Anti-money laundering enforcement, banks, and the real economy

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Abstract

We exploit a tightening of anti-money laundering (AML) enforcement that imposed disproportionate costs on small banks to examine the effects of a change in bank composition on real economic outcomes. In response to intensified enforcement, counties prone to high levels of money laundering experience a departure of small banks and increased activity by large banks. This results in an increase in the number of small establishments and real estate prices. Consistent with a household demand channel, wages and employment increase in the non-tradable sector. Last, we document secured lending as a potential driver of this outcome.

Keywords: Money laundering, Financial Institutions, Real economy, Deposits and lending, Financial crime.

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I. INTRODUCTION

While a large body of the banking literature has focused on the link between access to finance and economic conditions, the effects of bank concentration on the economy are open to debate. This issue is of relevance, given that the level of bank concentration in the US grew from 29% in 1997 to 46% in 2017.[1] A similar growth pattern persists across the globe (Figure 1).

--- Figure 1 about here---

Studying the effects of bank concentration on real economic outcomes is challenging due to the endogeneity between local economic conditions and financial services. The literature has sought to address this challenge by considering shocks such as mergers and acquisitions (Garmaise and Markowitz (2006), Bord, Ivashina and Talieferro (2018), Liebersohn (2018), Nguyen (2019)) or state-wide branching regulations (Jayaratne and Strahan (1996), Cetorelli and Strahan (2006), Goetz, Laeven and Levine (2016), Gilje, Loutskina and Strahan (2016), Jiang, Levine and Lin (2017)). These types of shocks generally affect bank composition as well as the number of branches, limiting the ability to exploit the shocks to examine the effect of higher bank concentration on economic outcomes independently of changes in the number of branches.

In this study, we focus on a recent shift in regulatory environment likely exogenous to local conditions—stricter enforcement of anti-money laundering (AML) regulations—to study whether a change in the composition of banks affects real economic activity. One important channel through which stricter regulatory enforcement may affect bank concentration is the disproportional compliance costs it imposes on small banks. While the total cost of AML compliance across U.S. financial services firms amounted to $25.3 billion in 2017, the cost as a percent of total assets is up to ten times higher among smaller banks (up to .83%) than among larger banks (up to .08%) due to overhead investment and economies of scale (Federal Reserve Bank of Saint Louis report (2018) and Lexis Nexis Solutions Study, 2018).[2] In examining the effect of bank composition, we exploit the fact that exposure to money laundering activity varies across counties in the US, which

[1] Data are from the Global Financial Development database by the World Bank. Bank concentration is the asset value of the five largest banks as a share of total commercial banking assets.

[2] Compliance Costs, Economies of Scale and Compliance Performance: Evidence from a Survey of Community Banks, April 2018, Report by the Federal Reserve Bank of Saint Louis. True Cost of AML Compliance Study Report, Lexis Nexis Solutions report, 2018.

generates cross-sectional within-state variation in the relevance of AML enforcement. Specifically, some counties are classified by the U.S. Drug Enforcement Administration (DEA) as High Intensity Drug Trafficking Areas (HIDTA), and such counties are more prone to money laundering.

The shift in AML enforcement is based on important changes in regulatory approach that took place in 2012. The Congressional Research Service report (Sykes, 2018) discusses them as (i) an increase in the size and frequency of civil money penalties and (ii) an emphasis on acknowledgment of wrongdoing. The first significant enforcement action in the spirit of this new approach was a regulatory $1.92 billion fine imposed on HSBC in December 2012 for violations of AML regulations. This enforcement action was pursued concurrently by the Department of Justice, the Office of the Comptroller of the Currency, the Federal Reserve, and the Department of the Treasury, who found that HSBC was used as an intermediary for drug cartels to launder money, for terrorist financing, and for circumventing U.S. sanctions. The fine imposed on HSBC was extraordinary in terms of saliency and impact, which reflected a shift towards stricter enforcement of anti-money laundering. According to the U.S. Government Accountability Office Reports (GAO-18-263 and GAO-18-642T) (2018), the large enforcement action against HSBC and the changing nature of enforcement response on AML were cited by many banks as the reason for reducing operations in the South West border. Furthermore, a report issued in 2016 by the economic consulting firm National Economic Research Associates (NERA) states that, while only half of the AML enforcement actions from 2002 through 2011 involved an assessment of money penalties, approximately 90% did between 2012 and 2015. In addition, while historically financial institutions subject to enforcement actions could consent to a penalty without accepting responsibility for its criminal conduct, by 2012 regulators started pressing firms to admit to allegations as part of the settlements (Brown-Hruska 2016). Moreover, in 2013, FinCEN Director Jennifer Shasky Calvery indicated in regard to AML enforcement that “acceptance of responsibility and acknowledgment of the facts is a critical component of corporate responsibility”. Last, in early 2012 FinCEN sent a notice to financial institutions mandating the filing of Suspicious

Activity Reports (SARs) electronically by April 1, 2013.[3] Thus, these important developments drastically altered the landscape of AML enforcement.[4]

We start our analysis by showing that the strengthening of AML enforcement at the end of 2012 indeed affected bank composition in HIDTA counties. Using difference-in-difference techniques, we find that stricter AML enforcement lead to a significant change in the composition of banks in HIDTA counties relative to non-HIDTA counties but had no differential effect on the total number of branches across counties (Figure 2, Panel A). Large banks gained market share in HIDTA counties as measured by the number of bank branches, consistent with a disproportional compliance cost imposed on small banks operating in high-risk areas (Figure 2, Panel B). As further evidence that intensified AML enforcement led to higher bank concentration, we find an increase in the volume of aggregate deposits for large banks in HIDTA counties after 2012. Specifically, deposits in large banks relative to those in small banks increase by approximately 30% in HIDTA counties. Overall, these findings suggest a considerable increase in the banking activities of large banks both at the extensive and intensive margin, i.e., branches and deposits, in high risk areas following tighter AML enforcement.

--- Figure 2 about here---

Next, we look at the effects of the change in bank composition on the real economy and explore likely channels of such effects. On the one hand, a greater presence by large banks could be detrimental for the local economy considering that small banks have an advantage in terms of collecting and processing soft information and can lend to borrowers that would otherwise be underserved (Stein 2002; Petersen and Rajan 2002; Berger et al 2005; Degryse and Ongena 2005; Mian 2006; DeYoung, Glennon, and Nigro 2008; Agarwal and Hauswald 2010, Liberti and Mian 2009, Qian, Strahan, and Yang 2015, Skrastins and Vig 2019). In addition, large banks have a

[3] Details on the NERA report and the stance of FinCEN are available at the Sykes (2018) Congressional Research Service report on "Trends in Bank Secrecy Act/Anti-Money Laundering Enforcement" and details on FinCEN notification on electronic SARs filing mandate are at Federal Register 77(30), February 14, 2012.

[4] "In 2013, JPMorgan added 4,000 employees to their compliance team and spent an additional $1 billion on controls. Citigroup reported that of the $3.4 billion in costs that they had saved in the past year through greater efficiency, 59 percent of that was then being consumed by new compliance spending. UBS spent nearly $1 billion in 2014 in order to meet regulatory requirements. HSBC grew their compliance department from 2,000 to 5,000 in 2013, and it currently stands at over 7,000." See Financial Times, "Banks face pushback over surging compliance and regulatory costs", May 25, 2015 by Laura Noonan, accessed on March 12, 2020.

broader network of branches, allowing funds sourced in high-risk regions to be lent in other areas and reducing the availability of credit in the local economy. On the other hand, the incentives for large banks to lend under programs such as the Community Reinvestment Act (CRA) (Calomiris and Haber 2015) or Small Business Administration loans (SBA) as well as potentially shifting funds from other regions to lend locally may increase access to finance and boost the real economy. Additionally, large banks might be less prone to sanctions --as argued by those that deem executives of large banks as "too big to jail"-- or able to access risk management systems that are more rigorous than those that can be implemented by smaller banks[5], allowing banks to service a broader set of customers.

Our results show that the shift towards large banks has a positive impact on the economy as observed in an increase in the aggregate number of firms. By exploiting cross sectional characteristics of firms, we find that the effect is driven by small firms and firms in the non-tradable sector, consistent with a household demand channel (Mian, Sufi, and Verner 2020). This finding is also consistent with Di Maggio and Kermani (2017) who find an increase in the non-tradable sector activity following a surge in bank credit supply. We then study two additional outcomes that the literature has linked to the availability of financial services: real estate prices and crime. We find that real estate prices in counties more exposed to money laundering activity increase relative to prices in other counties. In addition, we find evidence that suggests that the effect is not driven by the composition of the properties listed, but by a general increase in prices. Moreover, the effect is more pronounced in lower-income areas within counties more exposed to money laundering activity, suggesting that the shift in the banking system towards large banks improves conditions in areas that are likely to benefit more from access to finance. While these results could respond to a decline in crime related to drug-money laundering activity, we find no effect on crime around stricter AML enforcement.

Finally, we consider several potential channels on how a shift in bank composition towards larger banks affects real economic outcomes. As discussed in Jayaratne and Strahan (1996), banking system may affect the real economy through increased lending, or through more efficient lending. To study this, we analyze bank lending under the Community Reinvestment Act, the

[5] Small banks use less AML compliance technology to support due diligence according to the True Cost of AML Compliance Study Report, Lexis Nexis Solutions (2018)

Small Business Administration program, as well as secured lending through mortgages. We find evidence of a decline in CRA lending -in particular for larger loan sizes- and no difference in lending through the SBA programs. The decline in CRA lending is in line with findings in Chen, Hanson and Stein (2017) and Bohr, Ivashina and Taliaferro (2018) who find a reduction in CRA lending with increasing bank size. Thus, shifting bank composition to large banks does not lead to more lending through CRA or SBA programs in the high-risk areas following tighter AML enforcement. We do, however, find an increase in secured lending through mortgages in high risk counties following the change in the composition of banks. We further find that the effect is stronger in lower-income regions within these counties, suggesting an improvement in access to finance in areas that are mostly likely to benefit from this access. These results are in line with those in Favara and Imbs (2015) and Di Maggio and Kermani (2017), who find increased mortgage lending following a positive shock to bank credit supply, and with those in Landvoigt, Piazzesi, and Schneider (2015), who find credit to poorer households as a driver of house prices in lower income neighborhoods. This finding is also consistent with the evidence on increasing real estate prices in these areas within high risk counties.

Overall, our study advances the knowledge on the implications of bank concentration in the real economy. We first look at the effects of AML enforcement in the banking system and find that intensifying AML enforcement actions lead to a shift towards large banks in areas that are more exposed to money laundering due to disproportionately large AML compliance costs for smaller banks. This plausibly exogenous shock to the bank composition in high risk counties allows us to isolate other determinants of the structure of the banking system in a granular manner, within a county, and to study how an increased presence of large banks affects real economic outcomes. In the aftermath of the change in the composition of banks, we find an increase in the number of small establishments and an overall positive effect in the non-tradable sector, suggesting a household demand channel (Di Maggio and Kermani 2017, Mian, Sufi, and Verner 2020). We further explore potential channels and observe that secured lending increases in these areas through mortgages while CRA or SBA loans do not increase. These findings are consistent with several ideas. First, large banks may be deemed “too big to jail” or able to implement better monitoring systems, allowing for better screening and improving access to finance for a group of underserved borrowers in areas more exposed to money laundering. Second, large banks may provide secured lending to compensate for possible increased risk due to their relatively limited ability to process soft information in lending compared to small banks.

Our contribution to the banking literature is twofold. First, we add to the literature on the effect of banking and finance on economic growth that follow the seminal work of King and Levine (1993a, 1993b), and includes papers such as Rajan and Zingales (1998), Peek and Rosengren (2000), Klein, Peek, and Rosengren (2002), Burgess and Pande (2003), Guiso, Sapienza and Zingales (2004), Levine (2005), Cetorelli and Strahan (2006), Garmaise and Moskowitz (2006), Bertrand, Schoar and Thesmar (2007), Kerr and Nanda (2009), Butler and Cornaggia (2011), Krishnan, Nandy and Puri (2015), Levine and Warusawitharana (2019), among others. This branch of the literature has mostly focused on the availability of bank branches and financial services. Another branch of the literature, including papers such as Cetorelli and Gambera (2001), Beck, Demirguc-Kunt, and Maksimovic (2004), Claessens and Laeven (2005), and Diallo and Koch (2018), has studied the effect of bank concentration on firms and industrial activity by analyzing cross-country data. In terms of within country analyses, Bonaccorsi Di Patti and Dell'Ariccia (2004) study the effects of banks competition on firm creation across provinces and industries in Italy, and Black and Strahan (2002) find that the deregulation of branching restrictions and interstate banking that fostered competition resulted in higher firm incorporation rates. Our contribution is to study how a plausible exogenous shift in the composition of banks within counties in the United States driven by tightening AML enforcement affects real economic activity. This setting allows us to examine the effects of bank concentration without the impediments of the regulatory, institutional, or measurement differences across states or countries encountered by cross-state, cross-country studies, and mitigates omitted variable biases that might simultaneously affect bank concentration and economic activity. In addition, we can study a broader set of economic outcomes in a more granular geographical setting,[6] and explore alternative channels that might drive the effects.

