller's Handbook. Washington, D.C. Office of the Comptroller of the Currency.

APPENDICES

APPENDIX A

BANK ATTRITION & LIST OF BANKS

An important aspect of bank management is the anticipation and response to risk, so small community banks that anticipate marijuana legalization and decide to exit the market prior to recreational sales have the potential to bias my estimations. If bank management foresees the increase in regulatory compliance costs and decides to leave a marijuana state, this may represent self-selection out of treatment and possibly bias the coefficients on *MJ* × *medium-to-large bank*, since this decision-making could arguably represent "better" management and therefore represent small banks that would not move as far from the best practice frontier as those that stay. To examine this problem, I graph the density of bank branches by size between medium-to-large and small community banks in each of the four marijuana states reviewed (Colorado, Washington, Oregon, and Alaska) compared to all others in figure 23.[22] The years of legalization are 2012 for Colorado and Washington and 2014 for Oregon and Alaska, while sales began in 2014 and 2016 for each set of states, respectively. Density for 2012 and after is shown in figure 24.

The density of small bank branches has declined overall during the period, with the most significant years for small bank branch closure occurring after 2010. The Dodd-Frank Wall Street Reform and Consumer Protection Act was signed into law in July 2010. 2011 represented a restructuring of the regulatory environment, with the Office of Thrift Supervision (OTS) closing and the Office of the Comptroller of the Currency obtaining the banks previously under OTS supervision. Low interest rates, high occupancy expenses, and increased online banking activity also contributed to brick-and-

[22] Density is calculated as follows: density = counts / sum(counts * bar width).

mortar branch closures industry-wide. Finally, small banks continue to be acquired at a steady rate by larger banks, regardless of location (FDIC 2012). Figure 23 shows that the trends for branches in both marijuana and non-marijuana states are similar: medium-to-large banks are increasing their physical presence while small community banks steadily reduce theirs.

In t-tests for each year after 2011 comparing the density of small community banks in marijuana and non-marijuana states, I did not find the differences in densities to be statistically significant. Similarly, medium-to-large bank branch density is similar between marijuana and non-marijuana states within each year, with 2014 representing the only statistically significantly different year.

In conclusion, inspection of bank branch density by bank size does not indicate significant declines in small community bank branching associated with the anticipation of marijuana legalization. The declines that are present also occur in national data and can be explained by pre-existing trends or changes in technology and rent prices for bank property. Therefore, I conclude that the estimated effect of legalization on bank distance to the best practice frontier is not driven by small community bank management deciding to exit the marijuana state markets.

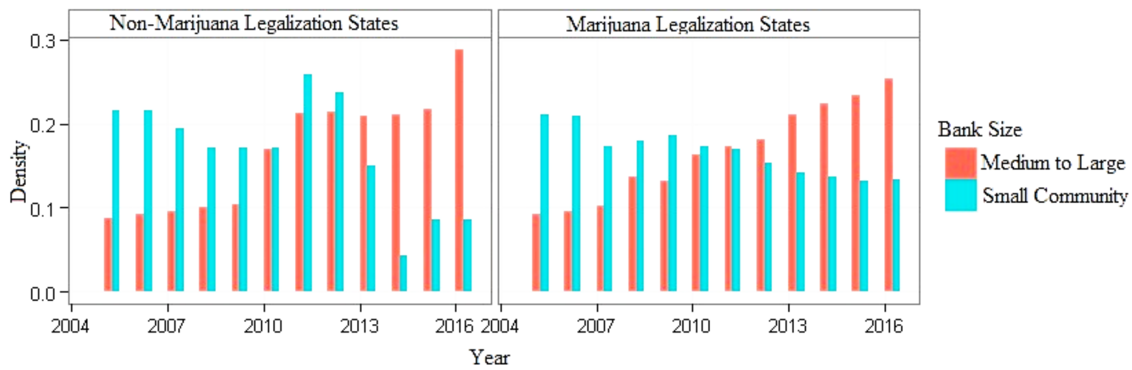

Figure 23: Bank Branch Density by Bank Size and State Type 2005-2016.

