The Weight of Compliance: Anti-Money Laundering Enforcement, Banking Sector Composition, and Lending

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Abstract

We examine how strengthened anti-money laundering (AML) enforcement affects the U.S. banking sector. Heightened enforcement disproportionately raises compliance costs for small banks, especially in counties more exposed to money laundering. In these areas, small banks contract while large banks expand, increasing standardized, government-supported, and secured lending. While aggregate county-level credit does not decline differentially, local outcomes improve. Small establishments grow, non-tradable employment and wages rise, and real estate prices increase. The evidence is consistent with a reallocation mechanism in which AML enforcement shifts activity toward large banks, potentially improving intermediation quality through changes in the composition of local financial intermediation.

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I. Introduction

The U.S. banking sector is among the most heavily regulated industries and plays a crucial role in economic development (King and Levine, 1993a; Rajan and Zingales, 1998; Peek and Rosengren, 2000; Cetorelli and Gambera, 2001; Black and Strahan, 2002). Recent debate has focused on how regulatory changes impact small banks and reshape the composition of the banking sector, particularly given banks' heterogeneous lending practices (Petersen and Rajan, 1994; Berger, Miller, Petersen, Rajan, and Stein, 2005). This issue has become particularly relevant in light of recent structural shifts in the industry: community banks account for 97% of the decline in the number of U.S. banks over the past two decades, and recent bank failures have accelerated deposit outflows from regional to large banks.[1]

We examine this issue in the context of a major regulatory shift: the tightening of anti-money laundering (AML) enforcement beginning in late 2012. That year marked a turning point with multiple regulatory changes and high-profile enforcement actions that substantially increased AML enforcement intensity in the U.S. A prominent example is the December 2012 settlement between United States authorities and HSBC, a $1.9 billion fine for money laundering charges, equivalent to 8.7% of the bank's prior-year pre-tax profits. In response, financial institutions expanded their compliance operations, though the burden was uneven. While AML compliance costs averaged 0.08% of total assets for large banks, it averaged 0.83% for small banks.[2] This heterogeneity suggests that heightened AML enforcement may have altered the composition of local

[1]See Trends in Urban and Rural Community Banks, Vice Chairman of the Federal Reserve for Supervision Randal K. Quarles, October 4, 2018, and "Small US Banks Lose $109 Billion in Deposits in a Single Week," Bloomberg, by Daniel Taub, March 27, 2023.

[2]See the True Cost of AML Compliance Study Report, LexisNexis Risk Solutions (2018) This difference arises

banking markets, with potential implications for credit supply and local economic outcomes. We analyze these dynamics in this paper.

We start by showing that the stricter enforcement of anti-money laundering (AML) regulations altered the composition of the banking sector in areas more exposed to money laundering activities. While all areas operate under the same national enforcement regime, exposure to laundering-related compliance burden varies across locations. We proxy for this exposure using counties designated by the White House Office of National Drug Control Policy as High Intensity Drug Trafficking Areas (HIDTA). In these counties, small banks face disproportionately higher compliance costs.[3] Consistent with this mechanism, small banks reduce their presence in HIDTA counties, while large banks expand. Importantly, the total number of bank branches remains stable, allowing us to isolate the implications of this compositional shift for bank activity, lending patterns, and real economic outcomes. Our results are robust to a battery of additional tests, such as matching HIDTA and non-HIDTA counties on economic and demographic attributes, using neighboring non-HIDTA counties as controls, using alternative definitions of bank size, excluding strong housing markets, and using alternative measures of exposure to money laundering.

Next, we examine whether the compositional shift towards large banks has implications for credit provision and the real economy. A priori, the effects on credit supply are ambiguous.

because some of the required investment in overhead when implementing AML programs does not depend on the scale of the bank.

[3]Using proprietary data shared with us by the Conference of State Bank Supervisors, we show that compliance costs are higher in areas more exposed to money laundering activities, particularly for small banks. Additionally, a report by the Federal Reserve Bank of Saint Louis finds that the relative cost of AML compliance is eight times larger among small banks than large banks. See Compliance Costs, Economies of Scale and Compliance Performance: Evidence from a Survey of Community Banks, April 2018.

The loss of small banks may harm the local economy, particularly smaller firms that rely on relationship lending, considering that small banks have advantages in collecting and processing soft information and can lend to otherwise underserved borrowers (Petersen and Rajan, 2002; Stein, 2002; Berger et al., 2005; Mian, 2006). Additionally, large banks may reallocate deposits across their networks, potentially reducing local credit availability (Gilje, Loutskina, and Strahan, 2016). On the other hand, large banks may expand local credit through internal capital markets, standardized lending technologies, and government-supported programs such as the Community Reinvestment Act (CRA) and Small Business Administration (SBA) lending, due to their greater scale and heightened regulatory expectations (Stein, 1997, 2002; Calomiris and Haber, 2015). Large banks might also access more rigorous risk management and compliance systems, allowing them to serve a broader customer base.[4] Further, large banks may be less prone to sanctions, consistent with the "too big to jail" hypothesis, potentially enabling them to serve higher-risk customers previously excluded from banking services.[5]

We find that large banks increase lending activity in counties exposed to heightened money laundering activity, effectively compensating for the reduction in credit supply by small banks. This expansion concentrates on lending to small firms and households through standardized government-supported programs and secured credit channels. Specifically, large banks increase the number of CRA loans to small firms by 14%, primarily through small loans. SBA lending increases by 7%,

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

[5]In 2013, then U.S. Attorney General Eric Holder testified before the Senate Judiciary Committee that it was difficult for the Justice Department to bring criminal charges against large financial institutions, given the potential impact on national and global economies.

and secured household lending rises by 14% to 20%, depending on loan purpose. Loan volumes show a similar pattern: CRA lending to small firms increases by 14%, SBA lending rises by 40%, and secured household lending grows by 33% to 50%. These findings are consistent with large banks having a comparative advantage in hard-information-based lending, where underwriting can be centralized and standardized (Stein, 2002, 2003).

We then examine county-level lending activity to assess how the shift in bank composition affects credit availability within a county. We find no significant differential effect on the total number and volume of loans under the CRA or SBA programs. Similarly, for mortgage lending, we do not find statistically significant effects on lending for home purchases and refinancing, although we observe an increase in home improvement loans. Overall, our evidence suggests that the expansion of lending by large banks occurs alongside the decline in small-bank activity, without a significant differential change in county-level credit supply. Our results indicate that, in our setting, the lower ability of large banks to process soft information does not result in lower access to credit. Large banks increase credit supply through standardized lending channels, specifically through government-supported programs such as CRA and SBA loans, as well as secured household lending, where collateral mitigates potential losses.[6]

Next, we explore the effects of the compositional shift on real economic outcomes. We document a relative increase in the number of establishments, primarily small businesses, in impacted counties, consistent with Beck and Demirgüç-Kunt (2006) and Adelino, Schoar, and Severino (2015), who point to the importance of bank lending and collateralized lending for small business growth. We also find relative increases in the number of establishments, employment,

[6]Our results are consistent with the idea that collateralized lending helps mitigate potential adverse selection and moral hazard, leading to improved credit supply (Ioannidou, Pavanini, and Peng, 2022).

and wages for non-tradable sector firms, supporting a household demand channel (Mian, Sufi, and Verner, 2020). These results suggest that, while overall lending volume remains relatively unchanged in these counties, differences in lending practices between large and small banks impact local economic activity. When we focus on small businesses, we find that the effects are stronger in counties with smaller banking markets, consistent with the role of large-banks' internal capital markets in reallocating lending capacity across markets (Stein, 1997, 2002; Mian et al., 2020). We do not find that distance to large-banks headquarters affects small businesses' outcomes, suggesting that geographic proximity or soft-information frictions are not the primary drivers of our results.

Taken together, these findings are consistent with a mechanism in which real outcomes improve despite little change in aggregate credit because the AML shock altered the composition of local intermediation and potentially its quality. Large banks expanded through standardized, collateralized, and government-supported channels, while the contraction of small banks in HIDTA counties may have disproportionately affected intermediaries with weaker compliance systems or less effective lending practices. This intermediation-quality channel provides a complementary explanation alongside the hard-information lending channel.

We then explore residential real estate prices, which previous studies link to financial services availability (Mian and Sufi, 2009). Real estate prices in HIDTA counties increase relatively more than in other counties. Importantly, the effect is more pronounced in lower-income areas within counties more exposed to money laundering activity, suggesting that the shift towards large banks improves conditions in areas likely to benefit more from access to finance.

Finally, we consider several alternative explanations for our findings. First, we examine whether the results are driven by worsening outcomes in non-HIDTA areas. Our evidence does not support this channel. Second, we test whether the expansion of lending by large banks results in changes in lending risk patterns, and find no indication of higher delinquency or default rates following the shift toward large banks. Third, we examine whether our results point to broader non-credit channels. We find no evidence that AML enforcement affects local crime patterns or that the expansion of small businesses is driven by cash-intensive businesses that could be used to facilitate money laundering. Taken together, these tests suggest that our findings are not driven by these alternative mechanisms. In combination with our earlier evidence, this supports the interpretation that AML enforcement primarily imposes disproportionate compliance costs on small banks in HIDTA counties, thereby reshaping the composition of the banking sector through a reallocation of lending toward larger institutions and consistent with improved intermediation.

Our paper contributes to the literature on regulation, banking, and economic growth by examining how tightening AML enforcement leads to a plausibly exogenous shift in bank composition from smaller to larger banks, affecting lending patterns and local economic activity.[7] This

[7]The literature on the finance-growth nexus follows the seminal work of King and Levine (1993a,b), and includes papers such as Rajan and Zingales (1998); Peek and Rosengren (2000); Klein, Peek, and Rosengren (2002); Burgess and Pande (2005); Guiso, Sapienza, and Zingales (2004); Levine (2005); Cetorelli and Strahan (2006); Garmaise and Moskowitz (2006); Becker (2007); Bertrand, Schoar, and Thesmar (2007); Kerr and Nanda (2009); Alessandrini, Presbitero, and Zazzaro (2010); Butler and Cornaggia (2011); Krishnan, Nandy, and Puri (2015); Levine and Warusawitharana (2021), among others. This branch of the literature mostly focuses 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 (2004); Diallo and Koch (2018), examines 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 bank competition on firm creation across provinces and industries in Italy, Black and Strahan (2002) find that the

setting allows us to examine, in a recent regulatory context, the effects of changing bank composition without confounding factors such as changes in the number of bank branches or governmental, institutional, and measurement differences across states or countries. The closest papers to ours are Huber (2021), who explores how the 1950s consolidation of German banks affected firms and bank managers, and Bord, Ivashina, and Taliaferro (2021), who explores changes in lender composition following the 2007 real estate price collapse. We contribute by exploiting a novel experiment and showing that large banks' increased lending fills the void created by small bank contraction, with evidence suggesting positive impacts on small businesses and residential real estate prices.

Our paper also contributes to the relatively scant literature on AML enforcement implications. We provide evidence on the effects of AML regulations on the banking sector and real economy by focusing on areas more susceptible to money laundering. To the best of our knowledge, we are the first to systematically examine AML provisions' impact on the U.S. banking system by focusing on areas prone to high money laundering activity. By contrast, Slutzky, Villamizar-Villegas, and Williams (2026) focuses on liquidity shocks following AML regulations in Colombia transmitted via the branching system, Gara, Manaresi, Marchetti, and Marinucci (2024) explores how AML inspections impact suspicious transaction reporting in Italy, and Gao, Pacelli, Schneemeier, and Wu (2023) studies banks' incentives for reporting suspicious activity. To the extent that recent leaks of the so-called FinCEN files characterize AML enforcement tools as ineffective,[8] our results

deregulation of branching restrictions and interstate banking that fostered competition resulted in higher firm incorporation rates, Alessandrini, Presbitero, and Zazzaro (2009) study how bank size and functional distance affects SMEs innovation, and Li, Loutskina, and Strahan (2023) study how deposit market power affects loans' maturity and maturity premiums.

[8]See "What the FinCEN leaks reveal about the ongoing war on dirty money" by Matthew Collin, September 25,

suggest that AML enforcement may nevertheless affect banking and economic activity through its impact on compliance costs that affect bank composition.

The rest of the paper proceeds as follows. Section II discusses the institutional background. Section III describes the data. Section IV describes the empirical design and provides results on the effects of anti-money laundering on the banking system and real economy. Section V discusses alternative explanations. Section VI concludes.

II. Institutional Background

A. Anti-Money Laundering (AML) Regulation

Due to the negative consequences associated with money laundering—facilitating corruption and distorting resource allocation, among others—governments worldwide have implemented anti-money laundering policies. In the United States, the first tool introduced was the Bank Secrecy Act of 1970, which was subsequently expanded and amended several times. Following the terrorist attacks of 2001, the U.S. Congress enacted the USA PATRIOT Act, which contained provisions to strengthen existing AML regulations. These included requiring financial institutions to implement customer identification programs, maintain transaction records, and report suspicious activities through Suspicious Activity Reports (SARs).

2020, Brookings. `https://www.brookings.edu/articles/what-the-fincen-leaks-reveal-about-the-ongoing-war-on-dirty-money/`.

B. The 2012 Shift in AML Enforcement Intensity

A significant change in U.S. anti-money laundering enforcement occurred in 2012, when multiple developments reflected a substantial intensification of regulatory scrutiny in the banking sector.

Regulatory and institutional changes. In early 2012, the Financial Crimes Enforcement Network (FinCEN) mandated electronic filing of SARs by April 1, 2013. That year, FinCEN incorporated a stand-alone Enforcement Division, and regulators began requiring firms to admit wrongdoing in settlements, a marked departure from earlier practice (Brown-Hruska, 2016). FinCEN Director Jennifer Shasky Calvery emphasized that *"acceptance of responsibility and acknowledgment of the facts is a critical component of corporate responsibility."*

High-profile enforcement actions. One of the most salient actions was the fine imposed in December 2012 on HSBC for money laundering charges, amounting to \$1.9 billion and equivalent to 8.7% of HSBC's prior-year pre-tax profits and 1.4% of its market capitalization. Another example was the "death penalty" imposed on First Bank of Delaware in November 2012, when the regional bank was stripped of its charter due to AML failures. The volume of civil money penalties imposed by the Office of the Comptroller of the Currency also increased significantly, as seen in Internet Appendix Figure A1, Panel A.

Industry-wide response. According to the U.S. Government Accountability Office (U.S. Government Accountability Office, 2018a,b, 2020), many banks cited these fines and enforcement changes as reasons for scaling back operations in the U.S. Southwest border region. As discussed in Simons (2013), AML enforcement actions prompted exits by small and regional banks. Moreover, a 2016 NERA report shows that while only half of AML enforcement actions from 2002–2011 involved monetary penalties, approximately 90% did between 2012 and 2015.[9]

Compliance costs and operational impact. Banking institutions expanded compliance capacity on an unprecedented scale: by 2013, JPMorgan and HSBC added 4,000 and 3,000 employees to their compliance teams, respectively. JPMorgan and Citibank increased annual regulatory and compliance spending by $1 billion and $2 billion, respectively.[10]

Public salience. The heightened enforcement intensity was accompanied by increased public attention to money laundering. The number of Wall Street Journal articles mentioning money laundering roughly doubled after 2012 (Internet Appendix Figure A1, Panel B), suggesting the issue had become more prominent in public discourse.

Taken together, these developments reflect a marked increase in AML enforcement intensity beginning in 2012, which we use as the regulatory shift underpinning our empirical analysis.

C. High Intensity Drug Trafficking Areas

In 1988, the U.S. Congress created the High Intensity Drug Trafficking Areas (HIDTA) program, aimed at reducing drug trafficking and production. The program provides assistance to local enforcement agencies in areas identified as critical drug-trafficking regions. To qualify, a county must meet four criteria: (i) be a significant center of illegal drug production, manufacturing,

[9]Details on the NERA report and the stance of FinCEN are available in 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.

[10]See Financial Times, "Banks face pushback over surging compliance and regulatory costs", May 25, 2015, by Laura Noonan: www.ft.com/content/e1323e18-0478-11e5-95ad-00144feabdc0, accessed on July 5th, 2025

importation, or distribution; (ii) have drug-related activities with significant harmful impact locally and nationally; (iii) demonstrate commitment of local law enforcement resources; and (iv) require significant additional Federal resources.[11] As of 2025, approximately 23% of all counties were designated as HIDTA. We map the distribution of HIDTA counties as of 2012 in Figure 1.

[Insert Figure 1 approximately here]

We compare HIDTA and non-HIDTA counties as of 2010, the closest census year to our shock, in a series of observable characteristics in Table 1. We find that HIDTA counties are generally larger in population, have higher median income, and their population has a higher percentage of individuals with higher education degrees (Panel A). However, establishments per capita, unemployment, general education levels, and poverty rates are similar across county types.

In Panel B, we compare the banking system across HIDTA and non-HIDTA counties as of 2012. While we find differences in the level of deposit volumes and branches per capita, we find no differences in prior growth rates. In addition, consistent with a positive relationship between drug trafficking and money laundering, we find that a larger fraction of SARs is issued in HIDTA counties. In 2012, 74% of SARs were issued in HIDTA counties, which account for 53% of bank branches. In the following three years, the percentages rose to 80%, 80%, and 78%, respectively.