Second, we contribute to the literature studying the effects of anti-money laundering enforcement on the banking system and the real economy. We bring evidence on these effects by focusing on areas that are more susceptible to money laundering and thus exposed to high potential

[6] Our data is at the county- or zip code-level, with more than 3,000 and 41,000 observations per year, respectively.

compliance costs. To the best of our knowledge, this is the first study that examines the impact of AML provisions on the U.S. banking system and real economy in a systematic manner by focusing on areas that are prone to high money laundering activity.[7] To the extent that the recent revelations of the so-called FinCEN files characterize AML enforcement tools as being ineffective, our results suggest that AML enforcement tools may nevertheless have benefits for economic activity through their impact on bank composition. To that end, we complement our analysis by showing that increased presence of large banks in high-risk areas is associated with a disproportionate increase in Suspicious Activity Reports (SARs) in these areas.[8]

The rest of the paper is as follows. In Section 2, we discuss the institutional background, data and empirical method. Section 3 provides the results on the effects of anti-money laundering on banking system and real economy. Section 4 explored possible channels. Section 5 concludes.

II. BACKGROUND, DATA AND METHODOLOGY

In this section, we first discuss the institutional background on anti-money laundering regulations and on areas more exposed to high drug trafficking activity. Next, we describe the multiple datasets used in our study, and then present our empirical method to examine how anti-money laundering (AML) enforcement affects bank activities and local economies.

A. Institutional Background

A.1. Money laundering and anti-money laundering (AML) regulation.

Due to the negative consequences associated with money laundering (it facilitates corruption and distorts prices, among other effects), the US government has implemented multiple regulations to fight it. The first tool introduced is the Bank Secrecy Act of 1970. With it, financial institutions are required to collaborate with the US government in detecting and preventing money laundering. More specifically, financial institutions are required to record and report suspicious activity, such as cash transactions in excess of $10,000 within one business day. The act was subsequently

[7] In contrast, Slutzky et. al. (2019) focus on the effects of the liquidity shock that followed AML regulations in Colombia and that were transmitted via the branching system from areas more exposed to drug trafficking activity into other areas.

[8] For a summary of the FinCEN files, see, for instance, https://www.icij.org/investigations/fincen-files/about-the-fincen-files-investigation/. The FinCEN files focus on 2,100 Suspicious Activity Reports. Overall, banks filed approximately 7 million such reports over 2009-2017.

amended and complemented in 1986, 1988, 1992, 1994, and 1998 to broaden the type of transactions that require reporting and the type of agents required to report, to strengthen sanctions, and to include additional operations as federal crimes, among other changes.

Following the terrorist attacks of 2001, the US Congress enacted the USA PATRIOT[9] Act that contained multiple titles, or chapters. Title III of the Act is the International Money Laundering Abatement and Financial Anti-Terrorism Act, intended at preventing, detecting, and prosecuting international money laundering activity and financing of terrorism. Among other changes, the Act strengthened procedures to identify potentially riskier customers, prohibited financial institutions from doing business with foreign shell banks, expanded anti-money laundering program requirements for financial institutions, and increased penalties for money laundering, among others.

Around 2012, multiple events highlighted a stricter commitment to enforce AML regulations. The volume of the civil money penalties imposed by the Office of the Comptroller of the Currency increased significantly (Figure 3, Panel A), regulators started to press firms to admit wrongdoing as part of settlements related to enforcement actions, and FinCEN mandated the electronic filing of SARs, followed by the incorporation of a stand-alone Enforcement Division in 2013. A salient example of the stricter enforcement is the fine imposed on HSBC on December 2012, following a year-long investigation by the Permanent Subcommittee on Investigations, a Senate subcommittee. HSBC was charged with being used by Mexican drug cartels to launder money, by Saudi Arabian banks with terrorist ties that needed access to US dollars, and by Iranians who wanted to circumvent United States sanctions. The amount of the fine was equivalent to 8.7% of HSBC's pre-tax profits in the prior year, and about 1.4% of its market capitalization.

In response to these changes, banks increased significantly spending on compliance. JPMorgan and HSBC added 4,000 and 3,000 employees to their compliance teams, respectively. JPMorgan and Citibank spent an additional USD 1 billion and approximately 2 billion on regulatory and

[9] The full name of the Act is "Uniting and Strengthening America by Providing Appropriate Tools Required to Intercept and Obstruct Terrorism".

compliance activities on controls.[10] Meanwhile, the number of articles in the Wall Street Journal related to money laundering more than doubled (Figure 3, Panel B).

--- Figure 3 about here---

A.2. High Intensity Drug Trafficking Activity counties.

In 1988 the U.S. Congress created the *High Intensity Drug Trafficking Activity (HIDTA)* program, aimed at reducing drug trafficking and production in the United States. The program provides assistance to local enforcement agencies operating in areas identified as critical drug-trafficking regions. To qualify as a HIDTA area, a county must meet the following criteria:[11] i) it has to be a significant center of illegal drug production, manufacturing, importation, or distribution; ii) drug-related activities in the area have a significant harmful impact in the area and in other areas of the country; iii) local law enforcement agencies have committed resources to respond to the drug trafficking problem in the area, and iv) a significant increase in allocation of Federal resources is necessary to respond adequately to drug related activities in the area. At the end of 2019, approximately 18% of all counties were designated as HIDTA by the DEA. We map the distribution of HIDTA counties in Figure 4.

--- Figure 4 about here---

We compare HIDTA and non-HIDTA counties as of 2010 in a series of observable characteristics in Table 1. We find that HIDTA counties are in general larger in terms of population, have higher median income, and their population is more educated when looking at higher education degrees (Panel A). In contrast, unemployment, basic education, and poverty rates are similar across HIDTA and non-HIDTA counties, and the number of establishments per capita is also similar across types of counties.

--- Table 1 about here---

In Panel B we compare the banking system and its evolution across HIDTA and non-HIDTA counties. While we find significant differences in terms of volume of deposits and number of branches per capita across counties, we find that the evolution of these two variables over the last

[10] www.ft.com/content/e1323e18-0478-11e5-95ad-00144feabdc0, accessed on July 5th, 2020.
[11] Adapted from https://www.dea.gov/hidta, accessed on March 2nd, 2020.

several years follows similar patterns. More specifically, we find no differences in terms of growth of deposits or number of branches per capita over the previous years across types of counties. In addition, and consistent with a relationship between drug trafficking and money laundering, in unreported results we find that a larger fraction of suspicious activity reports is issued in HIDTA counties. In 2012, 73.6% of the reports were issued in HIDTA counties. In the following three years, the percentages were 80.47%, 79.53%, and 77.52%, respectively.

B. Data and variables

Deposits and bank branches. Our first source of data is the summary of deposits published by the Federal Deposit Insurance Corporation (FDIC). This database contains yearly information on deposits at the bank-branch level. We collect data from 2010 until 2016 for all brick and mortar bank branches in the 50 US states and the District of Columbia. The resulting data set contains an average of approximately 85,800 bank-branch observations per year for close to 8,000 different banks.

Money laundering activity. Our second source of data helps us measure exposure to money laundering activities, and in particular to those originated in the production and distribution of illegal drugs. We collect data on the counties identified by the United States Drug Enforcement Administration (DEA) as High Intensity Drug Trafficking Areas (HIDTA). Approximately 19 percent of all counties in the United States are designated as HIDTA, and are located across the 50 states as well as in US territories and the District of Columbia. We remove from the list the counties that were added after 2012 to mitigate concerns of look-ahead bias. For robustness, we construct an alternative measure of exposure to the production and distribution of illegal drugs by measuring the distance between a county and the closest DEA office, with data obtained from the DEA's website. Our assumption is that regional DEA offices are established in areas more exposed to the production and distribution of illegal drugs.[12]

Economic outcomes. Our measures of real economic outcomes are from the Bureau of Labor Statistics on employment, wages, and number of active establishments. This information is

[12] An alternative measure of exposure to money laundering activities is the High Intensity Financial Crime Area (HIFCA). This designation, made by the Financial Crimes Enforcement Network (FinCEN), identifies areas in which money laundering and related financial crimes are widespread. Unfortunately, even though this measure is at the county level, there is not significant within-state variation for our purpose. For instance, all 62 counties in New York, all 21 counties in New Jersey, and all 15 counties in Arizona are designated as HIFCA regions.

provided quarterly through the Quarterly Census of Employment & Wages. We obtain quarterly and yearly information at the county level with different levels of aggregation, including type of employer (government or private) and NAICS sector. In addition, we obtain data from the County Business Patterns series to study firms of different sizes in terms of number of employees.

Real estate. In addition, we obtain data on real estate prices from Zillow, the online real estate database company. More specifically, we obtain information on the real estate market at the zip code level that includes statistics such as median listing price, median listing price per sq. ft., fraction of listings with price reduction, among other variables.

Crime. We also collect data on crime from the FBI's Uniform Crime Reporting (UCR) Program. The database includes information at the zip-code level on the number of crimes for a series of different types of criminal activities, such as murder, manslaughter, rape, robbery, assault, and theft, among others.

CRA lending. To test the potential drivers of the effect of the change in the composition of banks on real economic outcomes, we use multiple datasets. First, we collect data on lending under the Community Reinvestment Act (CRA) published by the Federal Financial Institutions Examination Council (FFIEC). The CRA is a law enacted in 1977 that encourages financial institutions to lend to low- and moderate-income borrowers in the communities they operate. While financial institutions do not have specific targets they have to meet, they are overseen by the OCC, the FDIC, and the FRB, who determine whether the banks are fulfilling their legal obligations and rate them. The volume of loans under this program is large. In 2017 alone, reporting banks lent a total of 256 billion USD under CRA, an amount equivalent to 3.3% of total commercial and industrial loans by all commercial banks. We obtain county-level data from 2010 until 2016 on the number and volume of loans to small businesses, defined as those with annual revenues below one million dollars.

SBA and HMDA lending. In addition, we collect data on loans issued under the Small Business Administration (SBA) 7(a) Loan Guarantee program. Under this program, the SBA partially guarantees loans to make lenders more willing to lend to small businesses that might otherwise not be funded. We collect data on more than 370,000 loans issued between 2010 and 2016, including information on the amount of the loan, term, and interest rate. We also collect data on mortgages made available following the Home Mortgage Disclosure Act (HMDA). More specifically, we obtain lending data for each reporting financial institution at the county-year and aggregate lending data at the zip code-year level between 2010 and 2016. Our initial database contains information on more than 8,000 lenders in over 3,000 counties. *C. Empirical method*

C.1. AML and Banking Activity

We study the effects of tighter enforcement of AML regulations on banking activity using a difference-in-difference framework. The time-series difference is the timing of the tightening of AML enforcement in 2012, particularly when an investigation and later a substantial fine was imposed on HSBC for AML violations. The cross-sectional difference is between areas more and less exposed to money laundering, i.e. HIDTA and non-HIDTA counties. Later, we extend our tests to incorporate a third difference for cross-sectional differences in bank characteristics. An assumption in our difference-in-difference setting is that there are no pre-trends that might drive our results: treated (HIDTA) and control (non-HIDTA) counties should exhibit a common trend before the shock. Panel B of Table 1 shows that both bank deposit and bank branch growth is comparable in the treated and control sample as of 2012. In the following subsection, we describe the specifications used to establish the impact of AML enforcement on the extensive and intensive margin of bank activities.

C.1.1. Number of branches and deposits volume

We examine the effect of the tightening of AML enforcement on the number of branches and deposits volumes (extensive and intensive margin, respectively) in counties more exposed to money laundering activities with the following empirical specification:

$$y_{c,s,t} = \alpha_c + \alpha_{s,t} + \beta \; x \; Post_t \text{ x } HIDTA_c + \gamma_{\mathrm{c,t-1}} + \varepsilon_{c,s,t} \qquad (1)$$

where $y_{c,s,t}$ is one of our outcomes of interest (logarithm of one plus number of branches or logarithm of one plus volume of deposits) in county *c*, state *s*, year *t*. To measure exposure to criminal activity in the form of money laundering, we create an indicator variable, *HIDTA*, that is set to one for counties designated as High Intensity Drug Trafficking Areas (HIDTA). *Post* is an indicator variable that is set to one after 2012.