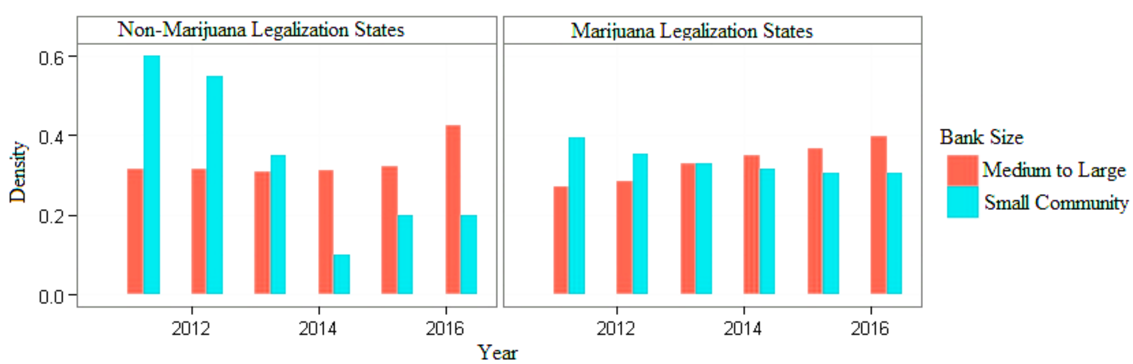

Figure 24: Bank Branch Density by Bank Size and State Type 2011-2012.

Table 18: List of Banks Sampled with Asset Size and Marijuana Status as of 2014

RSSDID	Name	Headquarters	Size Category	Treatment
455253	5Star Bank	Colorado Springs, CO	Small Community Bank	1
535753	Academy Bank, National Association	Kansas City, MO	Medium Community Bank	1
463650	Adams Bank & Trust	Ogallala, NE	Large Community Bank	1
869953	Alamosa State Bank	Alamosa, CO	Small Community Bank	1
828651	ANB Bank	Denver, CO	Medium-to-large Bank	1
983457	Armed Forces Bank, National Assoc.	Fort Leavensworth, KS	Medium-to-large Bank	0
69678	Baker Boyer National Bank	Walla Walla, WA	Large Community Bank	1
809856	Bank of Burlington	Burlington, CO	Small Community Bank	1
550354	Bank of Estes Park	Estes Park, CO	Small Community Bank	1
732758	Banker's Bank of the West	Denver, CO	Medium Community Bank	1
574976	Cashmere Valley Bank	Cashmere, WA	Medium-to-large Bank	1
896856	Castle Rock Bank	Castle Rock, CO	Small Community Bank	1
98463	Citizens Bank	Corvallis, OR	Large Community Bank	0
697754	Citywide Banks	Aurora, CO	Medium-to-large Bank	1
641579	Clackamas County Bank	Sandy, OR	Small Community Bank	0
56557	Cobiz Bank	Denver, CO	Medium-to-large Bank	1
622756	Collegiate Peaks Bank	Buena Vista, CO	Medium Community Bank	1
779360	Community Bank	Joseph, OR	Medium Community Bank	0
571265	Denali State Bank	Fairbanks, AK	Medium Community Bank	0
427858	Evergreen National Bank	Evergreen, CO	Small Community Bank	1
694771	Farmers State Bank	Winthrop, WA	Small Community Bank	1
956956	Farmers State Bank of Calhan	Calhan, CO	Small Community Bank	1
587752	First Colorado National Bank	Paonia, CO	Small Community Bank	1
355858	First National Bank	Fort Pierre, SD	Large Community Bank	0
474058	First National Bank in Trinidad	Trinidad, CO	Small Community Bank	1
513256	First National Bank of Las Animas	Las Animas, CO	Medium Community Bank	1