[Insert Table 1 approximately here]

D. Compliance Costs

Stricter AML enforcement may affect bank composition through disproportional compliance costs imposed on small banks, given that such banks face higher overhead investment and

[11] Adapted from `https://www.dea.gov/hidta`, accessed on March 2nd, 2025.

smaller economies of scale. We provide evidence that compliance costs are relatively higher for smaller banks and particularly in HIDTA counties by employing proprietary data compiled by the Conference of State Bank Supervisors (CSBS) and the state banking commissioners via its annual National Survey of Community Banks. In 2015, the first year for which we have data, more than six hundred banks responded to the survey.

Among other questions, bankers were asked to "identify the compliance costs they incurred in personnel, data processing, legal services, accounting and auditing, and consulting." Using bank-level data, we compare compliance costs across banks with different levels of exposure to HIDTA counties.[12] First, in Figure 2 we plot the compliance costs as a fraction of assets for banks that are highly exposed to HIDTA counties (share of deposits in HIDTA counties above 50%) and those that are less exposed to HIDTA counties in Panel A, and for small and large banks (assets above/below the median value across banks) in Panel B. We find that compliance costs are significantly higher for banks more exposed to HIDTA counties and for smaller banks.[13]

[Insert Figure 2 approximately here]

Moreover, we exploit the richness of the data to study how exposure to HIDTA counties

[12]As the first year for which we have data is 2015, we cannot study the change in compliance costs following the shift in the regulatory environment. In our study, we focus on personnel costs since it is the main cost for banks (approximately 60% of total regulatory costs) and the cost that is most consistently reported by banks. Furthermore, stricter AML regulation affected personnel costs substantially. For example, JPMorgan and HSBC added 4,000 and 3,000 employees to their compliance teams, respectively, as reported in 2015. Unfortunately, other cost items are not as thoroughly reported in this survey.

[13]While the direction is consistent, the magnitude differs from that in the Federal Reserve Bank of Saint Louis report (2018) and LexisNexis Risk Solutions (2018) given that our data is on general compliance costs, not only those related to AML.

affects compliance costs relative to bank size by estimating:

$$\text{(1)} \quad \text{Compliance Cost}_b = \beta_1 \text{Exposure HIDTA}_b + \beta_2 \text{Bank Size}_b + \\ \beta_3 \text{Exposure HIDTA}_b \times \text{Bank Size}_b + \varepsilon_b$$

where Compliance Cost$_b$ is the cost of compliance for Bank b scaled by total assets, Exposure HIDTA$_b$ is the share of deposits held in HIDTA counties, and Bank Size$_b$ is the inverse hyperbolic sine transformation of deposit volume to proxy for a bank's size. We present the results in Table 2, which show that bank size is negatively correlated with compliance costs, while HIDTA exposure is positively correlated. The interaction term is negative, indicating that compliance costs in HIDTA counties are relatively lower for larger banks. These results suggest that compliance costs in counties more exposed to money laundering are higher and even more pronounced for smaller banks. A one-standard deviation increase in HIDTA deposit share translates into a 0.73 percentage point (1.644×0.448) increase in compliance costs. To put this in perspective, LexisNexis Risk Solutions (2018) estimated that U.S. financial institutions spend roughly $25.3 billion annually on AML compliance; our estimates suggest that heightened HIDTA exposure could raise these costs significantly, with the burden falling disproportionately on smaller banks. For robustness, Column 4 normalizes compliance costs by deposits instead of assets with comparable results. As a placebo test in Columns 5 and 6, we examine whether general expenses (not related to compliance) exhibit similar patterns and find that they do not.

[Insert Table 2 approximately here]

III. Data

In this subsection, we describe the multiple datasets used in our study of the effect of stricter enforcement of AML regulations on the banking sector and the real economy. We provide summary statistics of the variables used in our study in Table 1, Panel C.

Deposits and Bank Branches Our first data source is the Federal Deposit Insurance Corporation's (FDIC) summary of deposits, containing yearly information on deposits at the bank-branch level. We collect data from 2010 to 2016 for all brick-and-mortar bank branches in the 50 U.S. states and the District of Columbia, yielding approximately 85,800 bank-branch observations per year for close to 8,000 different banks.[14]

Money Laundering Activity Our second source of data measures exposure to money laundering activities, and in particular to those originating in the production and distribution of illegal drugs. We collect data on counties identified by the White House Office of National Drug Control Policy (ONDCP) as High Intensity Drug Trafficking Areas (HIDTA). We remove counties added after 2012 to mitigate look-ahead bias. For robustness, we construct an alternative measure of exposure using the distance between a county and the closest Drug Enforcement Administration (DEA) office, assuming regional DEA offices are established in areas more exposed to illegal drug production and distribution. We also use distance to DOJ offices for robustness.[15]

[14]We start our empirical analysis in 2010 to mitigate the effect of the global financial crisis on our study.

[15]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

CRA Lending We collect data on lending to small businesses under the Community Reinvestment Act (CRA) from the Federal Financial Institutions Examination Council (FFIEC). The CRA, enacted in 1977, encourages financial institutions to lend to low- and moderate-income borrowers in their operating communities. While institutions lack specific targets, they are overseen by the OCC, FDIC, and FRB, who rate their performance. The program's volume is substantial: in 2021 alone, reporting banks lent $371 billion under CRA, considerable given that total commercial and industrial loans by all commercial banks are around $2.5 trillion.[16] We obtain county-level data from 2010 to 2016 on the number and volume of loans to small businesses (annual revenues below $1 million).

SBA and HMDA Lending We collect data on loans issued under the Small Business Administration (SBA) 7(a) Loan Guarantee program, where the SBA partially guarantees loans to encourage lending to small businesses that might otherwise not be funded. We collect data on more than 370,000 loans issued between 2010 and 2016. We also collect mortgage data from the Home Mortgage Disclosure Act (HMDA), obtaining lending data on mortgages for purchases, home improvement, and refinancing for each reporting financial institution at the county-year level between 2010 and 2016. Our database contains information on more than 8,000 lenders in over 3,000 counties.[17]

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county level, there is not significant within-state variation. 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.

[16]See Findings from Analysis of Nationwide Summary Statistics for 2021 Community Reinvestment Act Data Fact Sheet, December 15, 2022, Federal Financial Institutions Examination Council for CRA loans analysis and the Federal Reserve Bank of Saint Louis for commercial loan data.

[17]We exclude Fintech lenders from our sample to focus exclusively on bank lending.

Economic Outcomes Our real economic outcome measures come from the Bureau of Labor Statistics on employment, wages, and the number of active establishments through the Quarterly Census of Employment & Wages. We obtain quarterly and yearly information at the county level with different aggregation levels, including employer type (government or private) and NAICS sector. We also obtain data from the County Business Patterns series to study firms of different sizes by number of employees.

Real Estate We obtain real estate price data from Zillow at the zip code level, including statistics such as median listing price and median listing price per square foot.

Loan Performance and Underwriting Our first source of data is the Consumer Financial Protection Bureau (CFPB), which publishes data on delinquency rates using a nationally representative, five percent sample of all outstanding, closed-end, first-lien, 1-4 family residential mortgages. The data is provided at the county-month-year level for approximately 470 counties, out of which 268 were designated as HIDTA in 2012. Our second source is CoreLogic, which provides loan-level data, allowing us to explore outcomes for loans originated at different points in time. Our data are restricted to loans originated in the State of Maryland, which includes 10 HIDTA and 14 non-HIDTA counties.[18]

Crime We collect crime data from the FBI's Uniform Crime Reporting (UCR) Program, which includes information on the number of crimes for different criminal activities, such as murder, manslaughter, rape, robbery, assault, and theft.

[18] In our data, coverage of lender, interest rate, and other loan characteristics is very limited. For instance, fewer than 8% of all mortgages issued between 2010 and 2016 include information on the initial rate.

IV. Empirical Analysis

We study the effects of tighter AML enforcement using a difference-in-differences framework, exploiting cross-sectional differences in money laundering exposure and the timing of the 2012 AML enforcement tightening. Later, we extend our tests to incorporate a third difference for cross-sectional differences in bank characteristics. A key assumption in our study is that there are no pre-trends: the banking sectors in treated (HIDTA) and control (non-HIDTA) counties should exhibit common trends before the shock. In Panel B of Table 1, we show that both bank deposits' and bank branches' prior growth is comparable in treated and control counties as of 2012.

A. Bank Branches and Deposits Volume

We start by examining the effect of tightening AML enforcement on the number of branches and deposit volumes using the following specification:

$$y_{c,s,t} = \alpha_c + \alpha_{s,t} + \beta \times \text{Post}_t \times \text{HIDTA}_c + \gamma_c \times \text{Post}_t + \varepsilon_{c,s,t} \tag{2}$$

where $y_{c,s,t}$ is one of our outcomes of interest (inverse hyperbolic sine transformation of the number of branches or volume of deposits), Post_t is an indicator equal to one from 2013 onward, HIDTA_c is an indicator for counties designated as HIDTA as of 2012, and γ_c are county-level controls (unemployment rate, log population, log median income) fixed at pre-period (2011) values and interacted with the Post_t indicator to control for differential shocks across counties with varying economic and demographic profiles.[19] In addition, we control for spending by the DEA at the county-year level to account for initiatives that might have affected counties differently, using data obtained from `www.usaspending.gov`.[20] We include county (α_c) and state-year ($\alpha_{s,t}$) fixed effects to account for time-invariant characteristics of the banking sector at the county level and for state-specific shocks.

We present the results in Table 3. The coefficients in columns 1 and 2 show that the total number of branches in HIDTA counties does not decline relatively more compared to other counties following the shift in AML enforcement. More specifically, the coefficient for Post x HIDTA is statistically and economically indistinguishable from zero in both specifications. This evidence is in line with the graphical evidence presented in Panel A of Figure 3, which shows that the total number of branches follows similar patterns in both HIDTA and non-HIDTA counties. On the other hand, we find that the positive coefficient for the volume of deposits (columns 3 and 4) is economically and statistically significant. These results indicate that the volume of deposits increases in HIDTA counties relative to non-HIDTA counties following stricter AML enforcement. For robustness, we present the estimations excluding county-level controls in the Internet Appendix, Table A2, and find results that are comparable to the baseline evidence.

[Insert Table 3 approximately here]

[19]We employ inverse hyperbolic sine transformation to our outcomes of interest following Burbidge, Magee, and Robb (1988) and Bellemare and Wichman (2020).

[20]This data source contains approximately 75,000 contracts awarded by the DEA between 2010 and 2016, covering expenditures in categories such as IT services, translation services, communications, and small arms and ammunition. These data allow us to capture variation in DEA-related federal spending across counties. Data on DEA employment and detailed drug enforcement budgets, however, are only available at the national level and cannot be disaggregated to the county level.

[Insert Figure 3 approximately here]

B. Composition of Bank Branches and Deposit Volumes

Next, we study how stricter AML enforcement impacts large and small banks operating within affected counties. In particular, given the heterogeneous compliance costs shown in the previous section, this change likely impacts the composition of the banking sector. We expand our previous specification in the following way:

$$(3) \quad y_{b,c,s,t} = \alpha_{b,c} + \alpha_{s,t} + \beta_1 \times \text{Post}_t \times \text{HIDTA}_{c,s} + \beta_2 \times \text{Post}_t \times \text{Large}_b + \beta_3 \times \text{Post}_t \times \text{HIDTA}_{c,s} \times \text{Large}_b + \varepsilon_{b,c,s,t}$$

In this specification, the unit of observation is the bank-county-year. $y_{b,c,s,t}$ is one of the outcomes of interest (inverse hyperbolic sine transformation of the number of branches, volume of deposits). 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, thus excluding financial institutions associated with credit cards or investment banks. 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 a 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 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.

We present the results in Table 4. For the number of branches (columns 1–3), we find that small banks reduce their presence in HIDTA counties relative to non-HIDTA counties following the stricter enforcement of AML regulations, as reflected by the negative coefficient on Post x HIDTA. The triple interaction term is positive and significant, indicating that large banks increase their presence in HIDTA counties more than in non-HIDTA counties following the shock. Notably, this coefficient is statistically significant in all specifications, including column (3) where we include a strict set of fixed effects. This finding is consistent with the graphical evidence observed in Figure 3, Panel B, where we plot the raw evolution of the share of branches by large banks in HIDTA versus non-HIDTA counties. 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.

[Insert Table 4 approximately here]

These findings are consistent with the idea that higher compliance costs for small banks contributed to a shift toward large banks both at the extensive and intensive margin (branches and deposits, respectively) in the areas that are more prone to money laundering activity. For completeness, we plot the year-by-year coefficient for the triple interaction term in Figure 4, where we observe that the response is immediate and materializes fully two years after stricter enforcement of AML regulations. For deposit volumes (columns 4–6), we find a similar pattern. Small banks' deposit volumes decline in HIDTA counties, while large banks' deposit volumes increase. The triple interaction term is positive and statistically significant, indicating that large banks capture a larger share of deposits in HIDTA counties following the enforcement shift.

[Insert Figure 4 approximately here]

We explore several alternative sample specifications in this context. For conciseness, we present the results of the specifications that include the stricter sets of fixed effects in Table 5. Complete tables, including all specifications, are presented in the Internet Appendix, Tables A3, A4, A5, and A6. In Table 5, first, we consider an alternative definition of large banks (assets above $1 billion) in Columns 1 and 5, and find similar results. Next, we match each HIDTA county with the most similar non-HIDTA county based on income, population, and education and find broadly consistent results in Columns 2 and 6. We further repeat our analysis focusing on non-HIDTA counties that neighbor with HIDTA counties as controls in Columns 3 and 7, and find evidence supporting our baseline findings. We also consider the possibility that our results respond to the increased activity by large banks in strong housing markets (Chakraborty, Goldstein, and MacKinlay, 2018). To address this issue, we use the Federal Housing Finance Agency's data on House Price Indexes (HPI) and construct a list of county-years for which the HPI index's appreciation over the previous five years is in the top decile, equivalent to an increase of over 17%. As reported in Columns 4 and 8, we find that our results hold when we exclude these markets.

[Insert Table 5 approximately here]

A natural question is why large banks did not expand earlier in these markets. Our interpretation is that the enforcement shift changed relative profitability rather than revealing newly profitable markets. Before the shock, incumbent small banks benefited from local relationships, established branch networks, and customer-specific knowledge, while large banks faced entry and organizational frictions. Heightened AML enforcement raised fixed and quasi-fixed compliance costs disproportionately for small banks in high-exposure counties, weakening these incumbent advantages and making expansion by large banks relatively more attractive. This interpretation is consistent with theories emphasizing the role of organizational structure, soft information, and internal capital markets in shaping lending behavior across bank types (Stein, 1997, 2002, 2003; Berger et al., 2005).

We also explore whether our results can be driven by banks' failures and acquisitions. Figure A2 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), thus mitigating the concern that differential trends drive our results. In a placebo test, we randomly designate 17 percent of the counties as HIDTA –the proportion of counties designated as HIDTA as of 2012– and find small and statistically insignificant effects (Table A7), suggesting our results are not driven by spurious correlation. Our results are also robust to using natural logarithm for transformations, as shown in Table A8. In addition, in Table A9, we provide the results using a measure developed by Törnqvist, Vartia, and Vartia (1985) for relative change that accommodates entry and exit, as in Choi, Goldschlag, Haltiwanger, and Kim (2023), given that a key aspect in our analysis is the change in the composition of banks. We find similar results.

As additional robustness tests, we employ alternative measures of money laundering in Panel B of Table 5 with the stricter set of fixed effects, and provide results with alternative fixed effects in Tables A10 and A11. Given that the DEA likely locates regional offices in areas with greater exposure to drug production and trafficking, we construct two additional county-level exposure measures: (i) an indicator for counties within 50 miles of a DEA office and (ii) a continuous measure of proximity to the nearest DEA office.[21] For consistency and ease of interpretation, proximity is defined as the difference between the maximum distance from any county to a DEA office (approximately 2,600 miles, corresponding to Aleutians West, Alaska) and each county's distance

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

to the nearest office. Under this transformation, counties hosting a DEA office receive the highest value, while more distant counties receive lower values. Figure A3, Panel A, in the Internet Appendix provides a graphical representation of this measure. We run a similar exercise using proximity to DOJ offices, given that it provides a measure of enforcement intensity, since counties closer to DOJ offices are more likely to receive federal attention and resources. Figure A3, Panel B, in the Internet Appendix provides a graphical representation of this measure. We provide the results of these alternative specifications in Columns 1-4 and 6-9 in Panel B of Table 5, where we find results that are consistent with the ones in Table 4.

In addition, we combine the information on the location of DEA and DOJ offices and construct an intensity index ranging from zero to three that considers (i) whether the county has been designated as HIDTA, (ii) the presence of a DEA office within 50 miles, and (iii) the presence of a DOJ office within 50 miles. We map this index in Figure A3, Panel C. The results in Columns 5 and 10 of Table 5, Panel B, are largely consistent with the baseline findings. More specifically, we find that small banks reduce their operations by more in counties with higher treatment intensity, while large banks expand operations in these counties. Specifications with alternative fixed effects are in Table A10, Panel C.

We also examine whether pre-shock (2011) bank characteristics were associated with differential exit rates among small banks following the 2012 AML enforcement shift. Figure A7 reports interaction coefficients from complementary log-log and logit models relating post-shock exit probabilities to pre-shock bank characteristics. Across specifications, we find little evidence that exit rates varied systematically with banks' pre-shock profitability, capitalization, liquidity, funding structure, or labor-intensity measures. Overall, the results suggest limited heterogeneity in the exit response across banks based on the observable pre-shock characteristics available in our data. At the same time, our analysis cannot account for a range of potentially important but unobserved dimensions—such as managerial quality, compliance practices, organizational capacity, or risk-management systems—that may have influenced banks' ability to absorb the regulatory shock.