We include multiple sets of fixed effects. First, we include county fixed effect (α_c) to control for time invariant characteristics of the banking system in the county studied. Second, we include state-year fixed effects ($\alpha_{s,t}$) to control for common shocks and time varying factors at the state level. We further take into account potential time varying factors that may relate to banking activity at the county level by controlling for lagged values for number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. Including these time-varying county level factors alleviate the concern that banking activity may be driven by changing economic and demographic conditions within a county.[13] Standard errors are double clustered at the county and year level.

C.1.2. Composition of bank branches and deposits

We next examine the effects of tightening AML enforcement on banking activities in relation to bank composition in counties with higher money laundering activity. We expand the empirical specification as follows.

$$y_{b,c,s,t} = \alpha_{b,c} + \alpha_{s,t} + \beta_1 \text{ x } Post_t \text{ x } HIDTA_{c,s} + \beta_2 \text{ x } Post_t \text{ x } Large_b + \beta_3 \text{ x } Post_t \text{ x } HIDTA_{c,s} \text{ x } Large_b + \varepsilon_{b,c,s,t}, \quad (2)$$

In this specification, the unit of observation is the bank-county-year. $y_{b,c,s,t}$ is one of the outcomes of interest (logarithm of one plus number of branches or logarithm of one plus volume of deposits) for bank *b*, county *c*, state *s*, year *t*. The indicator variable $Large_b$ is set to one for banks in the top one percent in terms of deposits and that have at least 100 branches across the United States, excluding financial institutions associated with credit cards or investment banks.[14] We include multiple sets of fixed effects. In our stricter specification, we include bank-county fixed effects ($\alpha_{b,c}$) to control for time invariant characteristics of the operations of each bank in each county, bank-year fixed effects ($\alpha_{b,t}$) to control for general shocks to each bank, and county-year fixed effect ($\alpha_{c,t}$) to control for local shocks. Thus, in this tight specification, both local and general time-varying factors that may affect banking activity are controlled for, mitigating

[13] For robustness, we also match HIDTA counties with non-HIDTA counties on establishments, household income, population, and unemployment, and the results are comparable.
[14] For robustness, in the Appendix Table A1, we provide the results of an alternative specification where we set the indicator variable equal to one for banks with assets above 1 billion dollars.

concerns about county-level time-varying economic or demographic factors that might affect the findings. Standard errors are double clustered at the county and year level.

C.2. Real economic outcomes

After examining the effect of tighter AML enforcement on the banking sector, we analyze the implications for real economic outcomes. We first consider the impact of tighter AML enforcement on the real economy by focusing on variables such as number of establishments, wages, employment, real estate prices, and crime with a specification similar to that in equation (1) using these stated measures as the dependent variable. Where data at the zip-code level is available, we expand our specification in (1) including an interaction term that differentiates between low- and high-income zip codes within a county. Our expanded specification is the following:

$$y_{z,c,t} = \alpha_z + \alpha_{c,t} + \beta_1 \text{ x } Post_t \text{ x } HIDTA_{z,c} + \beta_2 \text{ x } Post_t \text{ x } Low\ Income_z + \beta_3 \text{ x } Post_t \text{ x } HIDTA_{z,c} \text{ x } Low\ Income_z + \varepsilon_{z,c,t}, \quad (3)$$

In this specification, the unit of observation is the zip code-year. $y_{z,c,t}$ is one of the outcomes of interest for zip code z, county c, year t. The indicator variable *Low Income* is set to one for zip codes wherein the median household income is below the median for the corresponding county. We include multiple sets of fixed effects. In our stricter specification, we include zip code and county-year fixed effects ($\alpha_{c,t}$) to control for time invariant characteristics of the outcome of interest within a zip code, and time varying factors and local shocks at the county level. Standard errors are double clustered at the county and year level.

We then explore possible channels for this finding in exploring CRA, SBA and secured lending through mortgages with specifications similar to that of Equation (1) but with alternative dependent variables.

III. RESULTS

We first look at the role of tightening AML enforcement on banking activities and bank composition in areas more exposed to money laundering activity. Then, we explore the impact of these changes on the real economy.

A. Bank branches and deposits volume

We examine how the tightening of enforcement of AML regulations and sanctions affect banking activity in the extensive and intensive margin by focusing on the number of bank branches and bank deposits, respectively, in counties more and less exposed to money laundering activity (HIDTA counties relative to non-HIDTA counties), following the empirical approach specified in Equation (1). We aggregate information on bank branches and volume of deposits at the county-year level. Our sample consists of more than 21,000 observations across more than 3,000 counties between 2010 and 2016.

The results in Table 2, columns 1 to 3, show that the number of branches in HIDTA counties does not decline relatively more compared to other counties following the shift in AML enforcement. The coefficient for *Post x HIDTA* for the number of branches is statistically and economically indistinguishable from zero in all three specifications. This evidence is in line with the graphical evidence presented in Panel A of Figure 2, which shows that the number of branches follow similar patterns in both HIDTA and non-HIDTA counties on the aggregate. In contrast, we find that the coefficient for the volume of deposits (columns 4 to 6) is economically and statistically significant in all the specifications. Results in Column (6) of Table 2 indicate that the volume of deposits increases by approximately 2 percentage points in these counties following stricter AML enforcement.

--- Table 2 about here---

We then study how the stricter AML enforcement affects large and small banks that operate within high-risk counties using the specification in Equation (2). As discussed in the introduction, small banks potentially have an advantage in terms of collecting and processing soft information, while large banks have access to better technology to detect suspicious activity. Our initial database includes information on over 7,800 financial institutions across more than 3,000 counties. We present the results in Table 3. In terms of number of branches (columns 1 to 3), we find that, with tighter AML enforcement, small banks withdraw from counties with higher money laundering activity, as reflected by the negative coefficient on *Post x HIDTA*. We find that this effect is compensated by an increased presence by large banks in these counties, as captured in the positive coefficient on *Post x HIDTA x Large*. Notably, this coefficient is also statistically significant in column (3), where we include a strict set of fixed effects. This strict specification suggests that, economically, the number of branches of large banks increases by 2.4% more than branches of small banks following enforcement. We plot the year-by-year coefficient for the triple interaction term in Figure 5, where we observe that this effect materializes fully two years after enforcement.

--- Table 3 about here---

--- Figure 5 about here---

When we analyze the volume of deposits (columns 4 to 6), we find a similar effect. The volume of deposits in small banks declines in counties more exposed to money laundering activity, while it increases in large banks. Again, the coefficient is large in magnitude and statistically significant in the specification that includes the stricter set of fixed effects (column 6). The result is economically substantial: deposits in branches of large banks increase by 31.3% relative to deposits in branches of small banks after enforcement.

These results are in line with the graphical evidence presented in Figure 2, Panel B, where we plot the evolution of the share of branches of large banks in HIDTA and non-HIDTA counties and a remarkable pattern arises. The presence of large banks in both types of counties follows a similar pattern between 2006 and 2012. However, following the tightening of the enforcement of anti-money laundering regulations, large banks increase their presence in HIDTA counties, vis-à-vis in non-HIDTA counties.

For robustness, we test two alternative specifications. Considering that the DEA establishes regional offices in areas more exposed to drug production and trafficking activity, we construct two additional county-level measures of exposure. First, an indicator variable that is set to one for counties within 50 miles of a DEA office.[15] Second, a continuous variable that measures the proximity from each county to the closest DEA office. For consistency and to facilitate interpretation of the results relative to the other specifications, the measure of proximity is calculated as the difference between the longest distance from any county to a DEA office (approximately 2,600 miles for the county of Aleutians West, Alaska) and the distance between each county and the closes DEA office. Thus, counties where there is a DEA office receive a value of 2,600 and the lowest values are given to counties further away from the DEA offices. Figure 6

[15] The results are robust to using 20, 30, 40, and 60 miles as the threshold.

provides a graphical representation of this measure. We provide the results of the alternative specifications in Appendix Tables A2 and A3. The results in Table A2 are similar to the ones in Table 3 both qualitatively and quantitatively. The results in Table A3, where we use a continuous measure of exposure, are also consistent with our findings in Table 3.

--- Figure 6 about here---

To alleviate concerns of spurious correlation, in a placebo test we randomize the designation of HIDTA counties. More specifically, we randomly assign to 17% of the counties (the proportion of counties designated as HIDTA as of 2012) the HIDTA designation and repeat the test using the specification in Equation (2). The results in Table A4 suggest that the previous findings do not respond to spurious correlation.

Last, we restrict the sample to a subset of matched counties and find similar results. We match each HIDTA county to the most similar non-HIDTA county within the same state in terms of population, median income, number of establishments, and unemployment rate. The results in Table A5 are similar to those of the non-matched sample.

A potential concern is that the results are driven by banks' failures and acquisitions. While our results survive the inclusion of bank-county fixed effects (columns 2, 3, 5, and 6) and thus draw inference from banks that remain present following the shift in enforcement, we provide additional evidence to mitigate this concern by analyzing the data on failed and acquired branches across the US from the Federal Financial Institutions Examination Council. Figure 7 shows that branches in HIDTA counties and those in non-HIDTA counties follow similar patterns in terms of acquisitions (Panel A) and failures (Panel B), suggesting that mergers, acquisitions, or failures do not seem to drive our results.

--- Figure 7 about here---

B. Real economic effects

After establishing that the tightening of AML enforcement impacts bank composition in counties more exposed to money laundering activity, we then explore the effect of this change in bank composition on the real economy. In our setting, the change in the bank composition is driven by increasing compliance costs due to tighter AML enforcements and thus less susceptible to being driven by economic conditions. Furthermore, the evidence on bank concentration in HIDTA counties in the earlier sections is established by controlling for granular time varying fixed effects at the county-year level, addressing concerns on local common shocks. Thus, this framework allows us to explore in a causal manner how changing bank composition affects local economies.

B.1 Establishments, employment, and wages

We start by analyzing the effect of the change in the composition of banks that operate within a county on the number of establishments, aggregate employment, and wages. A priori, it is unclear how the increased presence of large banks would affect local economies. On the one hand, economic activity could be negatively affected due to two factors. First, because larger banks have a broader network of branches, the funds sourced in these counties could be lent in other areas. Second, since large banks are at a disadvantage in terms of processing soft information, an increased presence by large banks could lead to a reduction in lending. On the other hand, lending by large banks under programs such as the Community Reinvestment Act or the Small Business Administration Act could increase and lead to economic growth. Furthermore, if large banks are able to implement more effective compliance risk systems, these banks may screen the clients more efficiently and thus broaden access to finance for a wider group. Alternatively, if larger banks are less prone to sanctions (too big to jail), these banks might be willing to operate with riskier customers and therefore expand operations in high-risk counties.

In this subsection, we test the impact of the change in the composition of banks on economic outcomes, and in section IV we explore potential channels. We measure economic outcomes using information from the Quarterly Census of Employment and Wages (QCEW) and County Business Patterns and work with three levels of aggregation. First, the county-year level, to test the effect of the change in composition of banks on the aggregate economy. Second, we analyze the effect on firms of different sizes. Third, following the insights of Mian, Sufi and Verner (2020), we analyze the role of credit supply on the tradable and non-tradable sectors separately to shed light on the economic forces behind our results. Our empirical specification for studying aggregate outcomes at the county level is similar to that in Equation (1).

We provide the results at the county level in Table 4. We find a positive effect on the aggregate number of establishments. Following the change in the composition of banks, the total number of establishments in HIDTA counties increases by 0.94% (Column 1). In contrast, we find no significant effect on aggregate employment or wages.[16] We next exploit the richness of the data and exploit the cross section of firms and industries.

--- Table 4 about here---

In Table 5, Panel A, we use the County Business Patterns data to test the effect of the change in the composition of banks on firms of different sizes. We find that the positive effect in aggregate number of establishments is driven by small firms, particularly those with fewer than 20 employees and those with more than 20 but less than 100 employees. Given that small establishments are bank-dependent, one interpretation of this finding is that an increase in the presence of large banks improves access to finance. We find no effects on aggregate wages or employment.

--- Table 5 about here---

Next, we consider the real effects for tradeable and non-tradeable sectors separately as defined in Mian and Sufi (2014), classifying retail trade, accommodation, and food services as non-tradable sector, and agriculture, forestry, fishing, mining, and manufacturing as tradable sector. Mian, Sufi and Verner (2020) develop a methodology to test whether credit supply expansion affects economic outcomes by increasing productive capacity or by boosting household demand. The authors argue that a household demand channel would boost employment and prices in the non-tradable sector. Similarly, Di Maggio and Kermani (2017) find that increasing credit supply due to a change in banking regulation boost employment in the non-tradable sector. We explore this channel within our setting. This specification also serves as a falsification test. If changing bank composition is due to a common shock that affects overall economic growth in these counties, then we should not observe a differential impact between the tradeable and non-tradable sectors. If, on the other hand, positive effect in the local economy is driven by increased lending to households, we should find an effect mainly in the non-tradable sector in response to an increase in consumption.