RSSDID	Name	Headquarters	Size Category	Treatment
968155	First National Bank, Cortez	Cortez, CO	Small Community Bank	1
357553	First Pioneer National Bank	Wray, CO	Small Community Bank	1
744256	First State Bank	Scottsbluff, NE	Medium Community Bank	0
433859	Fowler State Bank	Fowler, CO	Small Community Bank	1
881478	Heritage Bank	Olympia, WA	Medium-to-large Bank	1
447874	Islanders Bank	Friday Harbor, WA	Small Community Bank	1
67151	Kirkpatrick Bank	Edmond, OK	Large Community Bank	0
584377	Kitsap Bank	Port Orchard, WA	Large Community Bank	1
399357	McClave State Bank	McClave, CO	Small Community Bank	1
475653	Mountain Valley Bank	Walden, CO	Small Community Bank	1
542667	Mt. McKinley Bank	Fairbanks, AK	Medium Community Bank	0
350750	North Valley Bank	Thornton, CO	Small Community Bank	1
693662	Pacific Continental Bank	Eugene, OR	Medium-to-large Bank	0
480059	Park State Bank & Trust	Woodland Park, CO	Small Community Bank	1
455972	Peoples Bank	Bellingham, WA	Medium-to-large Bank	1
602356	Peoples National Bank	Colorado Springs, CO	Medium Community Bank	1
643658	Pikes Peak National Bank	Colorado Springs, CO	Small Community Bank	1
852973	Pioneer Trust Bank, National Assoc.	Salem, OR	Medium Community Bank	0
444556	Points West Community Bank	Windsor, CO	Small Community Bank	1
479071	State Bank Northwest	Spokane Valley, WA	Small Community Bank	1
474759	Sunflower Bank, National Association	Denver, CO	Medium-to-large Bank	0
651756	The Bank of Denver	Denver, CO	Small Community Bank	1
98351	The Citizens State Bank of Ouray	Ouray, CO	Small Community Bank	1
63050	The Dolores State Bank	Dolores, CO	Small Community Bank	1
775054	The Eastern Colorado Bank	Cheyenne Wells, CO	Medium Community Bank	1
621151	The Farmers State Bank of Brush	Brush, CO	Small Community Bank	1
68859	The First National Bank of Durango	Durango, CO	Medium Community Bank	1

RSSDID	Name	Headquarters	Size Category	Treatment
502559	The Gunnison Bank and Trust Co.	Gunnison, CO	Small Community Bank	1
387055	The State Bank	Peyton, CO	Small Community Bank	1
427960	Twin River Bank	Lewiston, ID	Small Community Bank	0
806154	Valley Bank & Trust	Brighton, CO	Medium Community Bank	1
58971	Washington Trust Bank	Spokane, WA	Medium-to-large Bank	1
541754	Wray State Bank	Wray, CO	Small Community Bank	1
67254	Young Americans Bank	Denver, CO	Small Community Bank	1

APPENDIX B

EXAMPLE FOOTPRINT CALCULATION

For illustration of the footprint measures, I use Baker Boyer National Bank, a Large Community Bank headquartered in Walla Walla, WA, but with branches in two states: Washington and Oregon.

First, I list the 2010 census population in every county in which Baker Boyer National Bank has a branch within a given year in table 19. This county population represents the bank's county-level footprint; the theoretically servable population by the branches located within a selected county.

To obtain state level totals, I sum the county populations by year and state, where the counties included have at least one Baker Boyer National Bank branch. So, for example, Baker Boyer National Bank opened a branch in Yakima, Washington, in 2009. Therefore, in 2009, the state footprint changes from 233,958 to 477,189, representing the additional servable county population introduced to the bank via the new branch. The sum of county footprints by state and year are reported in table 20. For example, the Washington county footprints in 2005 are 175,177 in Benton County and 58,781 in Walla Walla, Washington. As a result, the sum of county footprints in Washington in 2005 is 175,177 + 58,781 = 233,958.