C. Lending by Large Banks

A priori, it is unclear how the shifting bank composition from smaller to larger banks would affect access to credit. On the one hand, this change could negatively impact credit. For instance, given that larger banks have a broader network of branches, funds sourced in these counties could be lent in other areas. Moreover, since large banks could be at a disadvantage in terms of processing soft information, it could lead to a reduction in lending to small businesses. On the other hand, large banks may benefit from greater diversification, access to internal capital markets, and the ability to spread fixed costs across a broader lending portfolio, enabling them to expand credit in local economies, particularly where banking markets are thin. In addition, lending by large banks under programs such as the Community Reinvestment Act or the Small Business Administration Act could increase access to finance, particularly for smaller firms and lower-income communities. Furthermore, if large banks are able to implement more effective compliance risk systems, these banks could screen and monitor 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 higher-risk counties.

We examine how the shift towards large banks affects bank lending with the following specification:

$$y_{b,c,s,t} = \alpha_{c,t} + \alpha_{b,t} + \alpha_{b,c} + \beta \times \text{Post}_t \times \text{HIDTA}_{c,s} \times \text{Large}_b + \varepsilon_{b,c,s,t} \quad (4)$$

where $y_{b,c,s,t}$ is one of the outcomes of interest (inverse hyperbolic sine transformation of the number or volume of loans), $\alpha_{c,t}$ is a county-year fixed effect, $\alpha_{b,t}$ is a bank-year fixed effect, and $\alpha_{b,c}$ is a bank-county fixed effect. This specification includes granular fixed effects that absorb bank-specific shocks, county-specific shocks, and time-invariant bank-county characteristics. To account for the presence of banks that stop making certain types of loans to small businesses, we balance each panel by setting missing observations to zero.

We focus on one type of lending at a time and present the results in Table 6. When analyzing CRA loans, we find that large banks relatively increase the number of loans in HIDTA counties following their expanded presence (Panel A). These results are mainly driven by small CRA loans (face value below $100,000), with no significant effects on medium and large loans.

[Insert Table 6 approximately here]

The results in Panel B show that large banks increase relatively the number of SBA loans, amount of loans, and receive a proportional increase in guarantee amounts, though the last two coefficients are only statistically significant at the 11% level.[22] The results in Panel C show that large banks increase HMDA lending for all purposes (home purchases, improvement, and refinanc-

[22] As an example, we plot the year-by-year coefficient for the triple interaction term in Figure A4.

ing) in HIDTA counties, both in number and volume of loans. The triple interaction term is large, positive, and statistically significant for numbers and amounts across loan purposes.

Overall, results across all loan types (CRA, SBA, and mortgages) suggest that following the compositional shift toward large banks, large banks increase lending to small firms under government-supported and guaranteed programs and also increase secured lending to households where collateral can compensate for potential losses. The increase in secured mortgage lending by large banks is consistent with the view that they have a comparative advantage in hard-information-based lending, where soft information is less critical, and underwriting can be centralized and standardized. A similar argument applies to SBA lending, which is government-guaranteed and relies heavily on standardized criteria, reducing the importance of relationship-specific soft information. These findings align with theories suggesting that hierarchical organizations have a comparative advantage in processing standardized hard information through centralized decision structures (Stein, 2002, 2003).

D. Lending Across Banks

While we observe increased lending by large banks following the change in the composition of the banking sector, it is unclear whether this increase under-, over-, or just compensates for the reduction in small bank activity, and how this change affects total credit supplied to the local economy. To explore this, we aggregate lending across banks at the county-year level for each program and estimate Equation (2) with aggregate lending as the outcome.

We present the results in Table 7. The coefficients in Panel A (CRA) suggest that there are no significant effects on the total number of loans (total, small, medium, or large) or the volume of loans. This is in line with the idea that the expansion of credit by large banks compensates for the decline in activity by small banks. Similarly, Panel B (SBA loans) shows that there are no changes in SBA credit supplied at the county level, with the number, amount, and guarantees showing no significant changes. Panel C (HMDA loans) finds mostly no impact on the total number or volume of loans, except for home improvement loans (columns 2 and 5), where we find a significant increase.

[Insert Table 7 approximately here]

While our earlier results show marked shifts in branch and deposit composition toward large banks, we find limited evidence of corresponding changes in the overall volume of lending at the county level. The results suggest a reallocation of lending across institutions. Strengthened AML enforcement, and the resulting increase in compliance costs, appear to have shifted lending activity from small banks toward large banks with no significant relative change in total credit supply at the county level.

E. Real Economic Effects

The absence of a strong effect on aggregate county-level credit does not imply that the change in bank composition is economically neutral. A key implication of our setting is that local outcomes may respond not only to the quantity of credit, but also to the identity of the intermediaries supplying it and the terms or channels through which that credit is delivered. In our context, the expansion of large banks is concentrated in standardized, government-supported, and secured lending channels. At the same time, in counties more exposed to laundering activity, the contraction of small banks may disproportionately affect incumbents whose intermediation was less efficient or whose compliance systems were weaker. These two forces together provide a mechanism through which relatively unchanged aggregate credit can still be associated with changes in real outcomes.

1. Establishments, Employment, and Wages

We analyze the effect of changing bank composition on employment, wages, and number of establishments using information from the Quarterly Census of Employment and Wages (QCEW) and County Business Patterns (CBP) at three aggregation levels. First, at the county-year level, we estimate the effects on total outcomes using a specification similar to that of Equation 2. Second, we analyze effects on firms of different sizes, following Guiso et al. (2004), who suggest that local finance matters more for smaller firms. Third, following Mian et al. (2020), we analyze the role of credit supply in tradable and non-tradable sectors separately to shed light on the economic forces behind our results.

The results in Table 8, Panel A, show a small but positive relative effect on the total number of establishments at the county level. Following the compositional change, the total number of establishments in HIDTA counties increases relatively by approximately 1%. We find no significant effect on total employment or wages. We then use County Business Patterns data to explore the effect on firms of different sizes. The results in Panel B show that the positive effect on total establishments is driven by small firms, particularly those with fewer than 100 employees. We plot the year-by-year coefficient for the interaction term for small firms in Figure A5. This finding is consistent with our result that large banks continue providing loans to small firms through CRA and SBA programs and secured lending to households. This aligns with Beck and Demirgüç-Kunt (2006) and Adelino et al. (2015), which discuss that providing liquidity and financing through secured lending may spur growth in micro and small businesses. Given that small establishments are bank-dependent, our finding suggests that increased large bank presence maintains access to financing for these firms through government programs and secured lending, compensating for the potential lack of soft information processing ability by large banks. We observe a decline in employment and wages for small firms, potentially driven by the increasing number of smaller firms entering with lower initial wages.

[Insert Table 8 approximately here]

We also explore whether the results for small firms differ in counties that are further away from the headquarters of larger banks, where large banks' benefits such as diversification and internal capital markets could be outweighed by the increased costs.[23] We present the results in Table A12, focusing on micro (Columns 1 to 3) and small (Columns 4 to 6) firms. We find that the distance from the county to the headquarters of the largest banks does not differentially affect small firms in HIDTA counties, where soft-information frictions would traditionally be expected to bind most strongly. This pattern aligns with (Petersen and Rajan, 2002), who document that technological developments reduce the importance of proximity in small-business lending. We also explore potential heterogeneous effects across banking market sizes. We interact our explanatory variables with the number of branches in each county as of 2011, prior to our shock, as a proxy for market size.[24] The results in Table A13 show that the positive effect on micro and small firms is stronger in smaller banking markets. The finding is consistent with large banks' advantages in diversification, internal capital markets, and scale (Stein, 1997), which may be especially important

[23]These potential costs include management frictions, difficulty in collecting soft information, increased number of layers, and complexity of the hierarchical structure, among others. See Stein (2003) for a survey of related theories.

[24]We divide the number of branches by 100 to scale the coefficients.

in more constrained credit environments (Rajan and Zingales, 1998; Beck, Demirgüç-Kunt, and Maksimovic, 2005).

In Panel C of Table 8, we consider the real effects on tradable and non-tradable sectors separately, following Mian and Sufi (2014), classifying retail trade, accommodation, and food services as non-tradable, and agriculture, forestry, fishing, mining, and manufacturing as tradable. The idea is similar to that in Mian et al. (2020), who develop a methodology to test whether the expansion of credit supply 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 changes in banking regulation boosts employment in the non-tradable sector. The results show a positive effect mainly in the non-tradable sector, with positive and statistically significant coefficients for establishments, employment, and marginally insignificant for wages in the non-tradable sector, while we find no effect in the tradable sector. These results are consistent with increased household demand for local goods.

2. Real Estate Prices

We explore how the compositional change in the banking sector affects real estate prices, focusing on four outcomes: median listing price, median listing price per square foot, Zillow Home Value Index (ZHVI) for all home types, and ZHVI for single-family residences (excluding condo/co-op). The ZHVI has two advantages over the S&P/Case-Shiller index. First, it is available over more locations, and second, its methodology plausibly makes the data less sensitive to composition effects (Chinco and Mayer, 2016).

The results in Table 9, Panel A, show that following the compositional change from smaller to larger banks, median listing price and median listing price per square foot increase in HIDTA counties relatively more. Specifically, median listing price increases by 5%, while median listing price per square foot increases by 3.7%. These findings are consistent with two mechanisms: an increase in property prices and a change in the composition of properties being listed. To better understand whether results respond to increased real estate prices while holding type and quality constant, we study the ZHVI, constructed as the median estimated value of all homes within a county, not only those listed. Columns 3 and 4 find a positive and statistically significant effect on the ZHVI, suggesting that the results represent an increase in property prices and not merely a composition change. We plot the year-by-year coefficient for the interaction term in Figure A6.

[Insert Table 9 approximately here]

The richness of the data, available at the zipcode level, allows us to further explore which areas benefit the most. We expand our prior specification considering variation in income levels within a county, using the following specification:

$$\begin{aligned}(5)\quad y_{z,c,t} = \alpha_z + \alpha_{s,t} + \beta_1 \times \text{Post}_t \times \text{HIDTA}_{z,c} + \beta_2 \times \text{Post}_t \times \text{Lower Income}_z + \\ \beta_3 \times \text{Post}_t \times \text{HIDTA}_{z,c} \times \text{Lower Income}_z + \varepsilon_{z,c,t}\end{aligned}$$

where $y_{z,c,t}$ is one of the outcomes of interest, α_z is a zip code fixed effect, $\alpha_{s,t}$ is a state-year fixed effect, and Lower Income$_z$ is an indicator for zip codes with median income below the county median. In a stricter specification, we introduce $\alpha_{c,t}$, a county-year fixed effect to control for local time-varying effects.

The results in Table 9, Panel B, suggest that the increase in real estate prices is even more pronounced in lower-income areas than in higher-income areas within HIDTA counties. While the coefficient Post $\times$ HIDTA is positive and statistically significant for median listing price, median listing price per square foot, the Zillow Index for all residencies, and the Zillow Index for single-family residences, we find that the triple interaction term is also positive and statistically significant (or marginally insignificant) in all cases. Thus, changing bank composition toward large banks likely improves economic growth prospects in areas more in need of finance access as evidenced by increasing real estate prices.

An alternative interpretation is that real property can serve as a vehicle for storing wealth, including illicit gains, particularly in all-cash purchases, as AML strengthening may increase incentives to shift funds from the banking sector into real assets. During our sample period, title companies were not required to collect beneficial ownership information for such transactions, and FinCEN's Geographic Targeting Orders addressing this gap were only introduced starting in 2016 (Collin, Hollenbach, and Szakonyi, 2022). While our data do not allow us to separate legitimate from potentially illicit transactions, the positive effects we find are stronger in lower-income areas within HIDTA counties, which is more consistent with improved credit access than with high-end real estate investment patterns typically associated with money laundering.

V. Alternative Explanations

We consider alternative channels consistent with the findings on real economic outcomes and present the results in Table 10.[25]

[Insert Table 10 approximately here]

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[25] We thank an anonymous referee for several of these suggestions.

A. Removal of Good Actors

One possibility is that stricter enforcement of AML regulations drove out some "good" banks from non-HIDTA counties rather than potentially reflecting improvements in financial intermediation in HIDTA counties. This may result in worsening economic conditions in these areas and affect small business formation and relationship lending. Thus, our results could be driven by a deterioration of the counties used as controls, not an improvement in HIDTA counties.

To test this idea, we exploit heterogeneity in the composition of the banking sector across non-HIDTA counties prior to 2012. In particular, we explore whether small businesses experienced a differential effect in non-HIDTA counties that had varying presence of small banks that were previously subject to AML enforcement actions. If AML enforcement removed banks that were involved exclusively in legitimate financial intermediation, we would expect worse outcomes for small firms in non-HIDTA counties with little or no exposure to banks involved in AML violations.

We construct two exposure measures, (i) the number of small banks subject to AML enforcement actions prior to 2012 normalized by the total number of banks (*%Percentage*) and (ii) an indicator variable denoting whether the non-HIDTA county had no such banks (*None*).[26] We present the results in Panel A of Table 10. We report results both using the percentage of small banks subject to an enforcement action (*Intensive measure*), and using an indicator variable set to one if no small bank in the county was subject to such action (*Extensive measure*). In Columns (1)-

[26]We find that in the median non-HIDTA county, no small bank had been subject to an AML-related enforcement action prior to 2012. In contrast, in the median HIDTA county, 6.1% of small banks had been subject to such actions. However, there is meaningful cross-county variation in exposure to such banks within non-HIDTA areas with the 75th and 90th percentiles reaching 8.3% and 16.7%, respectively. This within-group variation allows us to examine heterogeneity in outcomes across non-HIDTA counties with different underlying exposure to sanctioned small banks.

(3), we focus on firms with fewer than 20 employees, and in Columns (4)-(6), we focus on firms with 20-99 employees. Across specifications, we find no statistically significant differential effects on employment, wages, or establishment counts after 2012 in counties with greater exposure to AML enforcement sanctioned small banks. Using an indicator variable, we find that small firms in non-HIDTA counties without prior AML-sanctioned small banks also do not experience worse outcomes systematically after 2012. The results, therefore, do not support the possibility that our prior findings respond to stricter enforcement of AML regulations driving out primarily "good" banks.[27]

B. Changes in Lending Practices

We next test whether the change in the composition of banks resulted in riskier lending practices. To explore this channel, we compile data on loan performance from the Consumer Financial Protection Bureau (CFPB) and CoreLogic. The CFPB uses a five-percent sample of all outstanding, closed-end, first-lien, 1-4 family residential mortgages and publishes monthly data on delinquency rate at the county level for approximately 450 counties. CoreLogic, in contrast, provides performance data at the mortgage level, which allows us to trace the performance of loans made at different points in time and explore changes in underwriting policies. The CoreLogic data we have access to, however, presents two limitations. First, it is restricted to loans made in

[27] As a complementary robustness, we also carry out a narrower test to examine whether banks previously subject to AML-related cease-and-desist orders by the OCC, FDIC, and Federal Reserve disproportionately exited HIDTA counties following AML tightening. As reported in Appendix Table A14, we find no evidence of disproportionate exit, suggesting that the shifts in financial intermediation was broader and not primarily driven by the exit of the small subset of banks previously subject to AML-related cease-and-desist orders.

the State of Maryland, with 10 HIDTA and 14 non-HIDTA counties. Second, it does not include reliable lender data.

Using our main specification, we test for changes in loan performance following changes in the composition of the banks. We present the results in Panel B of Table 10. In columns (1) and (2), we show the results of our analysis of CFPB's data. We use data as of December of each year, and find that delinquency rates do not change significantly after 2012. Moreover, while the coefficients are statistically insignificant, they directionally suggest a decline in delinquency risk, potentially reflecting improving local economic conditions. In columns (3) and (4), we present the results using CoreLogic's data, where we use the timing of the underwriting and test whether loans made after 2012 in HIDTA counties have a higher default rate, indicating changes in underwriting policies. Our evidence suggests no changes in default rates. That is, loans issued prior to stricter enforcement of AML perform similarly to those issued after 2012.

C. Crime

Stricter AML enforcement in the banking sector could directly affect criminal activity intensity and thereby impact economic conditions. In this case, our results would respond to a decline in criminal activity and not to a shift in bank composition. We test this by analyzing crime data from the FBI's Uniform Crime Reporting (UCR) Program. Following a specification similar to Equation (2) and using data from 2010 to 2016, we find that stricter AML enforcement does not result in any noticeable change in crime rates as reported in Panel C of Table 10. This finding also suggests that the increase in real estate prices is not driven by changes in crime but is more consistent with changes in financial intermediation that supported local economic growth.

D. Cash-Intensive Businesses

A potential alternative explanation is that stricter AML enforcement may divert financial flows away from the regulated banking sector into cash-intensive businesses such as restaurants, bars, or convenience stores. If true, our broader economic results could be an artifact of reallocation into these sectors.