The results in Table 5, Panel B, show a positive effect exclusively in the non-tradable sector, consistent with increased household demand for local goods. In particular, we find a positive and

[16] The results remain unchanged when we exclude control variables that might bias our estimates, primarily lagged number of establishments in estimations of establishments or unemployment rate in estimations of employment.

statistically significant coefficient in terms of number of establishments, employment, and wages. In contrast, we find no effect in the tradable sector.

B.2 Real estate prices

Next, we study the effect of the change in composition of banks within a county on the real estate market. We focus on four outcomes at the county-year level: median listing price, median listing price per square foot, Zillow Home Value Index (ZHVI) for all types of homes, and ZHVI for single family residences (excludes condo/co-op). One of the advantages that Zillow Home Value Index has over the S&P/Case-Shiller index is its availability over a larger number of locations. In addition, the methodology used plausibly makes the data less sensitive to composition effects (Chinco and Mayer 2016).

We find that following the regulation, median listing price and median listing price per square foot increase in HIDTA counties (Table 6). More specifically, the median listing price increases by 5%, while the median listing price per square foot increases by 3.7%. These findings are consistent with two different mechanisms: an increase in property prices; and a change in the composition of properties being sold. To better understand whether the results respond to an increase in real estate prices holding type and quality constant, we study the evolution of the ZHVI index, constructed as the median estimated value of all homes within a county and not only those that are listed. In columns 3 and 4, we find a positive and statistically significant effect on the ZHVI, suggesting that the results represent an increase in property prices and are not driven by a change in composition.

--- Table 6 about here---

Looking at real estate prices also allows us to explore real economic effects of changing bank composition due to AML enforcement in areas that are particularly in more need for access to finance. In this regard, we exploit heterogeneity across counties and consider variation in income levels within a county, following the specification in Equation (3), which allows a stricter specification with granular county-year level fixed effects that account for local time-varying effects.

The results in Table 7 suggest that the increase in real estate prices is more prominent in lower income areas than in higher income areas within HIDTA counties. In particular, while the coefficient *Post x HIDTA* is positive and statistically significant for median listing price, median listing price per square foot, the ZHVI for all types of residencies, and the ZHVI for single family residences, we find that the coefficient for the triple interaction term is also positive and statistically significant. Thus, changing bank composition towards large banks likely improves economic growth prospects in areas that are in more need for access to finance as evidenced from increasing real estate prices.

--- Table 7 about here---

B.3 Crime

Arguably, stricter AML enforcement could directly affect the intensity of criminal activity and thereby impact economic conditions. We test this idea by analyzing data on crime reported by the FBI under the Uniform Crime Reporting (UCR) Program. Following an empirical specification similar to that in Equation (1) and using data from 2010 to 2016, we find that stricter AML enforcement does not result in any noticeable change in crime rates (Table 8). This finding also suggests that the increase in real estate prices is not due to lower crime, but due to economic growth in these areas. In the Appendix, Table A6, we analyze potential heterogeneous effects on crime in zip codes with different income levels within a county, following the specification in Equation (3) and find no effects.

--- Table 8 about here---

IV. CHANNELS

There are multiple potential channels that relate to how changing bank composition affect real economic outcomes. In this section, we posit several hypotheses and explore them.

A. Lending under the Community Reinvestment Act (CRA)

A political subtlety in the process faced by banks seeking approval for mergers and acquisitions provides a first potential channel for the real economic results observed. As noted by Calomiris and Haber (2015), banks interested in merging or acquiring other banks require the approval of the Federal Reserve Bank, and the decision is based on three factors. First, the acquiring bank has to be financially strong. Second, the combined bank cannot have excessive market power. Third, the acquiring institution must be a good citizen of the communities it serves. A key component of this judgement is based on compliance with the Community Reinvestment Act (CRA) of 1977, which encourages financial institutions to lend to all segments in the locations where they operate. This third factor did not influence lending until the 1990s. Following the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994 that allowed banks to acquire other banks in any state, banks interested in obtaining high CRA ratings committed more than 3.6 trillion in CRA lending to underserved customers (Calomiris and Haber 2015) between 1992 and 2007. These commitments follow pressure by activist organizations such as the National Community Reinvestment Coalition (NCRC), which reports data on CRA commitments.

We test how the change in bank composition within counties prone to money laundering activity affects lending under the CRA program. More specifically, we start by analyzing aggregate data using an empirical specification similar to the one depicted in Equation (1), where our focus is on the following outcomes for CRA loans: number of loans, total volume of loans, and number and volume of small, medium, and large loans to small businesses.

We report the results in Table 9. We find that following the increased presence of large banks, the number of loans does not vary significatively (column 1) but the total volume declines (column 2). We then study whether there is a heterogeneous effect across loans of different sizes. We find that the decline in the total volume of loans is driven by a reduction in medium-size (between 100,000 and 250,000 US dollars) and large loans (between 250,000 and one million). These findings are in line with Chen, Hanson and Stein (2017), and Bord, Ivashina and Talieferro (2018) who find reduced CRA lending with large banks' presence.

--- Table 9 about here---

B. Lending under the Small Business Administration (SBA) program

A second potential channel that deserves attention is the Small Business Administration (SBA) 7(a) Loan Guarantee program. Under this program, lenders obtain a partial guarantee to lend to small businesses that might otherwise not be funded (see Brown and Earle (2017) for more details on SBA loans). Although most commercial banks participate in this program, out of the approximately 44,800 loans made by more than 1,800 banks in 2012, more than 17,700 (or about 40%) were originated by 10 large banks. This evidence suggests that an increased presence of large banks could result in more loans made to small businesses under this program.

We explore this channel and provide the result of the analysis in Table 10. We find no significant effect on the volume of total loans (column 1) or volume of guarantees provided by the SBA (column 2). Moreover, we find no effects on interest rates (column 3) or term of the loans originated (column 4).

--- Table 10 about here---

C. Secured Lending

We explore secured lending through mortgages, given that mortgage lending could affect economic activities via multiple channels. Increased liquidity in the real estate market could drive prices up, allowing homeowners to borrow against equity and increase consumption. It could also allow homeowners to refinance their mortgages, providing them with additional liquidity. Increased liquidity would also affect related industries such as construction and cause spillovers to other industries. Secured lending also decreases losses given default for the banks and thus may compensate for the limited ability of processing soft information by the large banks, allowing these banks to increase lending through this channel.

We use data on mortgage lending from the HMDA program and test whether the volume of mortgages exhibits a differential pattern across HIDTA and non-HIDTA counties following the change in the composition of banks in HIDTA counties. We provide the results in Table 11. In Columns 1 and 2, our dependent variables are the number and volume of loans issued for home purchases. In Columns 3 and 4, we study number and volume of loans for home improvement, and in Columns 5 and 6 our interest is on refinancing loans. We find that while the total number of loans for home purchases increases by approximately 2.4% in HIDTA counties relative to non-HIDTA counties, the total volume lent does not vary significantly. On the other hand, we find a significant and large effect on loans for home improvement, with the number and amount of loans increasing 7.4% and 8.6%, respectively. There is no significant effect on loans for refinancing.

--- Table 11 about here---

D. Too Big to Jail

While AML enforcement tightening leads to disproportionate compliance costs for smaller banks as discussed in our paper, another potential explanation for our results is that larger banks and their officials might be "too big to jail", thus allowing these banks to operate in riskier regions without fearing repercussions. This theory has been the center of debate both in the media and in political circles, following cases such as that of HSBC laundering close to a billion dollars for drug traffickers and Wells Fargo opening sham accounts. In both cases, bank executives were insulated.[17]

While we cannot directly test this hypothesis, we find that following the change in composition of banks towards large banks in high-risk areas, we find that the number of Suspicious Activity Reports issued in high-risk areas increases disproportionately.[18] This finding is consistent with several explanations: Large banks (i) increased AML compliance and were successful in unearthing more money laundering activities as reported in SARs; (2) increased defensive filing of SAR reports to be protected from prosecution and enforcement actions; (3) were more involved in providing banking services for illicit activities and "shadowy characters" due to being "too big to jail." [19]

--- Figure 8 about here---

Taken together, our findings on positive real effects on the non-tradeable sector and an increase in real estate prices suggest that the real economic impact is driven by an increase in credit supply to households through secured lending following the increased presence of large banks in counties more prone to money laundering activity. These findings are consistent with several notions. For instance, since large banks potentially have a disadvantage in processing soft information compared to small banks, the former expand their secured lending to compensate for the limited ability to process soft information. Similarly, large banks may be deemed "too big to jail" or have the ability to implement better compliance risk systems, which may allow them to better screen clients and thus expand the depositor base, which increases funding to support the local economy. On the overall, while stricter enforcement of AML shifts the composition of the banking system towards large banks, the effect on the real economy is favorable, plausibly driven by an increase in secured lending.

[17] Following these and other similar cases, Senator Elizabeth Warren introduced in the Senate in 2018 the "Ending Too Big to Jail Act".
[18] Data on Suspicious Activity Reports is available starting in 2013 through FinCEN.
[19] "Shadowy characters" is a denomination used by the International Consortium of Investigative Journalists in the "FinCEN Files" investigation.

V. Conclusion

We examine the effects of a change in bank composition towards larger banks on real economic outcomes. Following tighter anti-money laundering (AML) enforcement, large banks gain market share in counties more exposed to money laundering activities, a finding consistent with a disproportional compliance cost imposed on small banks operating in areas that are more prone to money laundering. This shift in the composition of banks towards large institutions affects the local economy. First, the aggregate number of firms increases, an effect driven by small firms. Second, number of establishments, employment, and wages increase in the non-tradable sector, which is consistent with credit supply to households driving an increase in demand. In addition, we find that real estate prices increase, particularly in lower income areas within these counties. Last, we explore potential channels. While we find no effect on lending under the Community Reinvestment Act (CRA) or Small Business Administration (SBA) programs, we observe an increase in mortgage lending in high risk counties following the change in the composition of banks. Thus, local economic growth is likely to be driven by increased secured lending of large banks, particularly in lower income areas where access to finance is more consequential.

Our study also provides insights on how recent AML enforcement actions affect the banking system and the real economy as a result. Contrary to the concerns in the policy circles about AML enforcement actions reducing access to finance and thus weakening the local economy, our findings show that while AML enforcement leads to a shift in the bank composition towards larger banks in areas more prone to money laundering, the impact of this shift on the local economy is mainly favorable.

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Figure 1
Banks' Assets Concentration

This figure shows the concentration of Bank assets in the G-20 countries in 1997 and 2017. The measure of concentration is calculated as the sum of assets for the five largest banks in each country over total assets by all banks in that country. The data are from the Global Financial Development database by the World Bank.