Because I want to know what percent of total population footprint is in a specific state, I need to know the national total of servable population calculated according to where all branches are located. To accomplish this, I sum the footprint in each state by year to obtain total population footprints. This represents the total servable population for Baker Boyer National Bank for each year, reported in table 20. For example, in 2005, the sum of county footprints in Oregon is 75,889, and in Washington it is 233,958. The total national footprint is therefore 75,889 + 233,958 = 309,847.

Now I can identify what percent of a bank's total servable population lies within a selected state. For Baker Boyer National Bank in 2005, Oregon contains 75,889/309,847 = 24.59 percent of Baker Boyer National Bank's total servable population. Washington contains 233,958/309,847 =75.51 percent of the total servable population in 2005. In 2014, because Washington legal marijuana sales began and Baker Boyer National Bank had over 50 percent of its business there, Baker Boyer National Bank is considered treated with *MJ 50%* = 1.

Table 19: Example County Footprint Data

Year	County	County Population	Branches in County
2005	Umatilla, Oregon	75889	2
2006	Umatilla, Oregon	75889	2
2007	Umatilla, Oregon	75889	2
2008	Umatilla, Oregon	75889	2
2009	Umatilla, Oregon	75889	2
2010	Umatilla, Oregon	75889	2
2011	Umatilla, Oregon	75889	1
2012	Umatilla, Oregon	75889	1
2013	Umatilla, Oregon	75889	1
2014	Umatilla, Oregon	75889	1
2015	Umatilla, Oregon	75889	1
2016	Umatilla, Oregon	75889	1
2005	Benton, Washington	175177	1
2006	Benton, Washington	175177	1
2007	Benton, Washington	175177	1
2008	Benton, Washington	175177	1
2009	Benton, Washington	175177	1
2010	Benton, Washington	175177	1
2011	Benton, Washington	175177	1
2012	Benton, Washington	175177	1
2013	Benton, Washington	175177	1
2014	Benton, Washington	175177	1
2015	Benton, Washington	175177	1
2016	Benton, Washington	175177	1
2005	Walla Walla, Washington	58781	5
2006	Walla Walla, Washington	58781	5
2007	Walla Walla, Washington	58781	5
2008	Walla Walla, Washington	58781	5
2009	Walla Walla, Washington	58781	5
2010	Walla Walla, Washington	58781	6
2011	Walla Walla, Washington	58781	6
2012	Walla Walla, Washington	58781	6
2013	Walla Walla, Washington	58781	6
2014	Walla Walla, Washington	58781	5
2015	Walla Walla, Washington	58781	5
2016	Walla Walla, Washington	58781	5

2009	Yakima, Washington	243231	1
2010	Yakima, Washington	243231	1
2011	Yakima, Washington	243231	1
2012	Yakima, Washington	243231	1
2013	Yakima, Washington	243231	1
2014	Yakima, Washington	243231	1
2015	Yakima, Washington	243231	1
2016	Yakima, Washington	243231	1

Table 20: Example Footprint Calculation

Year	State	Sum of County Populations by State	Sum of All County Populations	State Footprint
2005	Oregon	75889	309847	24.49%
2006	Oregon	75889	309847	24.49%
2007	Oregon	75889	309847	24.49%
2008	Oregon	75889	309847	24.49%
2009	Oregon	75889	553078	13.72%
2010	Oregon	75889	553078	13.72%
2011	Oregon	75889	553078	13.72%
2012	Oregon	75889	553078	13.72%
2013	Oregon	75889	553078	13.72%
2014	Oregon	75889	553078	13.72%
2015	Oregon	75889	553078	13.72%
2016	Oregon	75889	553078	13.72%
2005	Washington	233958	309847	75.51%
2006	Washington	233958	309847	75.51%
2007	Washington	233958	309847	75.51%
2008	Washington	233958	309847	75.51%
2009	Washington	477189	553078	86.28%
2010	Washington	477189	553078	86.28%
2011	Washington	477189	553078	86.28%
2012	Washington	477189	553078	86.28%
2013	Washington	477189	553078	86.28%
2014	Washington	477189	553078	86.28%
2015	Washington	477189	553078	86.28%
2016	Washington	477189	553078	86.28%