We estimate the differential effects on establishments, employment, and wages in cash-intensive industries, defined as those in the NAICS association list of cash-intensive businesses. Panel D of Table 10 shows that while HIDTA areas display on average higher cash-intensive economic activity, following AML tightening, economic activity as measured by establishments, employment, and wages contracts in cash-intensive sectors in HIDTA counties. This pattern is not consistent with the notion of money moving out of banks into cash-sensitive sectors in response to AML enforcement. Instead, this evidence is in line with the idea that stricter AML enforcement leads to lower cash-intensive activity, suggesting that our results are not driven by substitution into cash-based businesses in HIDTA counties.

E. Too Big to Jail

While AML enforcement tightening leads to disproportionate compliance costs for smaller banks, 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 in media and political circles, following cases such as HSBC laundering close to a billion dollars for drug traffickers and Wells Fargo opening sham accounts, where bank executives were insulated.

While we cannot directly test this hypothesis, we find that following the compositional change toward large banks in affected areas, the number of Suspicious Activity Reports issued in these areas increases disproportionately (Figure A8). 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; (ii) increased defensive filing of SAR reports to be protected from prosecution and enforcement actions; (iii) were more involved in providing banking services for illicit activities and "shadowy characters" due to being "too big to jail." Unfortunately, the nature of the data does not allow us to disentangle between these channels.

VI. Conclusion

We examine the impact of strengthened anti-money laundering enforcement on the U.S. banking sector and economic activity. We show that the regulatory shift at the end of 2012 altered bank composition in counties more exposed to money laundering activities. Small banks, facing disproportionate compliance costs, reduced their presence, while large banks expanded their branch presence, deposit base, and lending activity.

Despite this substantial change in bank composition, we find no evidence that aggregate county-level credit declined differentially in HIDTA counties following the enforcement shift. Rather than generating a contraction in credit supply, AML enforcement led to a reallocation of lending activity from small to large banks. These large banks expanded primarily through standardized, collateralized, and government-supported lending channels, offsetting the decline in lending by smaller institutions.

Importantly, this reallocation was associated with improvements in local economic outcomes. We find evidence of more small-business formation, stronger activity in the non-tradable sector, and higher residential real estate prices, particularly in lower-income areas. These findings suggest that changes in the composition of the banking sector can have meaningful economic consequences even when aggregate credit volumes do not change substantially.

Our results contribute to the policy debate on the unintended consequences of financial regulation by highlighting how AML enforcement can affect bank composition, lending patterns, and local economic activity. In our setting, stronger AML enforcement reshaped local banking markets without reducing overall credit availability, suggesting that regulatory interventions can influence economic outcomes through changes in the structure of financial intermediation and, potentially, its quality.

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FIGURE 1

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) as of 2012.

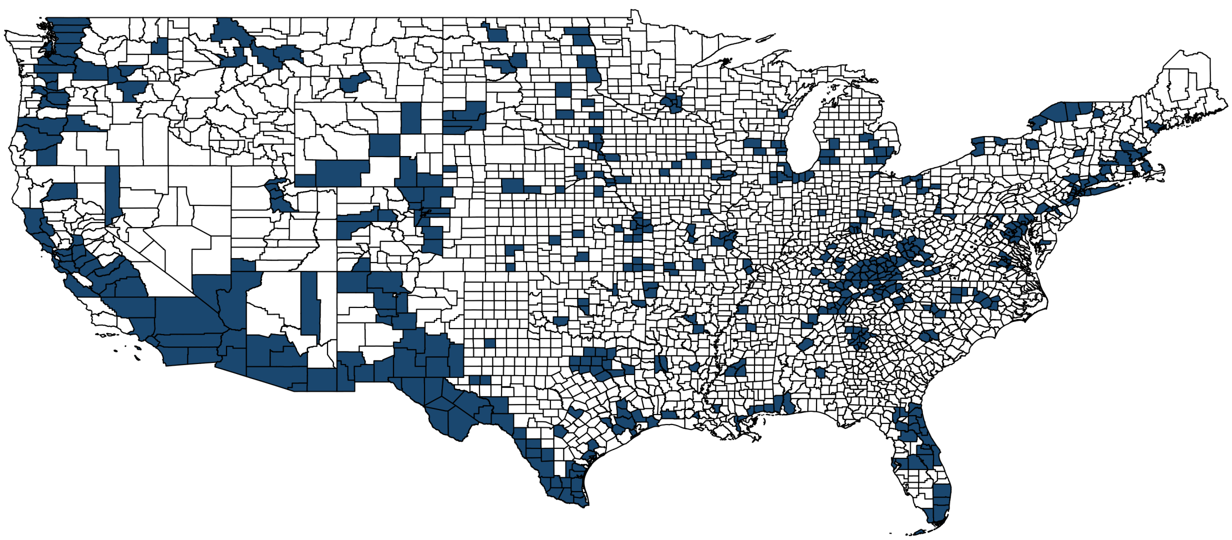
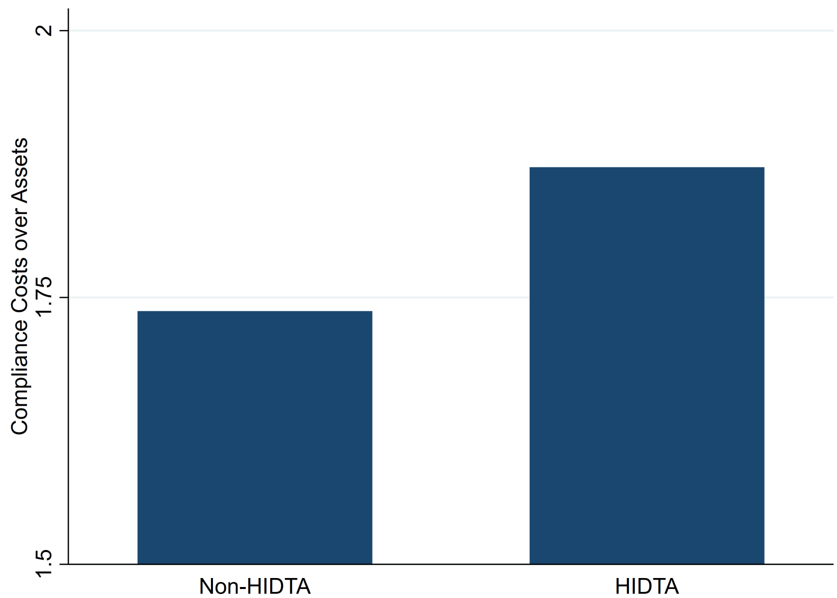


FIGURE 2

Compliance costs, exposure to HIDTA counties, and bank size

This figure shows the overall compliance costs for banks more (less) exposed to HIDTA counties (Panel A) and for small and large banks (Panel B). Banks that source more than 50% of their deposits from HIDTA counties are categorized as HIDTA. Banks with assets above the median value for all banks are categorized as large. The data are from the Conference of State Bank Supervisors' 2015 National Survey of Community Banks.

Panel A: Exposure to HIDTA counties



Panel B: Bank Size

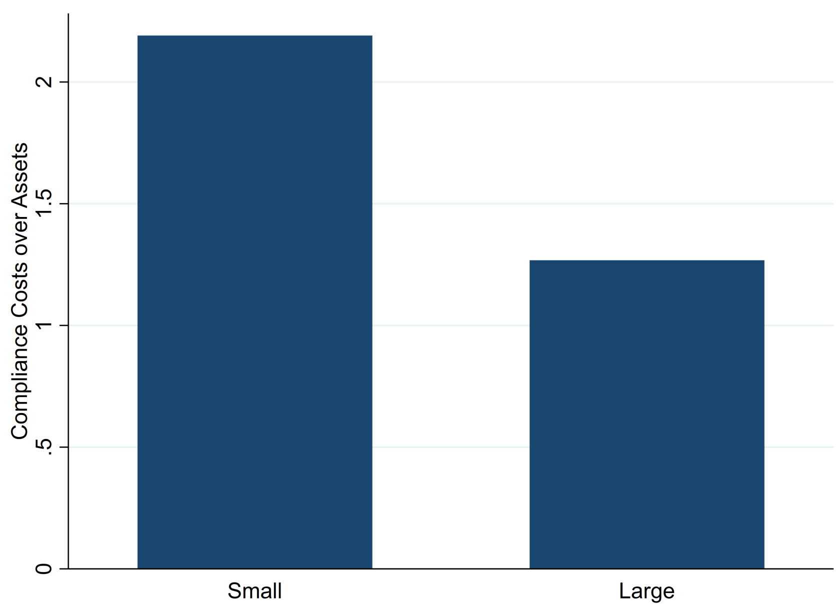
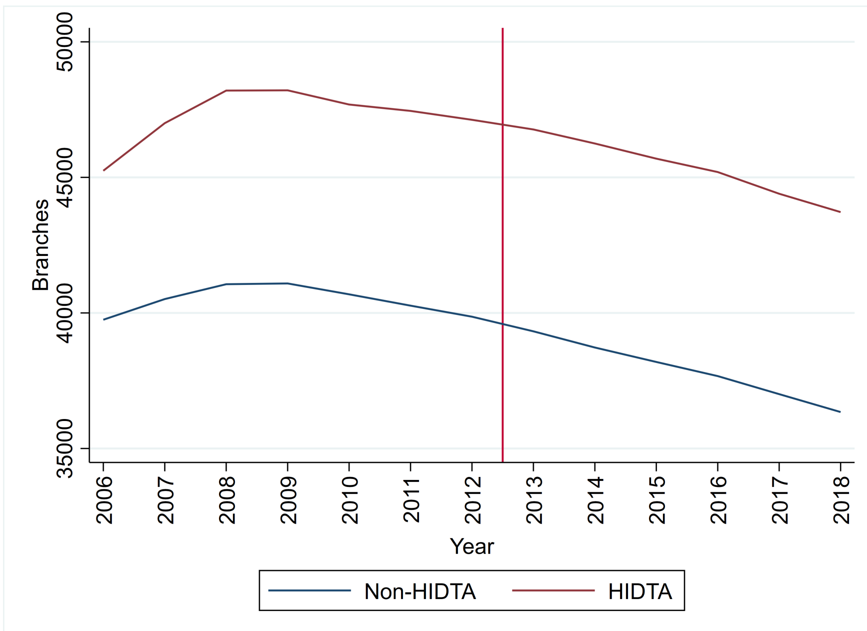


FIGURE 3

Bank branches in HIDTA and non-HIDTA counties

This figure shows the evolution of the total number of bank branches in 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

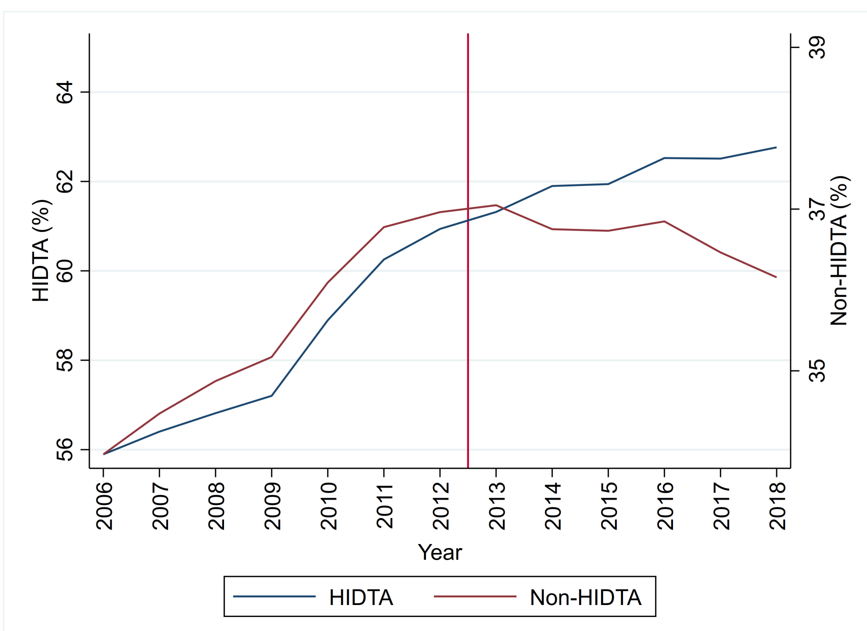


FIGURE 4

Bank branches in HIDTA counties

This figure shows the dynamic coefficients of a regression of the inverse hyperbolic sine transformation of the number of branches that 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.

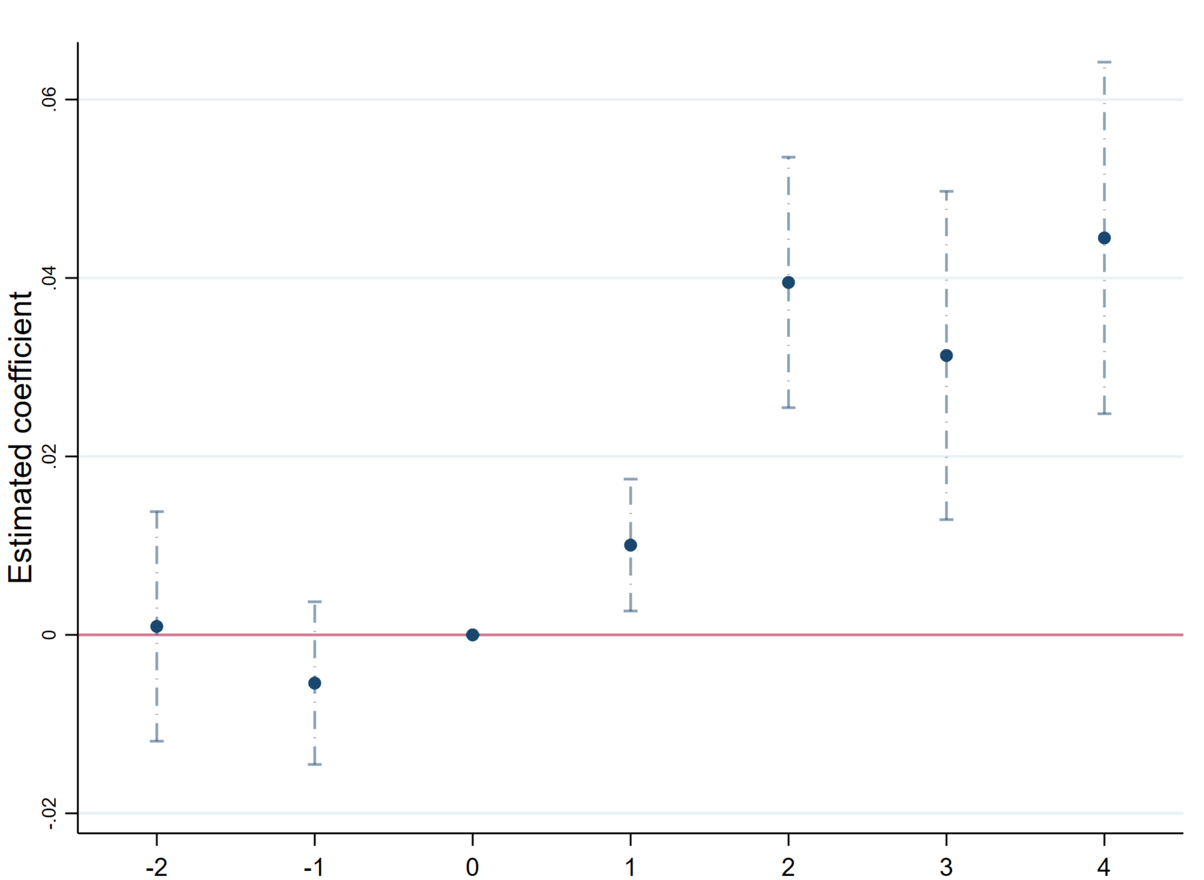


TABLE 1

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. Panel C presents summary statistics for the other variables used in the analysis. Data for Panels A and B are from the Census Bureau and the Summary of Deposits reported by the FDIC. Data sources for variables in Panel C are described in the Internet Appendix. Data are from the census bureau and the Summary of Deposits reported by the FDIC. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Demographic Information

	Non-HIDTA		HIDTA		
Variable	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		
Variable	Value	N	Value	N	Difference
Deposits per capita	3.43	2,580	3.49	528	−0.06*
Deposits per capita growth ($\Delta = 1$ year)	0.03	2,580	0.03	528	−0.01
Deposits per capita growth ($\Delta = 2$ year)	0.04	2,579	0.05	528	−0.01
Deposits per capita growth ($\Delta = 3$ year)	0.05	2,579	0.06	528	−0.00
Deposits per capita growth ($\Delta = 4$ year)	0.09	2,580	0.09	527	−0.01
Branches per thousand capita	0.44	2,580	0.30	528	0.15***
Branches per capita growth ($\Delta = 1$ year)	−0.00	2,580	−0.00	528	0.00
Branches per capita growth ($\Delta = 2$ year)	0.01	2,579	0.01	528	0.00
Branches per capita growth ($\Delta = 3$ year)	0.01	2,579	0.01	528	0.00
Branches per capita growth ($\Delta = 4$ year)	0.01	2,580	0.01	527	0.00