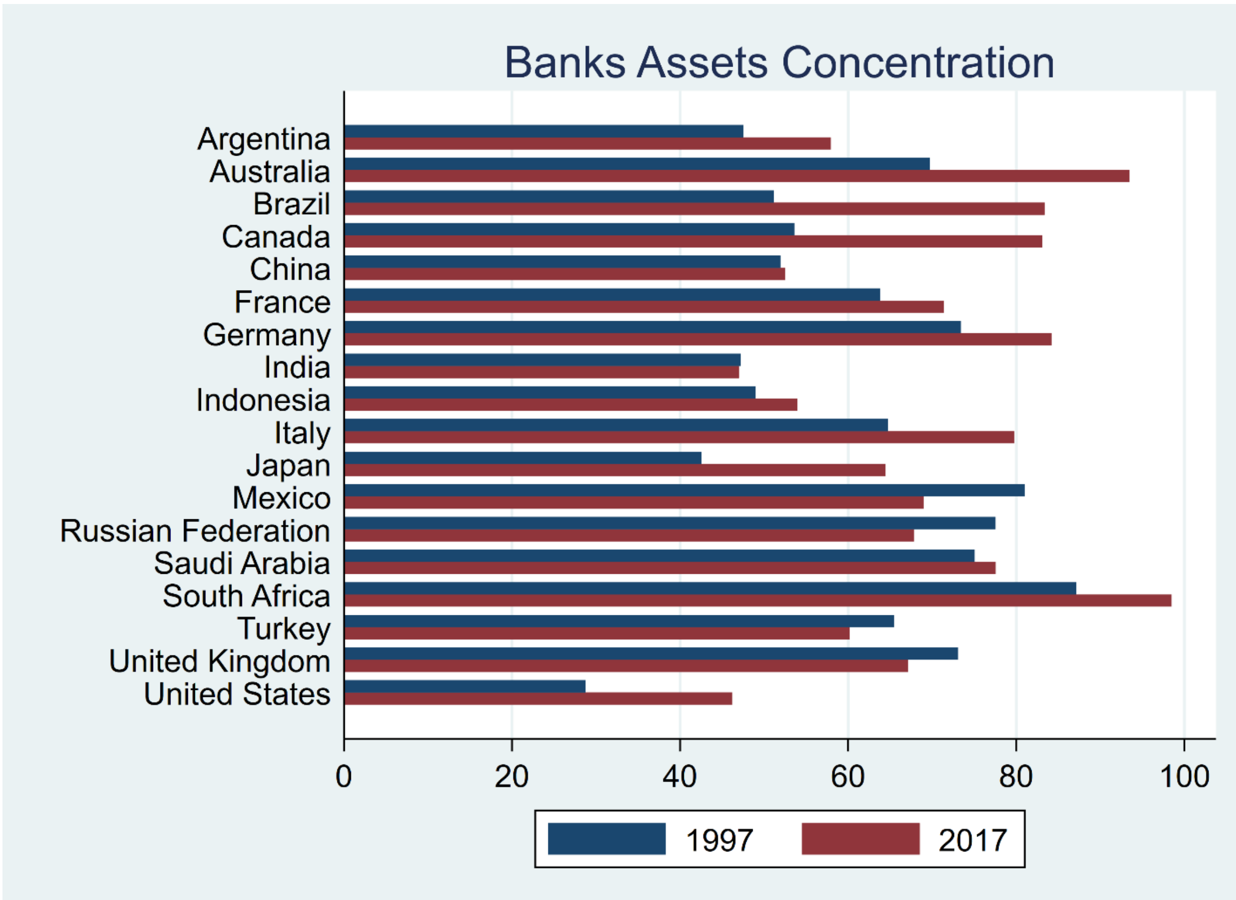
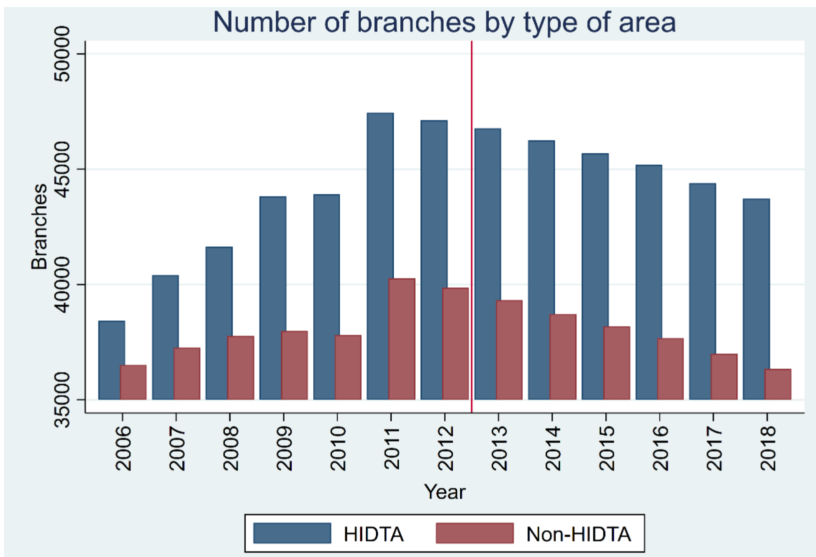


Figure 2
Bank branches in HIDTA and non-HIDTA counties

This figure shows the evolution of the total number of bank branches in High Intensity Drug Trafficking Areas (HIDTA) and non-HIDTA counties between 2006 and 2018 (Panel A) and the share of branches of large banks in HIDTA and non-HIDTA counties (Panel B). Large banks are defined as those that are in the top one percent in terms of volume of deposits and that have at least 100 branches across the United States. The data on bank branches are from the Summary of Deposits, reported by the FDIC. HIDTA counties are those identified by the White House Office of National Drug Control Policy as of 2012.

Panel A - Number of Branches in HIDTA and non-HIDTA regions



Panel B – Composition of Bank Branches in HIDTA and non-HIDTA regions

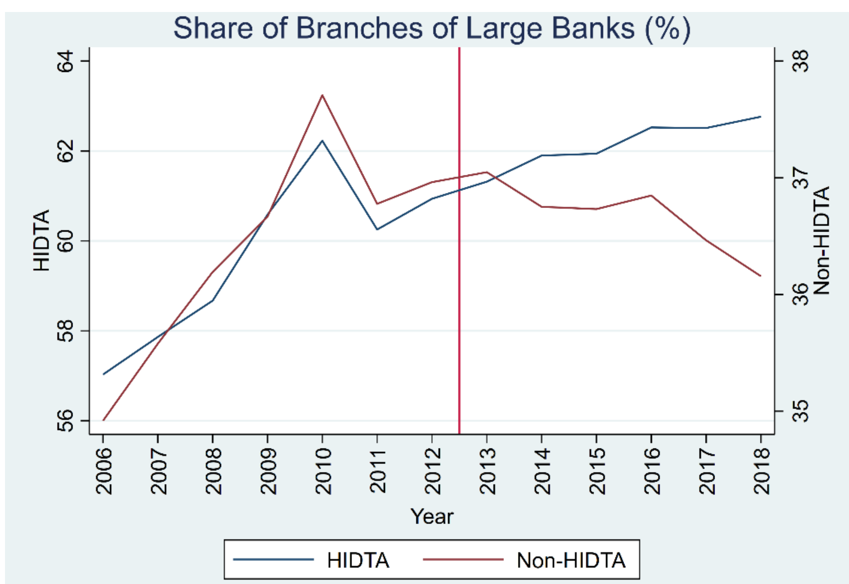
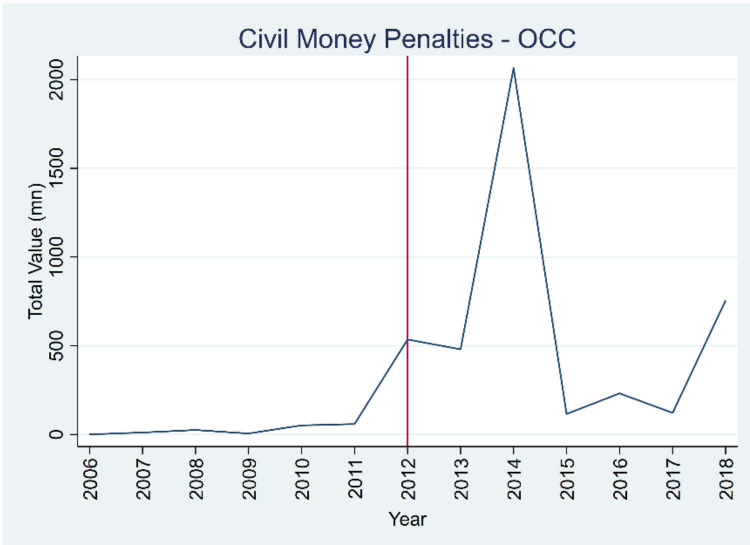


Figure 3
Money Laundering in perspective

This figure shows the aggregate value of civil money penalties imposed by the Office of the Comptroller of the Currency between 2006 and 2018 (Panel A), and the quarterly number of Wall Street Journal articles that contain the term 'Money Laundering' between 2010 and 2016 (Panel B). The red vertical line denotes the timing of the release of the Senate report on HSBC's money laundering investigations. The data on civil money penalties are from the Office of the Comptroller of the Currency. Wall Street Journal articles are obtained through ProQuest.

Panel A – Civil Money Penalties



Panel B – Newspaper Articles

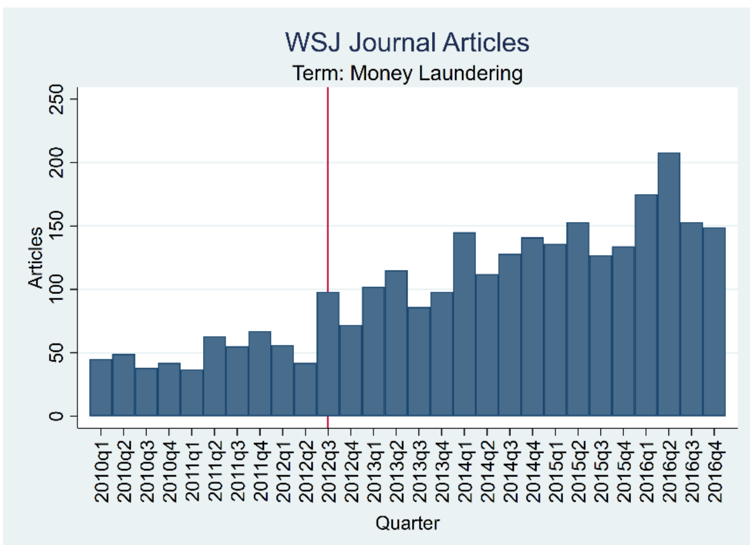


Figure 4
High Intensity Drug Trafficking Areas (HIDTA)

This map highlights counties identified by the White House Office of National Drug Control Policy as High Intensity Drug Trafficking Areas (HIDTA). Data are as of 2012.

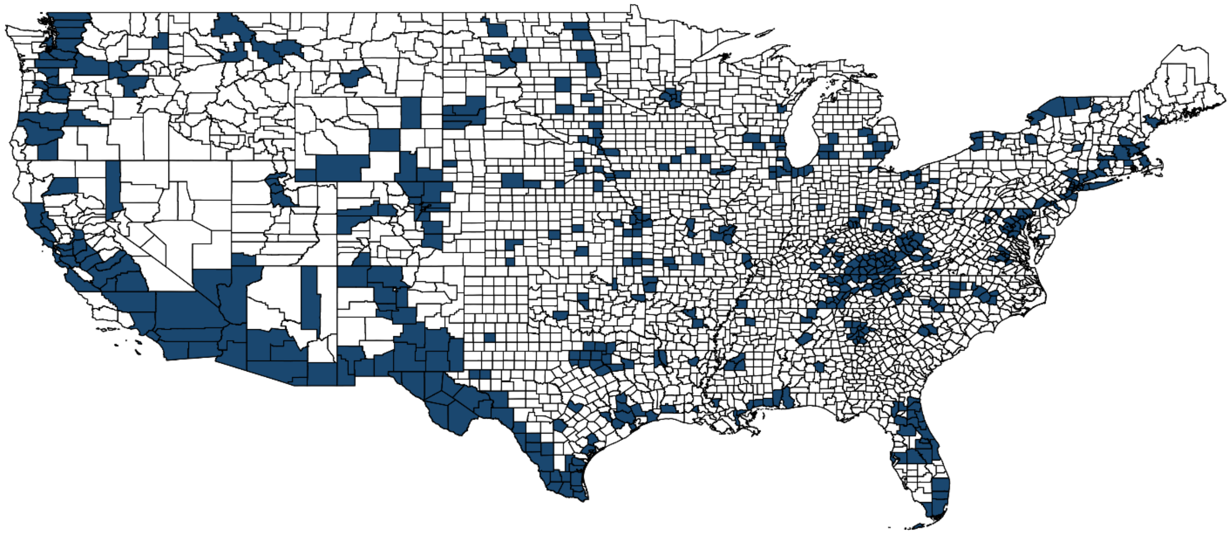


Figure 5
Bank branches in HIDTA counties

This figure shows the year-by-year evolution of the number of branches operated by large banks counties vis-à-vis small banks in HIDTA counties. Plotted are the year-by-year coefficients of a regression of the number of bank branches large banks have in HIDTA counties across time. Large banks are defined as those that are in the top one percent in terms of volume of deposits and that have at least 100 branches across the United States. The data on bank branches are from the Summary of Deposits as reported by the FDIC. HIDTA counties are those identified by the White House Office of National Drug Control Policy by 2012.