Panel C: Summary Statistics

Variables	Mean	SD	Min	Median	Max	N
Bank–County Level						
Deposits (asinh)	8.887	5.291	0.000	11.273	20.300	35,311
Branches (asinh)	1.115	0.923	0.000	0.881	6.238	35,311
County Level						
Deposits (asinh)	13.699	1.680	0.000	13.589	21.024	3,121
Branches (asinh)	2.729	0.860	0.000	2.644	6.050	3,121
Bank Costs						
Compliance Costs / Assets	0.854	0.544	0.000	0.753	1.738	529
General Costs / Assets	12.966	4.814	0.009	14.052	17.777	529
CRA Lending						
Loans (Number)	6.588	1.573	0.000	6.565	10.588	3,036
Loans (Number) – Small	6.149	1.534	0.000	6.114	10.181	3,036
Loans (Number) – Medium	2.820	1.748	0.000	2.776	6.951	3,036
Loans (Number) – Large	2.725	1.804	0.000	2.644	7.440	3,036
Loans (Amount)	9.990	2.017	0.000	10.076	14.437	3,036
Loans (Amount) – Small	8.629	1.753	0.000	8.667	12.892	3,036
Loans (Amount) – Medium	8.030	3.630	0.000	8.930	13.767	3,036
Loans (Amount) – Large	7.305	3.088	0.000	7.968	12.161	3,036
SBA Lending						
Loans (Number)	1.761	1.619	0.000	1.444	8.179	3,023
Loans (Amount)	10.640	6.871	0.000	13.892	21.326	3,023
SBA Guaranteed (Amount)	10.381	6.726	0.000	13.528	21.020	3,023
HMDA Lending – Home Purchase						
Loans (Number)	5.685	1.965	0.000	5.677	11.670	3,189
Loans (Amount)	10.438	2.528	0.000	10.485	17.707	3,189
HMDA Lending – Home Improvement						
Loans (Number)	4.206	1.717	0.000	4.331	9.330	3,181
Loans (Amount)	8.003	2.433	0.000	8.216	15.182	3,181
HMDA Lending – Refinancing						
Loans (Number)	6.321	2.158	0.000	6.394	12.925	3,189
Loans (Amount)	11.143	2.679	0.000	11.229	18.863	3,189
Local Economic Activity						
Establishments	7.195	1.481	2.312	7.026	13.627	3,137
Employment	9.501	1.803	0.000	9.418	15.775	3,137
Wages	18.593	2.172	0.000	18.523	25.513	3,137
Real Estate						
Median Listing Price	12.682	0.386	11.590	12.612	14.599	2,319
Median Listing Price per Sq. Ft.	5.262	0.369	4.290	5.201	7.725	2,319
Zillow Index (All Homes)	12.348	0.477	10.940	12.330	14.553	2,319
Zillow Index (SFR)	12.356	0.498	10.940	12.331	16.441	2,319
DEA Spending						
DEA Spending (asinh)	1.195	3.469	0.000	0.000	19.927	3,121

TABLE 2

Banks' Compliance Costs

This table provides the results of the analysis of compliance costs across banks. Exposure HIDTA is the share of deposits that each bank sources from counties identified as High Intensity Drug Trafficking Areas by the White House Office of National Drug Control Policy. Bank Size is the inverse hyperbolic sine transformation of the total volume of deposits for that bank. The dependent variables are Compliance costs normalized by assets (Columns 1-3), Compliance costs normalized by deposits (Column 4), General costs normalized by assets (Column 5), and General costs normalized by deposits (Column 6). t-statistics are given in parentheses; we use robust standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The data are from the Conference of State Bank Supervisors' 2015 National Survey of Community Banks.

	Compliance costs (assets) 1	Compliance costs (assets) 2	Compliance costs (assets) 3	Compliance costs (deposits) 4	General costs (assets) 5	General costs (deposits) 6
Bank Size	-0.168^{***}	-0.182^{***}	-0.138^{***}	-0.163^{***}	-0.237	-0.247
	(-7.76)	(-8.35)	(-4.32)	(-4.18)	(-0.69)	(-0.58)
Exposure HIDTA		0.176^{***}	1.406^{**}	1.644^{**}	7.131	7.671
		(3.49)	(2.29)	(2.21)	(1.26)	(1.09)
Bank Size × Exposure HIDTA			-0.096^{**}	-0.112^{*}	-0.404	-0.418
			(-2.03)	(-1.96)	(-0.91)	(-0.76)
N	498	498	498	498	509	509
Adj. R^2	0.114	0.133	0.138	0.132	0.032	0.028

TABLE 3

Bank branches and deposits volume

This table provides the results of the analysis of the number of branches and volume of deposits in counties subject to high levels of money laundering activity 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 inverse hyperbolic sine transformation of the number of branches operating within a county (Columns 1-2), and Deposits, the inverse hyperbolic sine transformation of the volume of deposits in bank-branches within a county (Columns 3-4). All estimations include county-level controls (unemployment rate, log population, log median income) fixed at pre-period 2011 values and interacted with the Post_t indicator and control for spending by the DEA at the county-year level. 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.

	Branches 1	Branches 2	Deposits 3	Deposits 4
Post × HIDTA	0.004	0.003	0.026^{**}	0.020^{*}
	(1.09)	(0.71)	(2.47)	(2.01)
N	21,745	21,738	21,745	21,738
Adj. R^2	0.996	0.996	0.996	0.997
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State × Year FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes

TABLE 4

Bank branches and deposits volume by bank size

This table provides the results of the analysis of the composition of bank branches and volume of deposits in small and large banks. 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 one percent in terms of deposits. The dependent variables are Branches, the inverse hyperbolic sine transformation of the number of branches operating within a county (Columns 1-3), and Deposits, the inverse hyperbolic sine transformation of the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 1-2 and 4-5 include county-level controls fixed at pre-period 2011 values and interacted with the $Post_t$ indicator and control for spending by the DEA at the county-year level. 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.

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × HIDTA	-0.028^{**}	-0.026^{**}		-0.392^{**}	-0.323^{**}	
	(−2.75)	(−2.48)		(−2.72)	(−2.47)	
HIDTA × Large	0.630^{***}			0.805^{***}		
	(20.24)			(5.45)		
Post × Large	0.026^{*}	0.030		0.660^{***}	0.753^{***}	
	(2.07)	(1.91)		(3.84)	(3.95)	
Post × HIDTA × Large	0.035^{***}	0.058^{**}	0.033^{**}	0.676^{**}	0.669^{**}	0.331^{***}
	(6.28)	(3.64)	(3.03)	(3.65)	(3.50)	(3.88)
N	232,571	231,558	202,784	232,571	231,558	202,784
Adj. R^2	0.575	0.865	0.946	0.684	0.786	0.930
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE 5

Alternative specifications - Branches and Deposits

This table provides alternative specifications for the analysis of the composition of bank branches and deposits. Panel A provides alternative sample specifications, and Panel B provides alternative measures of money laundering exposure. In Panel A, Columns (1) and (5) use an alternative definition of large bank as those with assets above one billion dollars as of 2012; Columns (2) and (6) use a matched sample where each HIDTA county is matched with three non-HIDTA counties within the same state with replacement based on income, population, and education; Columns (3) and (7) restrict non-HIDTA counties to those neighboring HIDTA areas, and Columns (4) and (8) exclude strong housing markets, defined as county-years with five-year housing price appreciation in the top decile. In Panel B, columns (1)-(2) and (6)-(7) measure money laundering exposure (ML-Exposure) using proximity to DEA offices, defined as an indicator for whether a DEA office is within 50 miles (proximity) and the distance to the nearest DEA office (distance). Columns (3)-(4) and (8)-(9) follow the same approach using DOJ offices. Columns 5 and 10 report results using an enforcement intensity index ranging from 0 to 3, constructed as the sum of indicators for HIDTA designation, DEA proximity, and DOJ proximity. 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: Alternative Sample Specifications

	Branches				Deposits			
	Alt. Bank Size	Matched Sample	Neighboring non-HIDTA	Excluding Strong Housing Markets	Alt. Bank Size	Matched Sample	Neighboring non-HIDTA	Excluding Strong Housing Markets
	1	2	3	4	5	6	7	8
Post × HIDTA × Large	0.094***	0.023	0.038**	0.030**	0.936***	0.211**	0.278**	0.276**
	(4.11)	(1.58)	(3.11)	(2.95)	(4.42)	(2.52)	(3.58)	(3.58)
N	202,784	41,735	129,855	178,440	202,784	41,735	129,855	178,440
Adj. R^2	0.949	0.946	0.953	0.952	0.930	0.926	0.934	0.933
Bank × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Alternative Measures of Money Laundering Exposure

	Branches					Deposits				
	DEA Proximity	DEA Distance	DOJ Proximity	DOJ Distance	Enforcement Intensity Index	DEA Proximity	DEA Distance	DOJ Proximity	DOJ Distance	Enforcement Intensity Index
	1	2	3	4	5	6	7	8	9	10
Post × Measure × Large	0.044^{**}	0.211^{*}	0.016	0.477^{**}	0.021^{**}	0.448^{**}	1.599^{**}	0.284^{**}	5.529^{***}	0.226^{***}
	(2.72)	(2.44)	(1.72)	(2.96)	(3.46)	(3.69)	(2.96)	(3.47)	(3.84)	(4.10)
N	202,784	201,693	202,784	201,693	202,784	202,784	201,693	202,784	201,693	202,784
Adj. R^2	0.949	0.949	0.949	0.949	0.949	0.930	0.930	0.930	0.930	0.930
Bank × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 6

Lending by Large Banks

This table provides the results of the analysis of lending by large banks following changes in the composition of banks at the county level. 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 one percent in terms of deposits. In Panel A, the dependent variables are Loans (Total), the number and volume of loans (columns 1 and 5, respectively), Loans (small), the number and volume of loans with face value at origination under 100,000 dollars (column 2 and 6, respectively), Loans (medium), number and volume of loans with face value at origination between 100,000 and 250,000 dollars (columns 3 and 7, respectively), and Loans (large), the number and volume of loans with face value at origination between 250,000 and 1,000,000 dollars (columns 4 and 8, respectively). In Panel B, the dependent variables are the number and volume of loans (columns 1 and 2, respectively), and the amount guaranteed by the SBA (column 3). In Panel C, the dependent variables are the number and volume of loans for home purchases, improvement, and refinancing, respectively. Across panels, we apply the inverse hyperbolic sine transformation to all dependent variables. 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: Community Reinvestment Act (CRA) Lending

	Loans (N)				Loans (A)			
	All 1	Small 2	Medium 3	Large 4	All 5	Small 6	Medium 7	Large 8
Post × HIDTA × Large	0.141^{*}	0.143^{*}	0.006	0.001	0.141	0.096	0.090	0.097
	(2.16)	(2.18)	(0.39)	(0.07)	(1.59)	(1.13)	(1.40)	(1.89)
N	925,822	925,822	925,822	925,822	925,822	925,822	925,822	925,822
Adj. R^2	0.872	0.883	0.781	0.788	0.752	0.791	0.651	0.648
Bank × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Small Business Administration (SBA) Lending

	Loans (N)	Loans (A)	SBA Guaranteed
	1	2	3
Post × HIDTA × Large	0.073^{*}	0.403	0.378
	(2.14)	(1.85)	(1.84)
N	193,882	193,882	193,882
Adj. R^2	0.659	0.399	0.399
Bank × Year FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Bank × County FE	Yes	Yes	Yes

Panel C: Home Mortgage Disclosure Act (HMDA) Lending

	Loans (N)			Loans (A)		
	Purch.	Impr.	Refi.	Purch.	Impr.	Refi.
	1	2	3	4	5	6
Post × HIDTA × Large	0.145^{**}	0.199^{***}	0.146^{**}	0.423^{**}	0.506^{**}	0.334^{*}
	(3.63)	(4.25)	(3.54)	(3.40)	(3.19)	(2.15)
N	2,704,079	850,061	3,477,755	2,704,079	850,061	3,477,755
Adj. R^2	0.782	0.757	0.796	0.663	0.644	0.700
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank × County FE	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 7

Lending Across Banks

This table provides the results of the analysis of the relation between changes in the composition of banks and aggregate lending under different programs. 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. In Panel A, the dependent variables are Loans (Total), the number and volume of loans (columns 1 and 5, respectively), Loans (small), the number and volume of loans with face value at origination under 100,000 dollars (column 2 and 6, respectively), Loans (medium), number and volume of loans with face value at origination between 100,000 and 250,000 dollars (columns 3 and 7, respectively), and Loans (large), the number and volume of loans with face value at origination between 250,000 and 1,000,000 dollars (columns 4 and 8, respectively). In Panel B, the dependent variables are the number and volume of loans (columns 1 and 2, respectively), and the amount guaranteed by the SBA (column 3). In Panel C, the dependent variables are the number and volume of loans for home purchases, improvement, and refinancing, respectively. Across panels, we apply the inverse hyperbolic sine transformation to all dependent variables. 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: Community Reinvestment Act (CRA) Lending

	Loans (N)				Loans (A)			
	All	Small	Medium	Large	All	Small	Medium	Large
	1	2	3	4	5	6	7	8
Post × HIDTA	0.115	0.116*	0.051	0.033	0.136	0.141	0.038	0.085
	(1.86)	(1.97)	(1.10)	(0.81)	(1.65)	(1.92)	(0.36)	(0.93)
N	21,140	21,140	21,140	21,140	21,140	21,140	21,140	21,140
Adj. R^2	0.936	0.941	0.911	0.920	0.903	0.914	0.748	0.755
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Small Business Administration (SBA) Lending

	Loans (N)	Loans (A)	SBA Guaranteed
	1	2	3
Post × HIDTA	0.038	−0.009	−0.002
	(1.34)	(−0.04)	(−0.01)
N	21,140	21,140	21,140
Adj. R^2	0.881	0.547	0.551
County FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Panel C: Home Mortgage Disclosure Act (HMDA) Lending

	Loans (N)			Loans (A)		
	Purch.	Impr.	Refi.	Purch.	Impr.	Refi.
	1	2	3	4	5	6
Post × HIDTA	0.009	0.085**	−0.028	0.019	0.107*	−0.024
	(0.81)	(2.95)	(−0.85)	(1.07)	(2.40)	(−0.82)
N	21,924	21,924	21,924	21,924	21,924	21,924
Adj. R^2	0.988	0.953	0.987	0.973	0.886	0.958
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 8

Real Economic Outcomes

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 money laundering activity. 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, the dependent variables are the inverse hyperbolic sine transformation of the number of establishments (column 1), the inverse hyperbolic sine transformation of the aggregate number of employees (column 2), and the inverse hyperbolic sine transformation of the aggregate wages (column 3) for the overall sample. In Panel B, the dependent variables are defined as in Panel A, and the results are provided for firms that are micro (column 1), small (column 2), medium (column 3), and large (column 4), which are defined as having fewer than 20 employees, 20-99 employees, 100-499 employees and more than 500 employees, respectively. In Panel C, the dependent variables are defined as in Panel A, with the results for the non-tradable sector in columns 1 to 3 and those for the tradable sector in columns 4 to 6. Sector classifications are from Mian and Sufi (2014). 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: Overall Sample

	Establishments 1	Employment 2	Wages 3
Post × HIDTA	0.010^{**}	0.001	-0.029
	(2.64)	(0.14)	(-1.29)
N	21,917	21,917	21,917
Adj. R^2	0.999	0.964	0.886
County FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Panel B: By Firm Size

	Micro <20 1	Small 20-99 2	Medium 100-499 3	Large 500+ 4
Establishments				
Post × HIDTA	0.014**	0.022**	−0.012	−0.001
	(3.09)	(3.04)	(−1.60)	(−0.25)
Adj. R^2	0.999	0.994	0.989	0.997
Employment				
Post × HIDTA	−0.032*	−0.138*	−0.376	−0.305
	(−2.00)	(−2.04)	(−1.80)	(−1.73)
Adj. R^2	0.928	0.863	0.777	0.820
Wages				
Post × HIDTA	−0.017	−0.223**	−0.422	−0.334
	(−1.64)	(−3.13)	(−1.58)	(−1.61)
Adj. R^2	0.974	0.833	0.734	0.778
N	21,917	21,820	21,614	21,730
County FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel C: By Sector

	Non-Tradable			Tradable		
	Establishments 1	Employment 2	Wages 3	Establishments 4	Employment 5	Wages 6
Post × HIDTA	0.019**	0.043*	0.095	0.004	−0.002	−0.011
	(2.58)	(1.98)	(1.86)	(0.73)	(−0.30)	(−0.53)
N	3,856,084	3,856,084	3,856,084	4,457,312	4,457,312	4,457,312
Adj. R^2	0.833	0.656	0.595	0.536	0.353	0.341
County FE	No	No	No	No	No	No
State × Qtr FE	No	No	No	No	No	No
NAICS 6d FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS 3d × County FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS 3d × State × Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 9

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 money laundering activity. 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, 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, in Panel B, Lower 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 inverse hyperbolic sine transformation of the median listing price (column 1), the inverse hyperbolic sine transformation of the median listing price per sq ft (column 2), the inverse hyperbolic sine transformation of the Zillow Home Value Index for all types of properties (column 3), and the inverse hyperbolic sine transformation of the Zillow Home Value Index for single-family residences (SFR) in column 4. Except where county x fixed effects are included, estimations include county-level controls fixed at pre-period 2011 values and interacted with the Post_t indicator and control for spending by the DEA at the county-year level. 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: County Level

	Median Listing Price 1	Median Listing Price per sq ft 2	Zillow Index All 3	Zillow Index SFR 4
Post × HIDTA	0.0514^{***}	0.0368^{***}	0.0176^{*}	0.0173^{*}
	(3.96)	(3.83)	(2.38)	(2.44)
N	11,778	12,585	13,618	13,595
Adj. R^2	0.965	0.973	0.991	0.992
County FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel B: Zip Code Level by Income

	Median Listing Price		Median Listing Price per sq ft		Zillow Index (All)		Zillow Index (SFR)	
	1	2	3	4	5	6	7	8
Post × HIDTA	0.040^{***}		0.044^{***}		0.029^{***}		0.028^{***}	
	(4.51)		(5.21)		(4.01)		(4.05)	
Post × Lower Income	-0.023^{***}	-0.020^{**}	-0.003	-0.004	-0.013^{**}	-0.013^{**}	-0.012^{**}	-0.013^{**}
	(-4.30)	(-3.64)	(-0.99)	(-0.72)	(-3.40)	(-2.89)	(-3.47)	(-2.91)
Post × HIDTA × Lower Income	0.020^{*}	0.021^{*}	0.015	0.021^{**}	0.016	0.017	0.017	0.017
	(1.99)	(2.22)	(1.59)	(2.58)	(1.60)	(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^2	0.980	0.985	0.983	0.989	0.992	0.996	0.993	0.996
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	No	Yes	No	Yes	No	Yes	No	Yes
State × Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Controls	Yes	No	Yes	No	Yes	No	Yes	No

TABLE 10

Alternative Explanations

This table reports results on alternative explanations. Panel A reports real effects for small firms in non-HIDTA counties with varying banking sector composition related to AML enforcement. In the Intensive Measure, Percentage is the percentage of small banks subject to AML enforcement actions prior to 2012 over the total number of banks and in the Extensive Measure, None is an indicator variable set to one for counties that had no such banks. Panel B is on lending practices examined in relation to loan delinquency and default in counties subject to high levels of money laundering activity. In Columns (1)-(2), the dependent variable is delinquency rate, measured using the Consumer Financial Protection Bureau's data, and in columns (3)-(4), the dependent variable is Default Rate, set to one for loans that eventually default and is measured using CoreLogic's data. Panel C is on the relation between stricter AML enforcement and crime in counties subject to high levels of criminal activity. The dependent variables in Columns (1)-(8) are the number of violent crimes, murders and manslaughters, robberies, aggravated assaults, property crimes, burglaries, larceny/theft, and motor vehicle thefts, respectively. For all the estimations in Panels A-C, the unit of analysis is county-level and the county-level controls are fixed at pre-period 2011 values and interacted with the Post indicator and control for spending by the DEA at the county-year level. Panel D is on real effects in cash intensive businesses in counties subject to high levels of money laundering activity, and the unit of analysis is the industry-county-year. Cash Intensive, an indicator variable set to one for industries identified as cash intensive businesses by the NAICS association. t-statistics are given in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Non-HIDTA Counties

	< 20 employees			20-99 employees		
	Employment	Wages	Establishments	Employment	Wages	Establishments
	1	2	3	4	5	6
Post × Percentage	0.018	-0.021	-0.022	-0.223	-0.170	0.035
	(0.14)	(-0.44)	(-1.37)	(-1.04)	(-0.68)	(0.82)
N	18,088	18,088	18,088	18,020	18,020	18,020
Adj. R^2	0.895	0.965	0.999	0.820	0.788	0.990
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

	< 20 employees			20-99 employees		
	Employment	Wages	Establishments	Employment	Wages	Establishments
	1	2	3	4	5	6
Post × None	-0.004	-0.007	-0.000	0.091	0.123	-0.004
	(-0.28)	(-0.41)	(-0.13)	(1.56)	(1.90)	(-0.60)
N	18,186	18,186	18,186	18,090	18,090	18,090
Adj. R^2	0.893	0.958	0.999	0.824	0.794	0.990
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Lending Practices and Loan Performance

	Delinquency Rate		Default Rate	
	1	2	3	4
Post × HIDTA	-0.047	-0.038	-0.008	-0.007
	(-1.50)	(-1.14)	(-1.38)	(-1.44)
N	3,241	3,199	168	168
Adj. R^2	0.916	0.923	0.812	0.848
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes
State × Year FE	No	Yes	No	No
Controls	Yes	Yes	No	Yes

Panel C: Crime

	Violent crime	Murder and manslaughter	Robbery	Aggravated assault	Property crime	Burglary	Larceny-theft	Motor vehicle theft
	1	2	3	4	5	6	7	8
Post × HIDTA	0.004	0.020	0.014	0.017	-0.003	-0.045^{*}	0.012	0.037
	(0.10)	(1.06)	(0.62)	(0.40)	(-0.11)	(-2.11)	(0.45)	(1.39)
N	17,532	17,821	17,821	17,779	17,763	17,797	17,803	17,800
Adj. R^2	0.868	0.589	0.830	0.856	0.887	0.874	0.886	0.829
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Cash-Intensive Industries

	Establishments 1	Employment 2	Wages 3
Post × HIDTA	0.034^{*}	0.071	0.141^{*}
	(2.36)	(1.92)	(1.96)
Post × Cash Intensive	0.012^{**}	-0.002	-0.004
	(2.46)	(-0.33)	(-0.40)
HIDTA × Cash Intensive	0.156^{***}	0.510^{***}	0.822^{***}
	(14.36)	(13.75)	(8.61)
Post × HIDTA × Cash Intensive	-0.030^{**}	-0.039^{**}	-0.066^{*}
	(-2.87)	(-2.62)	(-2.29)
N	3,856,084	3,856,084	3,856,084
Adj. R^2	0.833	0.657	0.595
NAICS 6d FE	Yes	Yes	Yes
NAICS 3d × County FE	Yes	Yes	Yes
NAICS 3d × State × Qtr FE	Yes	Yes	Yes

A. Internet Appendix

Variable Definitions

Variable	Definition	Source
Bank Size	Inverse hyperbolic sine transformation of the volume of deposits.	FDIC Summary of Deposits
Branches	Number of bank branches by county–year.	FDIC Summary of Deposits
Compliance Costs	Personnel-related compliance expenditures scaled by total assets.	CSBS
CRA Loans (Amt.)	Inverse hyperbolic sine transformation of the dollar volume of loans to small businesses under the Community Reinvestment Act in a county–year.	FFIEC CRA
CRA Loans (No.)	Inverse hyperbolic sine transformation of the number of loans to small businesses under the Community Reinvestment Act in a county–year.	FFIEC CRA
Crime	Reported crimes by category at the county–year level.	FBI UCR
Deposits	Inverse hyperbolic sine transformation of the volume of deposits held by bank branches in a county–year.	FDIC Summary of Deposits

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Internet Appendix: Variable Definitions – continued

Variable	Definition	Source
Distance to DEA Office	Relative distance of each county in the United States to its closest Drug Enforcement Agency (DEA) office.	Authors' calculations based on DEA data
Distance to DOJ Office	Relative distance of each county in the United States to its closest Department of Justice (DOJ) office.	Authors' calculations based on DOJ data
Employment	Inverse hyperbolic sine transformation of the aggregate number of employees in a county–year.	BLS QCEW
Establishments	Inverse hyperbolic sine transformation of the aggregate number of active establishments in a county–year.	BLS QCEW
HIDTA	Indicator equal to one if the county is designated as a High Intensity Drug Trafficking Area as of 2012; zero otherwise.	ONDCP/White House
HIDTA Exposure	Share of a bank's total deposits located in HIDTA counties.	FDIC Summary of Deposits
HMDA Loans (Amt.)	Inverse hyperbolic sine transformation of the dollar volume of mortgage loans by purpose (purchase, refinance, improvement).	FFIEC HMDA

Continued on next page

Internet Appendix: Variable Definitions – continued

Variable	**Definition**	**Source**
HMDA Loans (No.)	Inverse hyperbolic sine transformation of the number of mortgage loans by purpose (purchase, refinance, improvement).	FFIEC HMDA
Large Bank	Indicator equal to one if the bank is in the top 1% by deposits and operates at least 100 branches nationwide.	FDIC Summary of Deposits
Low-Income Zip Code	Indicator equal to one if zip-code median income is below the county median.	U.S. Census
Median Income	Median household income at the county–year level.	U.S. Census
Median Listing Price	Inverse hyperbolic sine transformation of the median listing price for properties at the county or zip-code–year level.	Zillow
Median Listing Price per sq. ft.	Inverse hyperbolic sine transformation of the median listing price per square foot at the county or zip-code–year level.	Zillow
Population	County population.	U.S. Census
Post	Indicator equal to one for years after 2012 (2013–2016); zero otherwise.	Authors

Continued on next page

Internet Appendix: Variable Definitions – continued

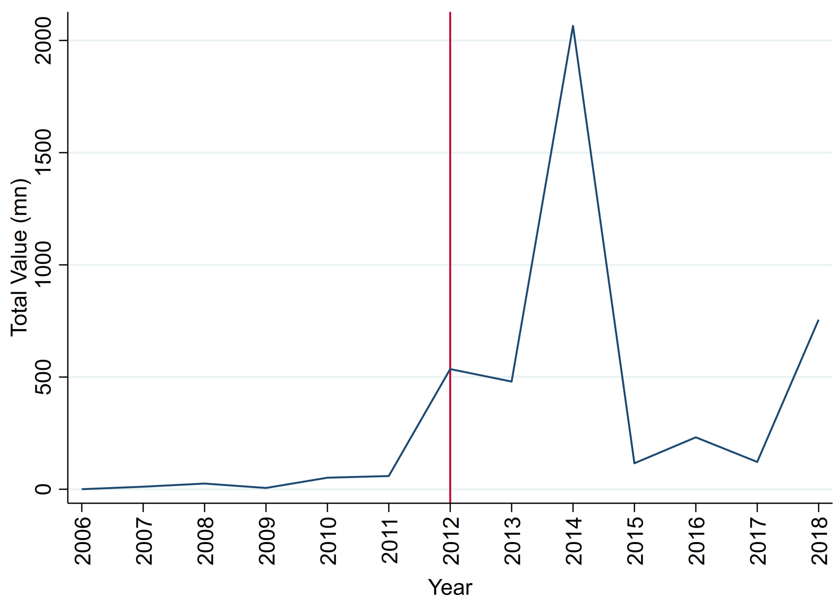
Variable	**Definition**	**Source**
SBA Loans (Amt.)	Inverse hyperbolic sine transformation of the dollar volume of SBA 7(a) loans in a county–year.	U.S. SBA
SBA Loans (No.)	Inverse hyperbolic sine transformation of the number of SBA 7(a) loans in a county–year.	U.S. SBA
Small Establishments	Inverse hyperbolic sine transformation of the number of establishments by employment size category.	County Business Patterns
Wages	Inverse hyperbolic sine transformation of the aggregate level of wages in a county–year.	BLS QCEW
Zillow Index All	Inverse hyperbolic sine transformation of the Zillow Home Value Index (ZHVI) for all types of properties.	Zillow
Zillow Index SFR	Inverse hyperbolic sine transformation of the Zillow Home Value Index (ZHVI) for single-family residences.	Zillow

FIGURE A1

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 year of the change in the enforcement of AML regulations. 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

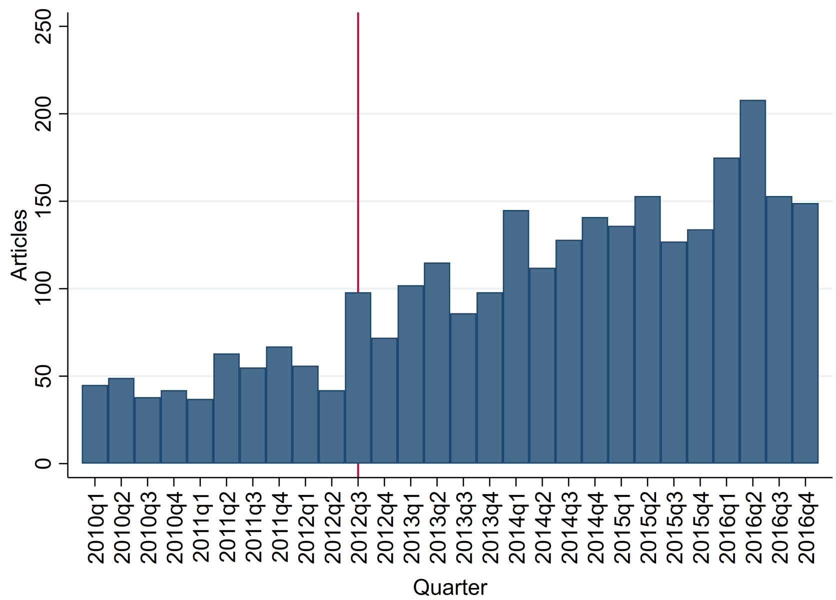
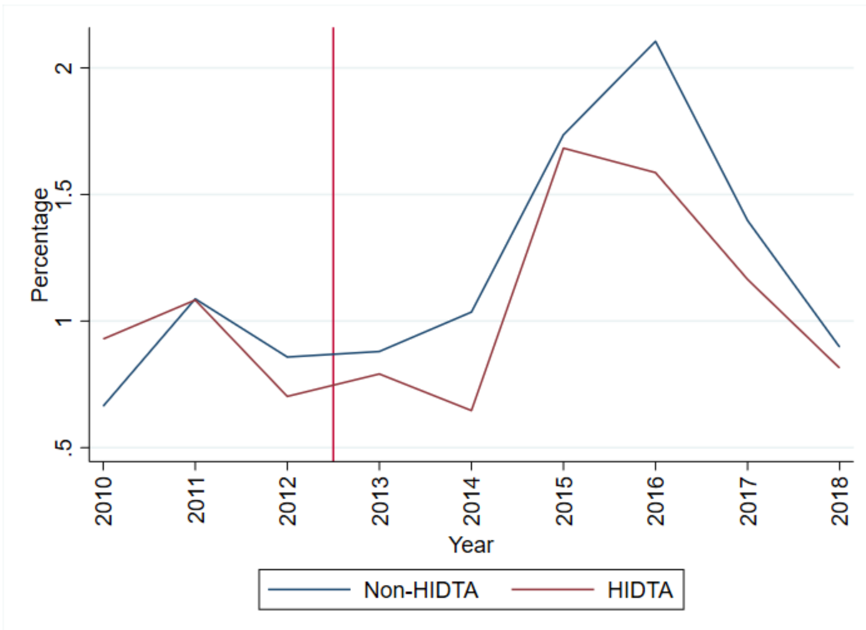


FIGURE A2

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

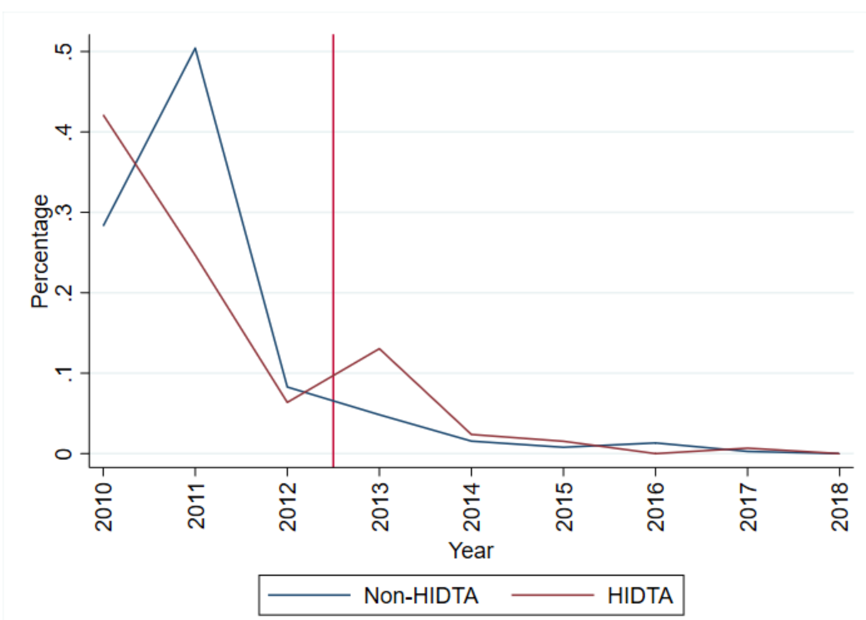
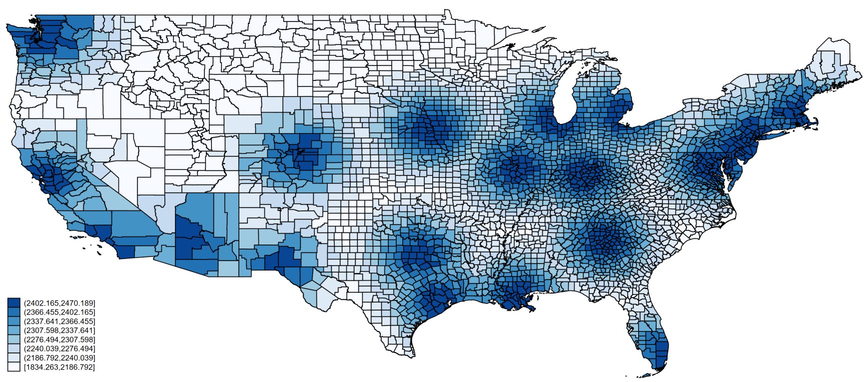


FIGURE A3

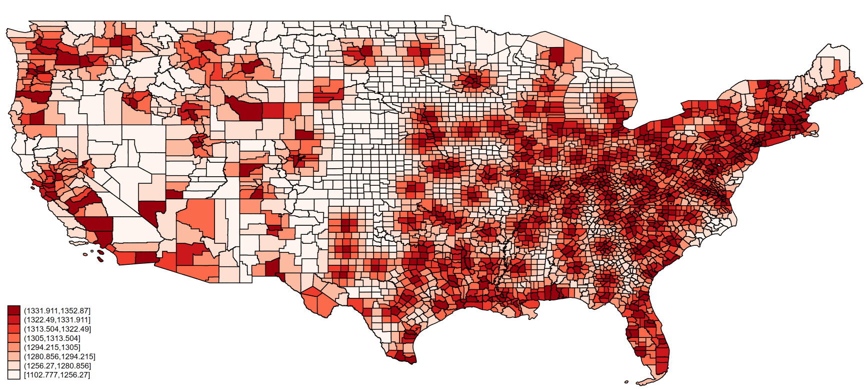
Distance to DEA and DOJ offices

The Figures in Panels A and B map the relative distance of each county in the United States to its closest Drug Enforcement Agency (DEA) and Department of Justice (DOJ) offices, respectively. The Figure in Panel C maps the Index that takes into account whether a county has been designated as HIDTA, and whether there are DEA and DOJ offices within 50 miles of the county. Data on regional offices are obtained from the United States Drug Enforcement Administration and United Stated Department of Justice websites.