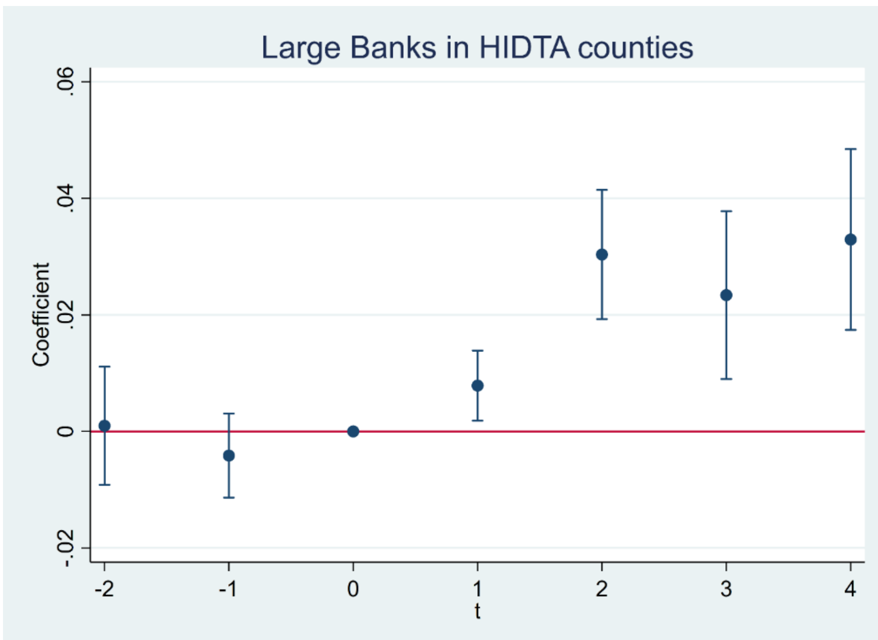


Figure 6
Distance to DEA offices

This figure maps the distance of each county in the United States to its closest Drug Enforcement Agency (DEA) office. Data on regional offices are obtained from the United States Drug Enforcement Administration website.

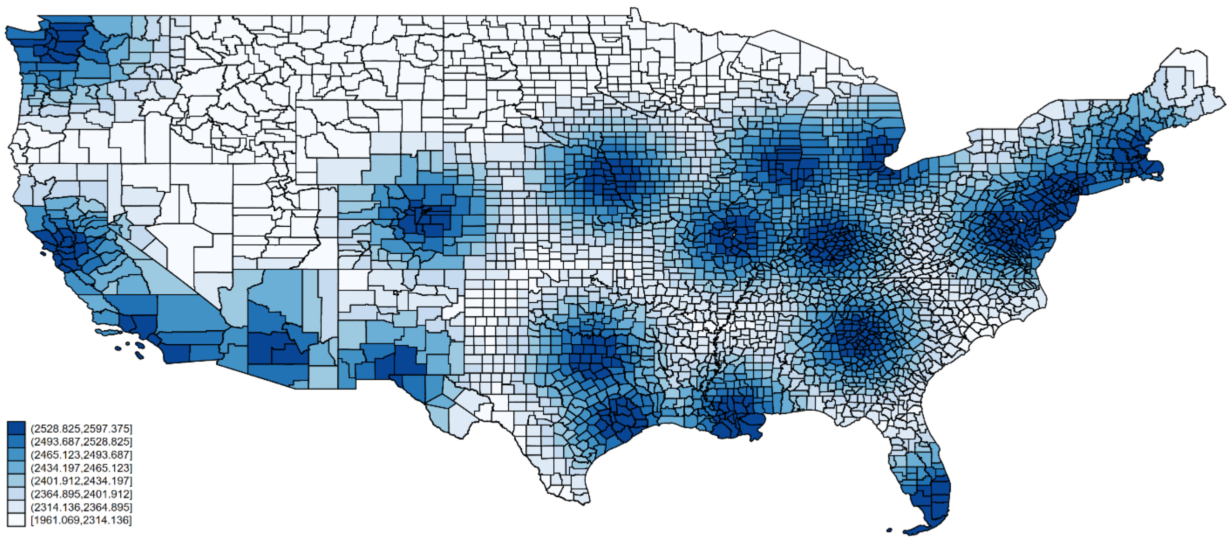
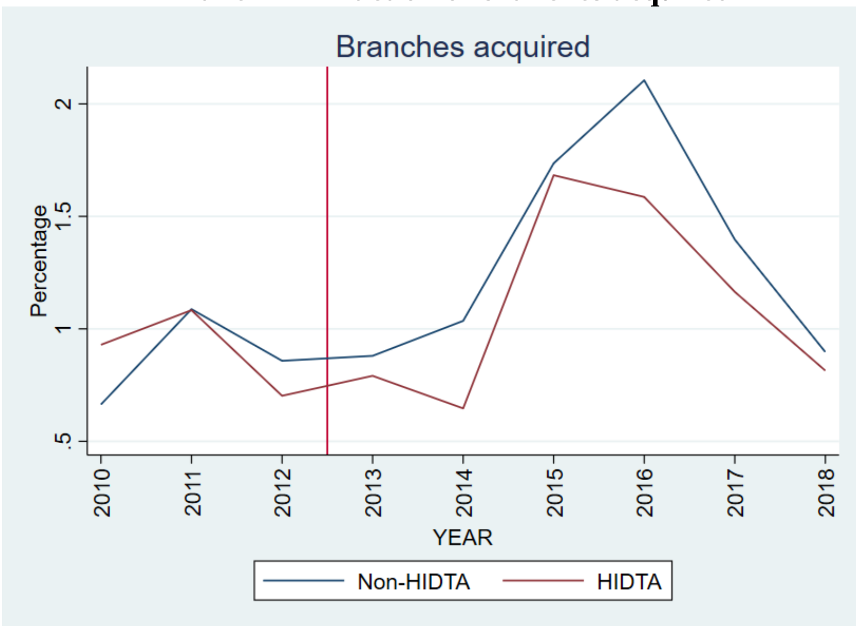


Figure 7
Acquired and failed bank branches

This figure plots the percentage of branches that were acquired (Panel A) and that failed (Panel B) over the 2010 to 2018 period by HIDTA and non-HIDTA counties. Data on acquired and failed branches are from the Federal Financial Institutions Examination Council and data on total number of branches are from the Summary of Deposits reported by the FDIC.

Panel A – Fraction of branches acquired



Panel B – Fraction of branches that failed

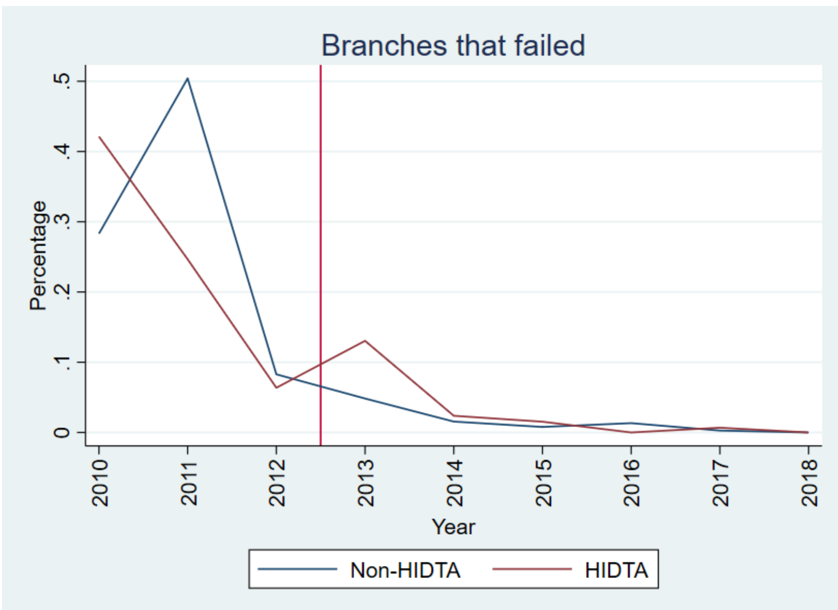


Figure 8
Suspicious Activity Reports filed

This figure plots the number of suspicious activity reports (SARs) filed by financial institutions over the 2013 to 2018 period by HIDTA and non-HIDTA counties. Data on SARs are from the Financial Crimes Enforcement Network (FinCEN) FDIC.

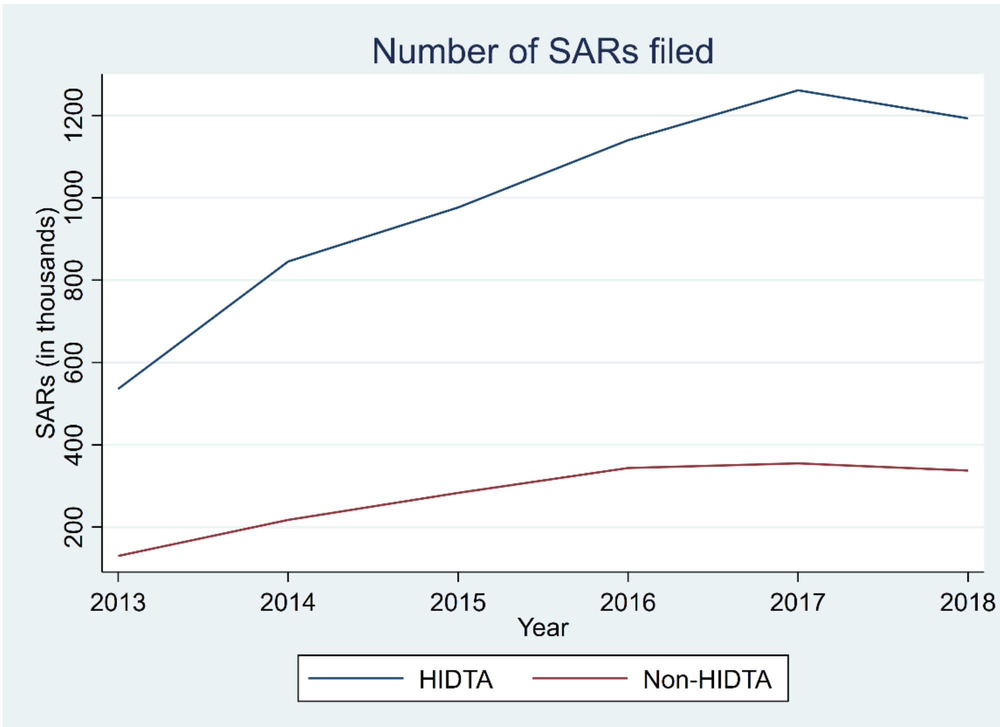


Table 1
Summary Statistics

This table shows summary statistics for High Intensity Drug Trafficking Areas (HIDTA) and non-HIDTA counties. Panel A presents summary demographic statistics at the county level as of 2010. Panel B presents summary statistics of the banking system at the county level as of 2012. Data are from the census bureau and the Summary of Deposits reported by the FDIC.

Panel A – Static demographic comparison as of 2010 (census data)

	Non-HIDTA		HIDTA		
	Value	N	Value	N	Difference
Median Income (log)	10.62	2,569	10.75	573	-0.13***
Population (log)	9.94	2,569	11.72	573	-1.78***
Unemployment rate	9.35	2,568	9.47	573	-0.12
Poverty Rate	16.35	2,570	16.06	572	0.28
Less than High School degree (%)	14.58	2,647	14.39	573	0.19
College degree (%)	19.54	2,647	26.56	573	-7.02***
Establishments per capita	0.02	2,560	0.02	573	-0.00

Panel B – Comparative banking statistics as of 2012

	Non-HIDTA		HIDTA		
	Value	N	Value	N	Difference
Deposits per capita (log)	2.81	2,580	2.87	528	-0.06*
Deposits per capita growth (Δ=1)	0.03	2,580	0.03	528	-0.01
Deposits per capita growth (Δ=2)	0.04	2,579	0.05	528	-0.01
Deposits per capita growth (Δ=3)	0.05	2,579	0.06	528	-0.00
Deposits per capita growth (Δ=4)	0.09	2,580	0.09	527	-0.01
Branches per thousand capita	0.37	2,580	0.26	528	0.11***
Branches per capita growth (Δ=1)	-0.00	2,580	-0.00	528	0.00
Branches per capita growth (Δ=2)	0.01	2,579	0.01	528	0.00
Branches per capita growth (Δ=3)	0.01	2,579	0.01	528	0.00
Branches per capita growth (Δ=4)	0.01	2,580	0.01	527	0.00

Table 2

Bank branches and deposits volume following anti-money laundering enforcement

This table provides the results of the analysis of the number of branches and volume of deposits in counties subject to high levels of criminal activity in the form of money laundering following the AML enforcement shift in 2012. The sample period is 2010-2016 and the unit of analysis is the county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, and *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy. The dependent variables are *Branches*, the logarithm of one plus the number of branches operating within a county (Columns 1-3), and *Deposits*, the logarithm of one plus the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 3 and 6 further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Branches	(2) Branches	(3) Branches	(4) Deposits	(5) Deposits	(6) Deposits
Post x HIDTA	0.00540	0.00601	0.000909	0.0407**	0.0346**	0.0196*
	(1.03)	(1.17)	(0.19)	(3.01)	(2.79)	(1.95)
N	21,773	21,766	21,750	21,773	21,766	21,750
Adj R-squared	0.996	0.996	0.997	0.996	0.997	0.997
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
State x Year FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes

Table 3

Bank branches and deposits by bank size following anti-money laundering enforcement

This table provides the results of the analysis of the composition of bank branches and volume of deposits in small and large banks in counties subject to high levels of criminal activity in the form of money laundering. The sample period is 2010-2016 and the unit of analysis is the bank-county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy, and *Large*, an indicator variable set to one for banks in the top 1% in terms of deposits. The dependent variables are *Branches*, the logarithm of one plus the number of branches operating within a county (Columns 1-3), and *Deposits*, the logarithm of one plus the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 1-2 and 4-5 further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Branches	(2) Branches	(3) Branches	(4) Deposits	(5) Deposits	(6) Deposits
Post x HIDTA	-0.0136	-0.0192*		-0.314**	-0.292**	
	(-1.30)	(-2.20)		(-2.85)	(-2.47)	
HIDTA x Large	0.536***			0.823***		
	(20.07)			(6.10)		
Post x Large	0.0192	0.0230		0.620***	0.707***	
	(1.91)	(1.92)		(3.74)	(3.95)	
Post x HIDTA x Large	0.0222***	0.0440**	0.0246**	0.620***	0.627**	0.313***
	(5.62)	(3.60)	(2.97)	(3.75)	(3.48)	(3.89)
N	232,592	231,579	202,784	232,592	231,579	202,784
Adj R-squared	0.571	0.859	0.948	0.682	0.788	0.931
County FE	Yes	-	-	Yes	-	-
Bank FE	Yes	-	-	Yes	-	-
Year FE	Yes	-	-	Yes	-	-
State x Year FE	No	Yes	-	No	Yes	-
Bank x Year FE	No	No	Yes	No	No	Yes
County x Year FE	No	No	Yes	No	No	Yes
Bank x County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	-	Yes	Yes	-

Table 4
Real Economic Outcomes following anti-money laundering enforcement

This table provides the results of the analysis of the relation between changes in the composition of banks and real economic outcomes in counties subject to high levels of criminal activity in the form of money laundering. The sample period is 2010-2016, and the unit of analysis is the county-year. The controls of interest are *Post*, an indicator variable set to one after 2012, and *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy. The dependent variables are the logarithm of one plus the number of establishments (column 1), logarithm of one plus aggregate number of employees (column 2), and logarithm of one plus aggregate wages (column 3). The estimations further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Establishments	(2) Employment	(3) Wages
Post x HIDTA	0.00938*	-0.000407	-0.0300
	(2.43)	(-0.05)	(-1.44)
N	21,922	21,922	21,922
Adj R-squared	0.999	0.970	0.891
County FE	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Table 5
Real Economic Outcomes by firm size and sector

This table provides the results of the analysis of the relation between changes in the composition of banks and real economic outcomes in counties subject to high levels of criminal activity in the form of money laundering. The sample period is 2010-2016, and the unit of analysis is the county-year. The controls of interest are *Post*, an indicator variable set to one after 2012, and *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy. In Panel A, Columns 1 to 4, the dependent variable is the logged number of firms within each category in terms of number of employees. In Columns 5 to 8 the dependent variable is the logged number of establishments within each category in terms of number of employees for firms with different number of employees. The unit of analysis is the county-year. In Panel B the dependent variables are the logged number of establishments (columns 1 and 4), logged number of employees (columns 2 and 5), and logged volume of wages (columns 3 and 6) for firms in the non-tradable sector (columns 1 to 3) and in the tradable sector (columns 4 to 6). Sector classifications are from Mian and Sufi (2014). The estimations further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A - By firm size

	(1) #Firms <20	(2) #Firms 20-99	(3) #Firms 100-499	(4) #Firms 500+	(5) #Establishmt <20	(6) #Establishmt 20-99	(7) #Establishmt 100-499	(8) #Establishmt 500+
Post x HIDTA	0.0121**	0.0188**	-0.00660	-0.00426	0.0121**	0.0190**	-0.0114	-0.000958
	(3.03)	(3.14)	(-1.20)	(-1.03)	(2.99)	(3.25)	(-1.85)	(-0.22)
N	21,936	21,835	21,629	21,747	21,936	21,835	21,629	21,747
Adj R-squared	0.999	0.995	0.992	0.997	0.999	0.994	0.991	0.997
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B - By Sector

	(1) Non-Tradable #Establishmt	(2) Non-Tradable Employmt	(3) Non-Tradable Wages	(4) Tradable #Establishmt	(5) Tradable Employmt	(6) Tradable Wages
Post x HIDTA	0.0219**	0.0552*	0.124*	0.00981	0.0145	0.0317
	(2.63)	(2.31)	(2.22)	(1.18)	(0.86)	(0.80)
N	3,856,940	3,856,940	3,856,940	4,457,864	4,457,864	4,457,864
Adj R-squared	0.837	0.666	0.598	0.538	0.355	0.342
Industry (6d) FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry (3d) x County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry (3d) x State x quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6

Real Estate

This table provides the results of the analysis of the relation between the change in the composition of banks and real estate prices in counties subject to high levels of criminal activity in the form of money laundering. The sample period is 2010-2016 and the unit of analysis is the county-year. The controls of interest are *Post*, an indicator variable set to one after 2012 and *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy. The dependent variables are the logarithm of one plus the median listing price (column 1), the logarithm of one plus the median listing price per sq ft (column 2), the logarithm of one plus the Zillow Home Value Index for all types of properties (column 3), and the logarithm of one plus the Zillow Home Value Index for single family residences (column 4. The estimations further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Median Listing Price	(2) Median Listing Price per sqft	(3) ZHVI All	(4) ZHVI SFR
Post x HIDTA	0.0508***	0.0371***	0.0174**	0.0173**
	(4.28)	(4.31)	(2.70)	(2.82)
N	11,778	12,585	13,618	13,595
Adj R-squared	0.966	0.974	0.991	0.992
County FE	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 7
Real Estate by zip code-level income

This table provides the results of the analysis of the relation between the change in the composition of banks and real estate prices in counties subject to high levels of criminal activity in the form of money laundering. The sample period is 2010-2016 and the unit of analysis is the zip code-year. The controls of interest are *Post*, an indicator variable set to one after 2012 and *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy, and *Low Income*, an indicator variable set to one for zip codes wherein the median household income is below the median for the corresponding county. The dependent variables are the logarithm of one plus the median listing price (columns 1 and 2), the logarithm of one plus the median listing price per sq ft (columns 3 and 4), the logarithm of one plus the Zillow Home Value Index for all types of properties (columns 5 and 6), and the logarithm of one plus the Zillow Home Value Index for single family residences (columns 7 and 8). The estimations further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Median Listing Price	(2) Median Listing Price	(3) Median Listing Price per sqft	(4) Median Listing Price per sqft	(5) ZHVI All	(6) ZHVI All	(7) ZHIV SFR	(8) ZHIV SFR
Post x HIDTA	0.0373***		0.0359***		0.0251***		0.0248***	
	(4.37)		(4.72)		(3.94)		(3.98)	
Post x Low Income	-0.0227***	-0.0200**	-0.00552	-0.00382	-0.0127**	-0.0132**	-0.0125**	-0.0128**
	(-4.35)	(-3.64)	(-1.49)	(-0.74)	(-3.32)	(-2.89)	(-3.38)	(-2.91)
Post x HIDTA x Low Income	0.0214*	0.0213*	0.0180*	0.0211**	0.0162	0.0170	0.0167	0.0172
	(2.18)	(2.22)	(2.06)	(2.57)	(1.62)	(1.71)	(1.70)	(1.76)
N	47,293	43,221	59,713	55,629	108,617	105,855	108,004	105,238
Adj R-squared	0.980	0.985	0.984	0.989	0.993	0.996	0.993	0.996
Zip code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
State x Year FE	Yes	No	Yes	No	Yes	No	Yes	No
County-level Controls	Yes	No	Yes	No	Yes	No	Yes	No

Table 8
Crime

This table provides the results of the analysis of the relation between stricter AML enforcement and crime in counties subject to high levels of criminal activity in the form of money laundering. The sample period is 2010-2016 and the unit of analysis is the county-year. The controls of interest are *Post*, an indicator variable set to one after 2012 and *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy. The dependent variables are the logarithm of one plus the number of murders (column 1), the logarithm of one plus the number of cases of manslaughter (column 2), the logarithm of one plus the number of cases of rape (column 3), the logarithm of one plus the number of cases of robbery (column 4), the logarithm of one plus the number of cases of assault (column 5), the logarithm of one plus the number of cases of burglary (column 6), the logarithm of one plus the number of cases of theft (column 7), and the logarithm of one plus the total number of crimes (column 8). The estimations further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth (in lag). *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Violent crime	(2) Murder and Manslaughter	(3) Robbery	(4) Aggravated Assault	(5) Property Crime	(6) Burglary	(7) Larceny / Theft	(8) Motor Vehicle Theft
Post x HIDTA	-0.00275	0.0100	0.00492	0.00692	-0.00532	-0.0400*	0.00725	0.0243
	(-0.08)	(0.68)	(0.27)	(0.19)	(-0.24)	(-2.27)	(0.31)	(1.02)
N	17537	17826	17826	17784	17768	17802	17808	17805
Adj R-squared	0.878	0.599	0.838	0.868	0.893	0.882	0.893	0.841
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9

Community Reinvestment Act (CRA) lending

This table provides the results of the analysis of the relation between changes in the composition of banks and lending under the Community Reinvestment Act program. The sample period is 2010-2016 and the unit of analysis is the county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, and *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy. The dependent variables are *Loans (N)*, the logarithm of one plus the number of loans (column 1), *Loans (A)*, the logarithm of one plus the volume of loans (column 2), *Small Loans (A)*, the logarithm of one plus the volume of loans with face value at origination under 100,000 dollars (column 3), *Medium Loans (A)*, the logarithm of one plus the volume of loans with face value at origination between 100,000 and 250,000 dollars (column 4), and *Large Loans (A)*, the logarithm of one plus the volume of loans with face value at origination between 250,000 and 1,000,000 dollars (column 5). The estimations further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth (in lag). *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Total Loans (N)	(2) Total Loans (A)	(3) Small Loans (N)	(4) Medium Loans (N)	(5) Large Loans (N)	(6) Small Loans (A)	(7) Medium Loans (A)	(8) Large Loans (A)
Post x HIDTA	-0.00608	-0.0442*	-0.000475	-0.0265	-0.0428**	-0.0124	-0.128*	-0.0849*
	(-0.37)	(-2.32)	(-0.03)	(-1.62)	(-2.68)	(-0.68)	(-2.39)	(-2.17)
N	21076	21076	21076	21076	21076	21076	21076	21076
Adj R-squared	0.986	0.956	0.988	0.936	0.944	0.973	0.772	0.784
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10
Small Business Administration (SBA) lending

This table provides the results of the analysis of the relation between changes in the composition of banks and lending under the Small Business Administration 7(a) Loan Guarantee program. The sample period is 2010-2016 and the unit of analysis is the county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, and *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control The dependent variables are the logarithm of one plus the *volume* of loans issued (column 1), the logarithm of one plus the *volume* of loans guaranteed under the program (column 2), the median initial interest rate for loans issued (column 3) and the median term for loans issued, in months (column 4). The estimations further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) SBA loans	(2) SBA guaranteed	(3) Interest Rate	(4) Term
Post x HIDTA	-0.0208	-0.0128	0.00755	1.263
	(-0.10)	(-0.07)	(0.30)	(0.68)
N	21,140	21,140	15,449	15,449
Adj R-squared	0.553	0.557	0.227	0.280
County FE	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 11
Home Mortgage Disclosure Act (HMDA) lending

This table provides the results of the analysis of the relation between changes in the composition of banks and mortgage lending under the Home Mortgage Disclosure Act program. The sample period is 2010-2016 and the unit of analysis is the county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, and *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy. The dependent variables are *Loans (N)*, the logarithm of one plus the number of loans (columns 1, 3, and 5), and *Loans (A)*, the logarithm of one plus the volume of loans (columns 2, 4, and 6) for loans with different purposes. The estimations further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Home Purchase		Home Improvement		Refinancing	
	Loans (N)	Loans (A)	Loans (N)	Loans (A)	Loans (N)	Loans (A)
Post x HIDTA	0.0248*	0.0174	0.0735**	0.0857*	0.0383	-0.0459
	(2.38)	(1.46)	(3.58)	(2.15)	(1.28)	(-1.30)
N	21,838	21,838	21,384	21,384	21,829	21,829
Adj R-squared	0.991	0.988	0.974	0.923	0.992	0.983
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Appendix

Table A1
Bank branches and deposits volume by bank size – Alternative definition of large banks