Panel A – Distance to DEA offices



Panel B – Distance to DOJ offices



Panel C – Index considering HIDTA, DEA, and DOJ offices

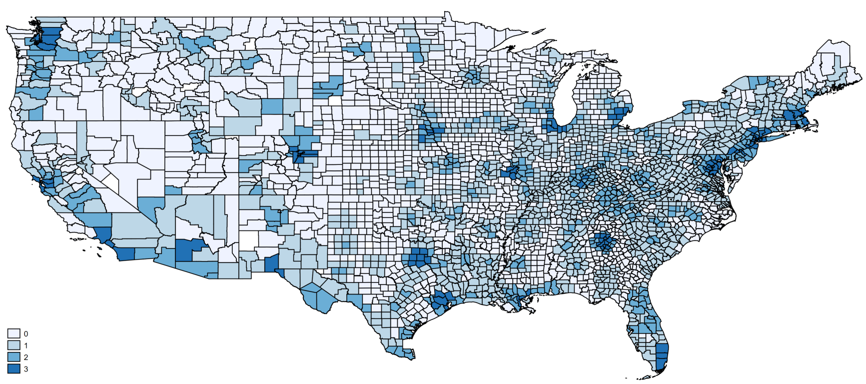


FIGURE A4

SBA Lending in HIDTA counties

This figure shows the dynamic coefficients of a regression of the inverse hyperbolic sine transformation of the number of SBA loans by large banks in HIDTA counties across time. The data on lending are from the U.S. Small Business Administration. HIDTA counties are those identified by the White House Office of National Drug Control Policy by 2012.

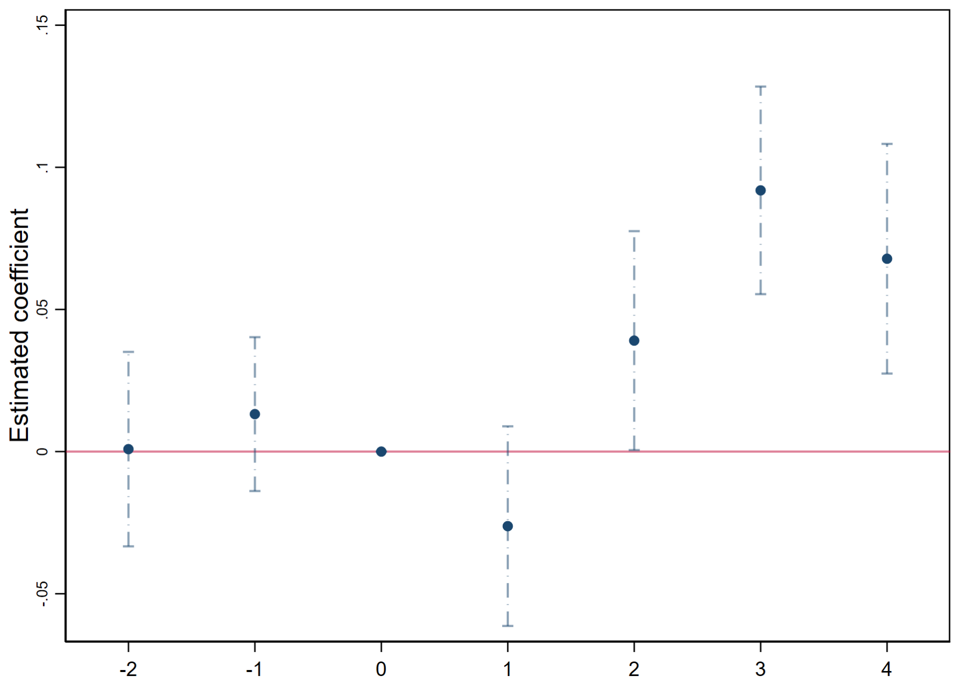


FIGURE A5

Small Establishments in HIDTA counties

This figure shows the dynamic coefficients of a regression of the inverse hyperbolic sine transformation of the number of small establishments in HIDTA counties across time. The data on small establishments are from the County Business Patterns. HIDTA counties are those identified by the White House Office of National Drug Control Policy by 2012.

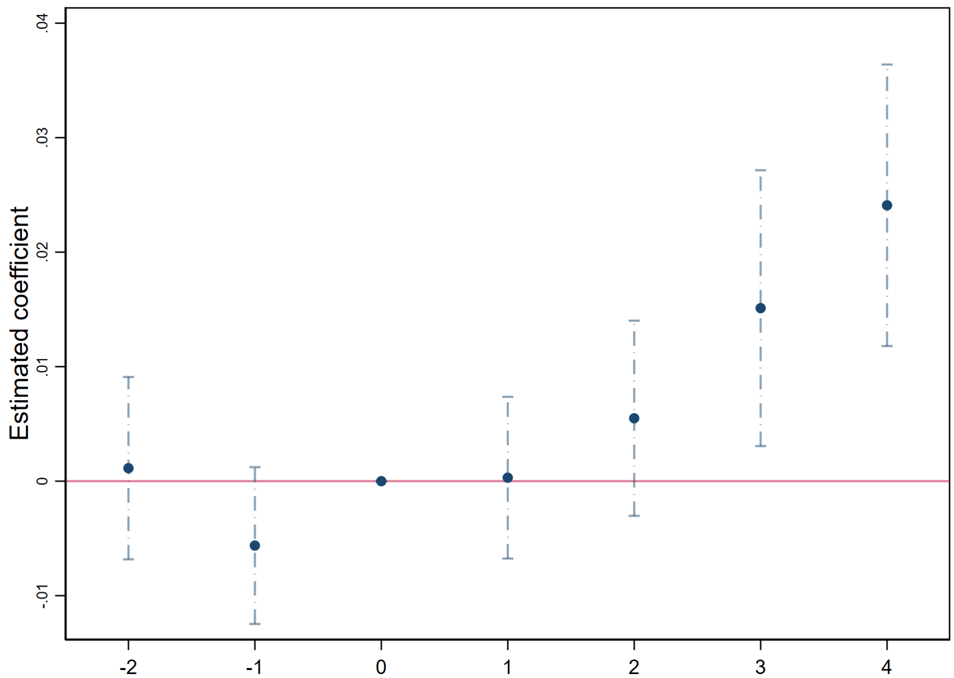


FIGURE A6

Zillow Home Value Index (ZHVI) in HIDTA counties

This figure shows the dynamic coefficients of a regression of the Zillow Home Value Index (ZHVI) in HIDTA counties across time. ZHVI data are from Zillow. HIDTA counties are those identified by the White House Office of National Drug Control Policy by 2012.

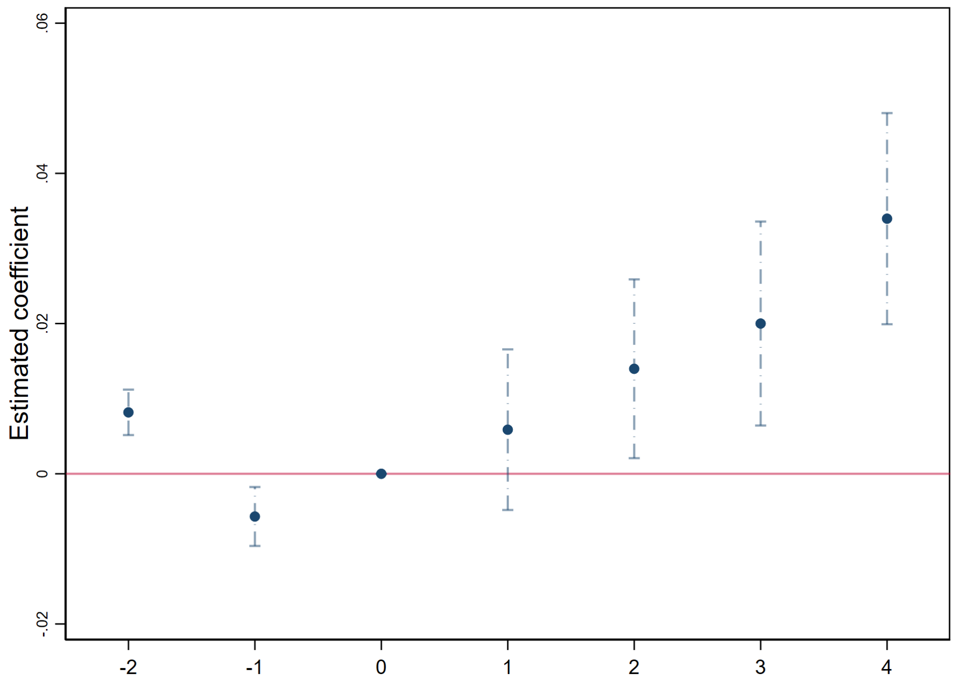


FIGURE A7

Characteristics of Small Banks Exiting After the AML Enforcement Shift

This figure reports estimated coefficients from bank-level exit models relating the probability that a small bank exits in the subsequent year to pre-2012 bank characteristics and their interactions with an indicator for the post-2012 AML enforcement period. Bank characteristics include return on assets (ROA), salary expenses over income, capital ratio, liquidity ratio, and deposits-to-assets ratio. Estimates are reported from complementary log–log and logit specifications with year fixed effects and standard errors clustered at the bank level.

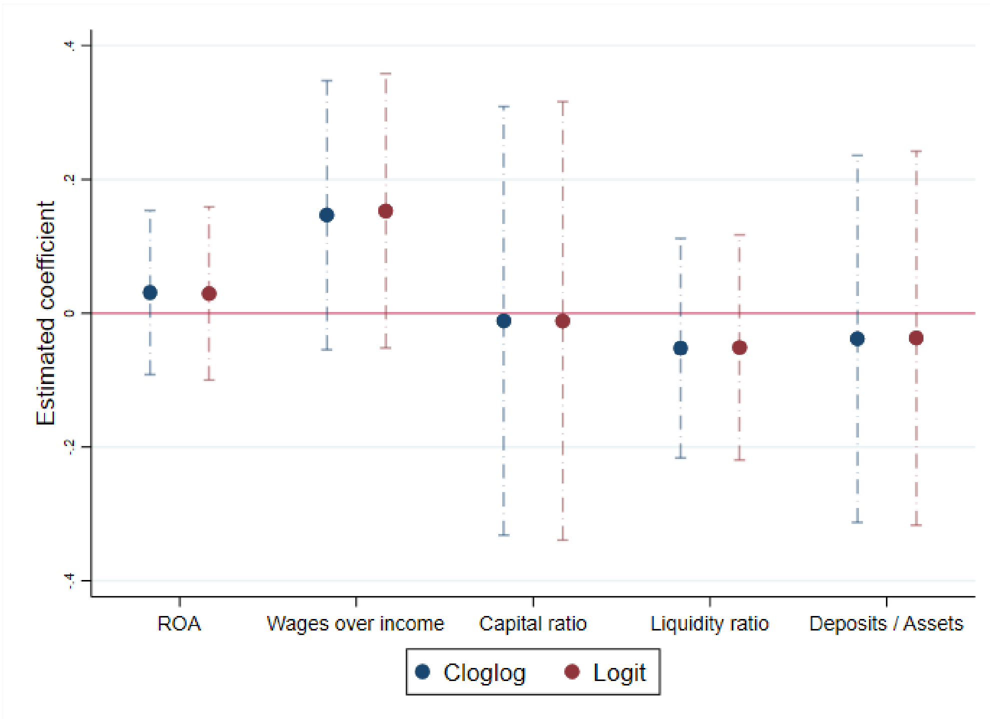


FIGURE A8

Suspicious Activity Reports (SARs) 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).

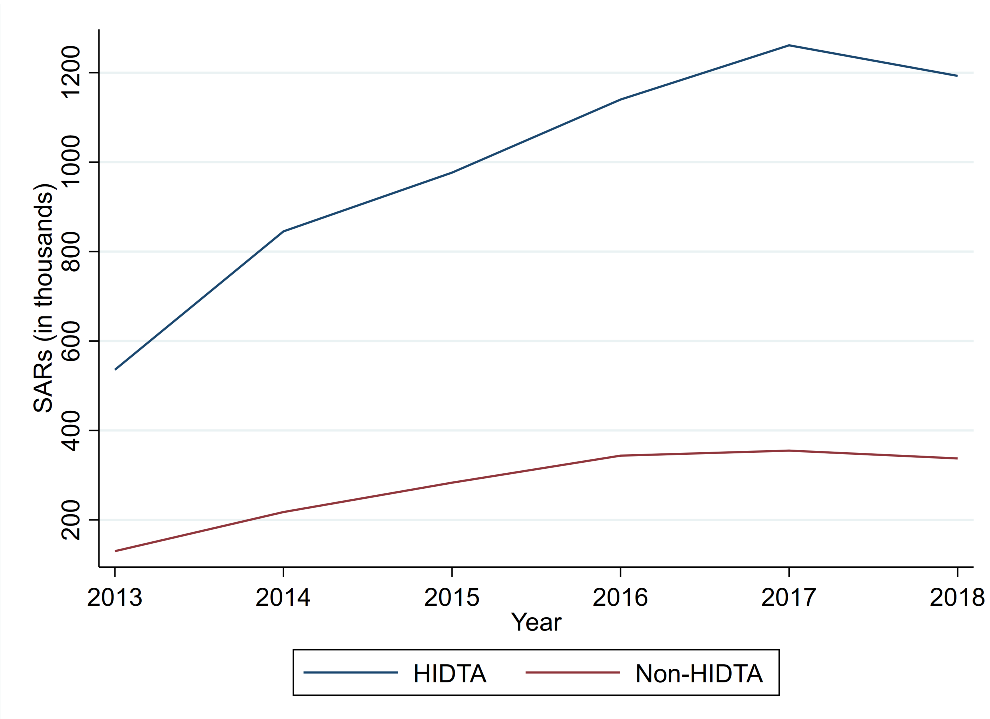


TABLE A2

Bank branches and deposits volume – No Controls

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 money laundering activity. In this specification, we exclude all the additional controls. 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: County level

	Branches 1	Branches 2	Deposits 3	Deposits 4
Post × HIDTA	0.007	0.008	0.041^{**}	0.035^{**}
	(1.50)	(1.60)	(3.01)	(2.78)
N	21,773	21,766	21,773	21,766
Adj. R^2	0.996	0.996	0.996	0.997
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State × Year FE	No	Yes	No	Yes
Controls	No	No	No	No

Panel B: Bank-county level

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × HIDTA	-0.065^{**}	-0.053^{**}		-0.473^{**}	-0.373^{**}	
	(-3.20)	(-2.64)		(-3.02)	(-2.57)	
HIDTA × Large	0.613^{***}			0.776^{***}		
	(18.91)			(4.93)		
Post × Large	0.047^{**}	0.062^{**}		0.620^{***}	0.753^{***}	
	(3.23)	(3.32)		(3.81)	(3.95)	
Post × HIDTA × Large	0.056^{***}	0.071^{**}	0.038^{**}	0.722^{**}	0.689^{**}	0.331^{***}
	(4.43)	(3.14)	(3.29)	(3.69)	(3.50)	(3.88)
N	232,690	231,677	202,784	232,690	231,677	202,784
Adj. R^2	0.586	0.885	0.949	0.683	0.786	0.930
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	No	No	No	No

TABLE A3

Bank branches and deposits volume – 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 money laundering activity. 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 as of 2012. The dependent variables are Branches, the inverse hyperbolic sine transformation of the number of branches operating within a county, and Deposits, the inverse hyperbolic sine transformation of the volume of deposits in bank-branches within a county. The estimations in Columns 1-2 and 4-5 include county-level controls fixed at pre-period 2011 values and interacted with the Post_t indicator and control for spending by the DEA at the county-year level. 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.