This table provides the results of the analysis of the composition of bank branches and volume of deposits in small and large banks in counties subject to high levels of criminal activity in the form of money laundering. For large banks, the indicator variable is equal to one for banks with assets above 1 billion dollars as of 2012. The sample period is 2010-2016 and the unit of analysis is the bank-county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy, and *Large*, an indicator variable set to one for banks with assets above one billion dollars. The dependent variables are *Branches*, the logarithm of one plus the number of branches operating within a county, and *Deposits*, the logarithm of one plus the volume of deposits in bank-branches within a county. The estimations in Columns 1-2 and 4-5 further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Branches	(2) Branches	(3) Branches	(4) Deposits	(5) Deposits	(6) Deposits
Post x HIDTA	-0.0133	-0.0118		-0.221**	-0.202*	
	(-1.27)	(-1.38)		(-2.73)	(-2.32)	
HIDTA x Large	0.711***			1.263***		
	(15.95)			(8.20)		
Post x Large	-0.0368**	-0.0340		-0.118	-0.0334	
	(-2.83)	(-1.94)		(-0.57)	(-0.16)	
Post x HIDTA x Large	0.0699***	0.0628**	0.0652***	1.140***	1.069***	0.880***
	(5.83)	(3.53)	(3.87)	(4.52)	(4.19)	(4.42)
N	232,592	231,579	202,784	232,592	231,579	202,784
Adj R-squared	0.568	0.871	0.948	0.681	0.786	0.931
County FE	Yes	No	No	Yes	No	No
Bank FE	Yes	No	No	Yes	No	No
Year FE	Yes	No	No	Yes	No	No
State x Year FE	No	Yes	No	No	Yes	No
Bank x Year FE	No	No	Yes	No	No	Yes
County x Year FE	No	No	Yes	No	No	Yes
Bank x County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

Table A2

Bank branches and deposits volume by bank size – Proximity to DEA office

This table provides the results of the analysis of the composition of bank branches and volume of deposits in small and large banks in counties subject to high levels of criminal activity in the form of money laundering. The sample period is 2010-2016 and the unit of analysis is the bank-county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, *DEA*, an indicator variable set to one for counties within 50 miles of a Drug Enforcement Agency (DEA) office, and *Large*, an indicator variable set to one for banks in the top 1% in terms of deposits. The dependent variables are *Branches*, the logarithm of one plus the number of branches operating within a county, and *Deposits*, the logarithm of one plus the volume of deposits in bank-branches within a county. The estimations in Columns 1-2 and 4-5 further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Branches	Branches	Branches	Deposits	Deposits	Deposits
Post x DEA	-0.00792	-0.0143*		-0.346**	-0.351**	
	(-0.53)	(-2.21)		(-2.91)	(-2.64)	
DEA x Large	0.467***			0.645***		
	(11.18)			(3.75)		
Post x Large	0.0171	0.0257		0.690**	0.779***	
	(1.46)	(1.83)		(3.66)	(3.85)	
Post x DEA x Large	0.0496***	0.0639**	0.0366**	0.755***	0.757**	0.423**
	(6.44)	(3.07)	(3.01)	(3.90)	(3.59)	(3.69)
N	232,592	231,579	202,784	232,592	231,579	202,784
Adj R-squared	0.562	0.871	0.948	0.681	0.788	0.931
County FE	Yes	No	No	Yes	No	No
Bank FE	Yes	No	No	Yes	No	No
Year FE	Yes	No	No	Yes	No	No
State x Year FE	No	Yes	No	No	Yes	No
Bank x Year FE	No	No	Yes	No	No	Yes
County x Year FE	No	No	Yes	No	No	Yes
Bank x County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

Table A3

Bank branches and deposits volume by bank size – Distance to DEA office

This table provides the results of the analysis of the composition of bank branches and volume of deposits in small and large banks in counties subject to high levels of criminal activity in the form of money laundering. The sample period is 2010-2016 and the unit of analysis is the bank-county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, *proximity DEA*, a relative measure of closeness to a DEA office, and *Large*, an indicator variable set to one for banks in the top 1% in terms of deposits. The dependent variables are *Branches*, the logarithm of one plus the number of branches operating within a county, and *Deposits*, the logarithm of one plus the volume of deposits in bank-branches within a county. The estimations in Columns 1-2 and 4-5 further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Branches	(2) Branches	(3) Branches	(4) Deposits	(5) Deposits	(6) Deposits
Post x proximity DEA	-0.0000483	0.0000245		-0.000645**	-0.000823	
	(-1.72)	(0.61)		(-2.78)	(-1.58)	
proximity DEA x Large	0.00172***			0.00299***		
	(8.75)			(4.23)		
Post x Large	-0.343*	-0.248		-3.124**	-2.841*	
	(-2.26)	(-1.61)		(-3.29)	(-2.35)	
Post x proximity DEA x Large	0.000151**	0.000117*	0.000150*	0.00162**	0.00154**	0.00152**
	(2.64)	(1.97)	(2.07)	(3.67)	(2.81)	(2.98)
N	232,592	306,322	202,784	232,592	306,322	202,784
Adj R-squared	0.571	0.859	0.948	0.682	0.771	0.931
County FE	Yes	No	No	Yes	No	No
Bank FE	Yes	No	No	Yes	No	No
Year FE	Yes	No	No	Yes	No	No
State x Year FE	No	Yes	No	No	Yes	No
Bank x Year FE	No	No	Yes	No	No	Yes
County x Year FE	No	No	Yes	No	No	Yes
Bank x County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

Table A4
Bank branches and deposits volume by bank size – Placebo test

This table provides the results of the analysis of the composition of bank branches and volume of deposits in small and large banks in a set of counties randomly assigned as HIDTA for robustness. The sample period is 2010-2016 and the unit of analysis is the bank-county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, *HIDTA random*, an indicator variable set to one for a random set of counties, and *Large*, an indicator variable set to one for banks in the top 1% in terms of deposits. The dependent variables are *Branches*, the logarithm of one plus the number of branches operating within a county (Columns 1-3), and *Deposits*, the logarithm of one plus the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 1-2 and 4-5 further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Branches	(2) Branches	(3) Branches	(4) Deposits	(5) Deposits	(6) Deposits
Post x HIDTA random	0.000165	0.000197		-0.0172	-0.0160	
	(0.04)	(0.04)		(-0.32)	(-0.29)	
HIDTA random x Large	-0.00254			0.0182		
	(-0.09)			(0.26)		
Post x Large	0.0278**	0.0405**		0.847***	0.945***	
	(3.23)	(3.25)		(3.89)	(4.02)	
Post x HIDTA random x Large	-0.00319	-0.00801	-0.00452	-0.0332	-0.0507	-0.00587
	(-0.63)	(-0.87)	(-0.63)	(-0.51)	(-0.62)	(-0.11)
N	232,592	231,579	202,784	232,592	231,579	202,784
Adj R-squared	0.554	0.871	0.948	0.680	0.788	0.931
County FE	Yes	-	-	Yes	-	-
Bank FE	Yes	-	-	Yes	-	-
Year FE	Yes	-	-	Yes	-	-
State x Year FE	No	Yes	-	No	Yes	-
Bank x Year FE	No	No	Yes	No	No	Yes
County x Year FE	No	No	Yes	No	No	Yes
Bank x County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	-	Yes	Yes	-

Table A5

Bank branches and deposits by bank size – Matched sample

This table provides the results of the analysis of the composition of bank branches and volume of deposits in small and large banks in counties subject to high levels of criminal activity in the form of money laundering on a subset of matched counties. The sample period is 2010-2016 and the unit of analysis is the bank-county-year level. The controls of interest are *Post*, an indicator variable set to one after 2012, *HIDTA*, an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy, and *Large*, an indicator variable set to one for banks in the top 1% in terms of deposits. Each HIDTA county is matched with a non-HIDTA county within the same state. The dependent variables are *Branches*, the logarithm of one plus the number of branches operating within a county (Columns 1-3), and *Deposits*, the logarithm of one plus the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 1-2 and 4-5 further control for lagged number of establishments, median household income, population, unemployment rate, both in levels and in percentage growth. *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Branches	Branches	Branches	Deposits	Deposits	Deposits
Post x HIDTA	-0.000308	-0.0126		-0.179*	-0.183	
	(-0.03)	(-1.64)		(-2.04)	(-1.90)	
HIDTA x Large	0.416***			0.582***		
	(13.80)			(5.32)		
Post x Large	0.0402***	0.0419**		0.895***	0.966***	
	(4.56)	(3.44)		(3.90)	(4.05)	
Post x HIDTA x Large	0.00454	0.0245*	0.0221**	0.360**	0.363**	0.212**
	(1.01)	(2.14)	(2.54)	(2.94)	(2.64)	(3.12)
N	132,079	131,476	109,042	132,079	131,476	109,042
Adj R-squared	0.603	0.880	0.955	0.700	0.799	0.939
County FE	Yes	-	-	Yes	-	-
Bank FE	Yes	-	-	Yes	-	-
Year FE	Yes	-	-	Yes	-	-
State x Year FE	No	Yes	-	No	Yes	-
Bank x Year FE	No	No	Yes	No	No	Yes
County x Year FE	No	No	Yes	No	No	Yes
Bank x County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	-	Yes	Yes	-

Table A6
Crime by zip code-level income

This table provides the results of the analysis of the relation between stricter AML enforcement and crime in counties subject to high levels of criminal activity in the form of money laundering. The sample period is 2010-2016 and the unit of analysis is the zip code-year. The controls of interest are *Post,* an indicator variable set to one after 2012 and *HIDTA,* an indicator variable set to one for counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy, and *Low Income*, an indicator variable set to one for zip codes wherein the median household income is below the median for the corresponding county. The dependent variables are the logarithm of one plus the number of murders (columns 1 and 2), the logarithm of one plus the number of cases of manslaughter (columns 3 and 4), the logarithm of one plus the number of cases of rape (columns 5 and 6), the logarithm of one plus the number of cases of robbery (columns 7 and 8), the logarithm of one plus the number of cases of assault (columns 9 and 10), the logarithm of one plus the number of cases of burglary (columns 11 and 12), the logarithm of one plus the number of cases of theft (columns 13 and 14), and the logarithm of one plus the total number of crimes (columns 15 and 16). *t*-statistics are given in parentheses; standard errors are double clustered at the county and year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Murder	(2) Murder	(3) Manslaughter	(4) Manslaughter	(5) Rape	(6) Rape	(7) Robbery	(8) Robbery
Post x HIDTA	0.00585		0.00282		0.0376*		-0.0176	
	(1.33)		(0.83)		(2.25)		(-1.38)	
Post x Low Income	0.0115***	0.0117***	-0.00122	-0.00112	-0.000703	0.00609	-0.0101	-0.0158
	(3.80)	(4.11)	(-0.74)	(-0.69)	(-0.06)	(0.45)	(-1.29)	(-1.67)
Post x HIDTA x Low Income	-0.0114	-0.0101	-0.000744	0.00170	-0.000152	-0.00634	-0.00255	0.000948
	(-1.06)	(-0.95)	(-0.15)	(0.37)	(-0.01)	(-0.27)	(-0.16)	(0.06)
N	75,253	69,254	75,254	69,255	75,220	69,219	75,252	69,253
Adj R-squared	0.727	0.691	0.266	0.231	0.776	0.755	0.850	0.830
Zip code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
State x Year FE	Yes	No	Yes	No	Yes	No	Yes	No
County-level Controls	Yes	No	Yes	No	Yes	No	Yes	No

	(9) Assault	(10) Assault	(11) Burglary	(12) Burglary	(13) Theft	(14) Theft	(15) All crimes	(16) All crimes
Post x HIDTA	0.0293		-0.0277		0.0400		0.0519	
	(1.07)		(-1.29)		(1.14)		(1.38)	
Post x Low Income	-0.0103	-0.0135	-0.00523	-0.00954	0.00745	0.00702	0.00688	0.000137
	(-0.41)	(-0.54)	(-0.25)	(-0.41)	(0.28)	(0.25)	(0.20)	(0.00)
Post x HIDTA x Low Income	0.00163	0.00331	-0.0157	-0.00829	-0.00484	-0.00378	-0.0255	-0.0169
	(0.05)	(0.10)	(-0.48)	(-0.25)	(-0.11)	(-0.08)	(-0.54)	(-0.35)
N	75,248	69,249	75,253	69,254	75,255	69,256	75,253	69,254
Adj R-squared	0.814	0.807	0.813	0.805	0.810	0.805	0.793	0.791
Zip code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
State x Year FE	Yes	No	Yes	No	Yes	No	Yes	No
County-level Controls	Yes	No	Yes	No	Yes	No	Yes	No