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × HIDTA	−0.044**	−0.034*		−0.276**	−0.215*	
	(−2.72)	(−2.44)		(−2.52)	(−2.22)	
HIDTA × Large	0.807***			1.252***		
	(15.60)			(7.53)		
Post × Large	−0.015	−0.012		−0.136	−0.033	
	(−0.73)	(−0.45)		(−0.62)	(−0.15)	
Post × HIDTA × Large	0.117***	0.103**	0.094***	1.236***	1.130***	0.936***
	(5.34)	(3.69)	(4.11)	(4.48)	(4.20)	(4.42)
N	232,571	231,558	202,784	232,571	231,558	202,784
Adj. R^2	0.583	0.885	0.949	0.682	0.784	0.930
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE A4

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 money laundering activity on a subset of matched counties. The sample period is 2010-2016 and the unit of analysis is the bank-county-year level. Panel A compares characteristics of matched treated and control counties. In Panel B, 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 three non-HIDTA counties within the same state (with replacement). The dependent variables are Branches, the inverse hyperbolic sine transformation of the number of branches operating within a county (Columns 1-3), and Deposits, the inverse hyperbolic sine transformation of the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 1-2 and 4-5 include county-level controls fixed at pre-period 2011 values and interacted with the Post_t indicator and control for spending by the DEA at the county-year level. 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: Comparison of characteristics of treated and control counties

	Mean		t-test	
Variable	Treated	Control	t	$p > t$
Median Income	43,587	42,297	1.16	0.245
Population	91,867	78,646	1.09	0.278
College degree (%)	21.776	21.169	0.65	0.513
Number of counties	264	543		

Panel B: Main results using matched sample of counties

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × HIDTA	-0.015	-0.024		-0.146	-0.177	
	(-1.23)	(-1.72)		(-1.36)	(-1.67)	
HIDTA × Large	0.112^{**}			0.211		
	(2.98)			(1.55)		
Post × Large	0.055^{**}	0.069^{**}		0.665^{**}	0.752^{**}	
	(3.10)	(2.96)		(3.60)	(3.70)	
Post × HIDTA × Large	0.031^{**}	0.038	0.023	0.335^{*}	0.358^{*}	0.211^{**}
	(3.29)	(1.90)	(1.58)	(2.23)	(2.13)	(2.52)
N	56,030	55,833	41,735	56,030	55,833	41,735
Adj. R^2	0.633	0.872	0.946	0.706	0.783	0.926
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE A5

Main results using neighboring non-HIDTA counties

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 money laundering activity for the sample that is restricted to non-HIDTA counties that are neighboring HIDTA areas. 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 inverse hyperbolic sine transformation of the number of branches operating within a county (Columns 1-3), and Deposits, the inverse hyperbolic sine transformation of the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 1-2 and 4-5 include county-level controls fixed at pre-period 2011 values and interacted with the $Post_t$ indicator and control for spending by the DEA at the county-year level. 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.

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × HIDTA	-0.043^{**}	-0.040^{**}		-0.312^{**}	-0.250^{**}	
	(-2.72)	(-2.65)		(-2.59)	(-2.47)	
HIDTA × Large	0.603^{***}			0.792^{***}		
	(18.08)			(6.31)		
Post × Large	0.063^{**}	0.075^{**}		0.792^{***}	0.903^{***}	
	(3.29)	(3.22)		(3.77)	(3.88)	
Post × HIDTA × Large	0.038^{***}	0.055^{**}	0.038^{**}	0.543^{**}	0.512^{**}	0.278^{**}
	(4.18)	(2.90)	(3.11)	(3.59)	(3.33)	(3.58)
N	153,254	152,572	129,855	153,254	152,572	129,855
Adj. R^2	0.607	0.892	0.953	0.694	0.792	0.934
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE A6

Bank branches and deposits by bank size – Exclusion of strong housing markets

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 money laundering activity. The sample period is 2010-2016 and the unit of analysis is the bank-county-year level. We exclude from the sample strong housing markets, as defined by those county-years for which the housing index appreciation over the previous five years is in the top decile. 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 inverse hyperbolic sine transformation of the number of branches operating within a county (Columns 1-3), and Deposits, the inverse hyperbolic sine transformation of the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 1-2 and 4-5 estimations include county-level controls fixed at pre-period 2011 values and interacted with the Post_t indicator and control for spending by the DEA at the county-year level. 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.

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × HIDTA	-0.037^{*}	-0.040^{*}		-0.345^{*}	-0.274^{*}	
	(−2.11)	(−2.33)		(−2.34)	(−2.16)	
HIDTA × Large	0.626^{***}			0.812^{***}		
	(19.90)			(5.67)		
Post × Large	0.043^{***}	0.058^{**}		0.620^{***}	0.735^{***}	
	(3.85)	(3.68)		(4.05)	(4.26)	
Post × HIDTA × Large	0.017	0.055^{**}	0.030^{**}	0.540^{**}	0.539^{**}	0.276^{**}
	(1.89)	(2.74)	(2.95)	(3.38)	(3.26)	(3.58)
N	206,092	205,114	178,440	206,092	205,114	178,440
Adj. R^2	0.590	0.891	0.952	0.694	0.799	0.933
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE A7

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 inverse hyperbolic sine transformation of the number of branches operating within a county (Columns 1-3), and Deposits, the inverse hyperbolic sine transformation of the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 1-2 and 4-5 estimations include county-level controls fixed at pre-period 2011 values and interacted with the Post_t indicator and control for spending by the DEA at the county-year level. 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.

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × HIDTA random	0.002	0.003		0.051	0.075	
	(0.39)	(0.48)		(0.90)	(1.37)	
HIDTA random × Large	-0.088^{**}			-0.067		
	(-2.71)			(-0.93)		
Post × Large	0.070^{***}	0.088^{**}		0.916^{***}	1.017^{***}	
	(3.81)	(3.40)		(3.93)	(3.97)	
Post × HIDTA random × Large	-0.006	-0.007	-0.000	-0.113	-0.133	-0.039
	(-0.79)	(-0.62)	(-0.04)	(-1.53)	(-1.42)	(-0.72)
N	232,571	231,558	202,784	232,571	231,558	202,784
Adj. R^2	0.572	0.885	0.949	0.682	0.786	0.930
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE A8

Bank branches and deposits volume by bank size – Log transformation

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 money laundering activity. 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 logarithmic transformation of the number of branches operating within a county, and Deposits, the logarithmic transformation of the volume of deposits in bank-branches within a county. The estimations in Columns 1-2 and 4-5 include county-level controls fixed at pre-period 2011 values and interacted with the $Post_t$ indicator and control for spending by the DEA at the county-year level. 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.

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × HIDTA	-0.037^{**}	-0.036^{**}		-0.371^{**}	-0.305^{**}	
	(−2.71)	(−2.60)		(−2.72)	(−2.48)	
HIDTA × Large	0.527^{***}			0.813^{***}		
	(19.50)			(5.79)		
Post × Large	0.040^{**}	0.048^{**}		0.620^{***}	0.706^{***}	
	(3.35)	(3.31)		(3.85)	(3.96)	
Post × HIDTA × Large	0.033^{***}	0.052^{**}	0.029^{**}	0.638^{**}	0.633^{**}	0.313^{***}
	(4.14)	(3.08)	(3.24)	(3.66)	(3.50)	(3.89)
N	232,571	231,558	202,784	232,571	231,558	202,784
Adj. R^2	0.581	0.891	0.951	0.682	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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE A9

Bank branches and deposits volume by bank size – Alternative transformation

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 money laundering activity. 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 Tornqvist et al (1985) transformation of the number of branches operating within a county (Columns 1-3), and Deposits, the Tornqvist et al (1985) transformation of the volume of deposits in bank-branches within a county (Columns 4-6). The estimations in Columns 1-2 and 4-5 include county-level controls fixed at pre-period 2011 values and interacted with the Post_t indicator and control for spending by the DEA at the county-year level. 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.

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × HIDTA	-0.059^{**}	-0.053^{**}		-0.047^{**}	-0.042^{**}	
	(−2.66)	(−2.52)		(−2.96)	(−2.86)	
HIDTA × Large	0.501^{***}			0.638^{***}		
	(17.25)			(18.13)		
Post × Large	0.067^{**}	0.080^{**}		0.061^{***}	0.056^{***}	
	(3.39)	(3.42)		(4.46)	(4.26)	
Post × HIDTA × Large	0.073^{***}	0.085^{**}	0.048^{**}	0.075^{***}	0.089^{**}	0.050^{**}
	(3.80)	(3.25)	(3.50)	(4.38)	(3.45)	(3.36)
N	232,571	231,558	202,784	232,571	231,558	202,784
Adj. R^2	0.608	0.861	0.943	0.530	0.914	0.951
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE A10

Bank branches and deposits volume – Proximity to DEA and DOJ offices

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 money laundering activity. Panel A uses proximity to Drug Enforcement Agency (DEA), Panel B uses proximity to Department of Justice (DOJ) offices, and Panel C uses an Index of Intensity that uses HIDTA designation and proximity to DEA and DOJ offices. 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 and DOJ are indicator variables set to one for counties within 50 miles of a DEA office and DOJ office, respectively, and Large, an indicator variable set to one for banks in the top 1% in terms of deposits. The dependent variables are Branches, the inverse hyperbolic sine transformation of the number of branches operating within a county, and Deposits, the inverse hyperbolic sine transformation of the volume of deposits in bank-branches within a county. The estimations in Columns 1-2 and 4-5 include county-level controls fixed at pre-period 2011 values and interacted with the Post$_t$ indicator and control for spending by the DEA at the county-year level. 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: Proximity to DEA offices

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × Proximity DEA	-0.037^{**}	-0.033^{*}		-0.405^{**}	-0.395^{**}	
	(-2.52)	(-2.43)		(-2.66)	(-2.72)	
Proximity DEA × Large	0.540^{***}			0.636^{**}		
	(11.48)			(3.48)		
Post × Large	0.057^{**}	0.071^{**}		0.739^{***}	0.831^{***}	
	(3.23)	(3.21)		(3.74)	(3.86)	
Post × Proximity DEA × Large	0.059^{***}	0.075^{**}	0.044^{**}	0.805^{***}	0.806^{**}	0.448^{**}
	(5.61)	(3.36)	(2.72)	(3.78)	(3.60)	(3.69)
N	232,571	231,558	202,784	232,571	231,558	202,784
Adj. R^2	0.578	0.885	0.949	0.683	0.786	0.930
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

Panel B: Proximity to DOJ offices

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × Proximity DOJ	-0.036^{*}	-0.020		-0.243^{*}	-0.174	
	(−2.38)	(−1.72)		(−2.03)	(−1.77)	
Proximity DOJ × Large	0.390^{***}			0.589^{***}		
	(12.61)			(5.12)		
Post × Large	0.045^{**}	0.063^{**}		0.544^{**}	0.650^{***}	
	(3.24)	(3.38)		(3.41)	(3.72)	
Post × Proximity DOJ × Large	0.035^{***}	0.033^{*}	0.016	0.503^{**}	0.480^{**}	0.284^{**}
	(4.07)	(2.19)	(1.72)	(3.63)	(3.23)	(3.47)
N	232,571	231,558	202,784	232,571	231,558	202,784
Adj. R^2	0.576	0.885	0.949	0.683	0.786	0.930
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

Panel C: Intensity Index

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × Index	-0.027^{**}	-0.022^{*}		-0.215^{**}	-0.179^{*}	
	(-2.64)	(-2.40)		(-2.54)	(-2.40)	
Index × Large	0.345^{***}			0.470^{***}		
	(21.06)			(5.77)		
Post × Large	0.036^{**}	0.040^{**}		0.400^{**}	0.485^{**}	
	(2.70)	(2.71)		(3.01)	(3.37)	
Post × Index × Large	0.028^{***}	0.036^{**}	0.021^{**}	0.399^{***}	0.397^{**}	0.226^{***}
	(4.77)	(3.18)	(3.46)	(3.83)	(3.63)	(4.10)
N	232,571	231,558	202,784	232,571	231,558	202,784
Adj. R^2	0.588	0.885	0.949	0.684	0.786	0.930
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE A11

Bank branches and deposits volume – Distance to DEA and DOJ offices

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 money laundering activity. Panel A uses the proximity to Drug Enforcement Agency (DEA) and Panel B uses the proximity to Department of Justice (DOJ) offices. 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 and proximity DOJ are relative measures of closeness to a DEA and DOJ offices, respectively, and Large, an indicator variable set to one for banks in the top 1% in terms of deposits. The dependent variables are Branches, the inverse hyperbolic sine transformation of the number of branches operating within a county, and Deposits, the inverse hyperbolic sine transformation of the volume of deposits in bank-branches within a county. The estimations in Columns 1-2 and 4-5 include county-level controls fixed at pre-period 2011 values and interacted with the Post_t indicator and control for spending by the DEA at the county-year level. 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: Distance to DEA offices

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × Close DEA	-0.070^{**}	-0.070		-0.677^{*}	-0.967	
	(-2.70)	(-1.21)		(-2.41)	(-1.68)	
Close DEA × Large	2.030^{***}			3.043^{***}		
	(9.40)			(4.10)		
Post × Large	-0.238^{***}	-0.233		-3.154^{**}	-2.999^{*}	
	(-16.24)	(-1.60)		(-3.17)	(-2.32)	
Post × Close DEA × Large	0.125^{***}	0.130^{*}	0.211^{*}	1.651^{**}	1.626^{**}	1.599^{**}
	(19.85)	(2.02)	(2.44)	(3.60)	(2.79)	(2.96)
N	231,581	230,581	201,693	231,581	230,581	201,693
Adj. R^2	0.575	0.885	0.949	0.682	0.786	0.930
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

Panel B: Distance to DOJ offices

	Branches 1	Branches 2	Branches 3	Deposits 4	Deposits 5	Deposits 6
Post × Close DOJ	-0.508^{*}	-0.325		-3.251	-2.351	
	(-2.28)	(-1.64)		(-1.88)	(-1.46)	
Close DOJ × Large	9.050^{***}			15.031^{***}		
	(14.96)			(8.30)		
Post × Large	-0.489^{***}	-0.556^{*}		-7.972^{**}	-7.951^{**}	
	(-7.77)	(-2.06)		(-3.10)	(-2.83)	
Post × Close DOJ × Large	0.426^{***}	0.489^{*}	0.477^{**}	6.758^{**}	6.809^{**}	5.529^{***}
	(7.23)	(2.22)	(2.96)	(3.23)	(2.98)	(3.84)
N	231,581	230,581	201,693	231,581	230,581	201,693
Adj. R^2	0.582	0.885	0.949	0.683	0.786	0.930
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 × Year FE	No	Yes	No	No	Yes	No
Bank × Year FE	No	No	Yes	No	No	Yes
County × Year FE	No	No	Yes	No	No	Yes
Bank × County FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	No	Yes	Yes	No

TABLE A12

Distance to Banks HQ

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 money laundering activity. 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, 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 Distance HQ, which measures the distance from the county to the headquarters of the closest large bank. The dependent variables are the inverse hyperbolic sine transformation of the number of establishments (columns 1 and 4), the inverse hyperbolic sine transformation of the aggregate number of employees (columns 2 and 5), and the inverse hyperbolic sine transformation of the aggregate wages (columns 3 and 6) for the overall sample. Columns 1 to 3 focus on micro firms (fewer than 20 employees) and Columns 4 to 6 focus on small firms (20-99 employees). 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.

	< 20 employees			20-99 employees		
	Establishments	Employment	Wages	Establishments	Employment	Wages
	1	2	3	4	5	6
Post × HIDTA	0.018**	−0.038**	−0.019	0.026**	−0.048	−0.067
	(2.82)	(−2.72)	(−1.77)	(2.72)	(−0.76)	(−0.82)
Post × distance HQ	−0.005	−0.052	−0.026	0.010	0.135	0.249
	(−0.27)	(−0.51)	(−0.41)	(0.24)	(0.73)	(0.71)
Post × HIDTA × distance HQ	−0.019	0.016	0.005	−0.016	−0.328	−0.576
	(−1.49)	(0.45)	(0.26)	(−0.54)	(−1.67)	(−1.87)
N	21,875	21,875	21,875	21,778	21,778	21,778
Adj. R^2	0.999	0.927	0.974	0.994	0.863	0.833
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

TABLE A13

Real economic outcomes - Firm and Banking Market Size

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 money laundering activity. 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, 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 Branches, the number of branches within a county as of 2011 divided by 100, as a proxy for banking market size. The dependent variables are the inverse hyperbolic sine transformation of the number of establishments (columns 1 and 4), the inverse hyperbolic sine transformation of the aggregate number of employees (columns 2 and 5), and the inverse hyperbolic sine transformation of the aggregate wages (columns 3 and 6) for the overall sample. Columns 1 to 3 focus on micro firms (fewer than 20 employees) and Columns 4 to 6 focus on small firms (20-99 employees). 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.

	$<$ 20 employees			20-99 employees		
	Establishments	Employment	Wages	Establishments	Employment	Wages
	1	2	3	4	5	6
Post × HIDTA	0.018^{**}	-0.041^{*}	-0.019	0.028^{**}	-0.182^{*}	-0.285^{**}
	(3.48)	(-2.04)	(-1.46)	(3.13)	(-2.01)	(-2.97)
Post × Branches	0.033^{**}	-0.021	-0.011	0.017	-0.231	-0.345^{*}
	(3.14)	(-0.68)	(-0.84)	(1.23)	(-1.53)	(-2.15)
Post × HIDTA × Branches	-0.023^{**}	0.044	0.014	-0.026^{**}	0.219	0.318^{*}
	(-3.31)	(1.61)	(1.01)	(-2.50)	(1.71)	(2.32)
N	21,756	21,756	21,756	21,688	21,688	21,688
Adj. R^2	0.999	0.932	0.978	0.994	0.859	0.825
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

TABLE A14

Removal of Previously Sanctioned Banks

This table reports results on exit of previously sanctioned banks. The dependent variable equals one if a bank exits in a given year. AML C&D, indicates banks that were subject to a cease-and-desist order related to money laundering or AML violations prior to 2012. Post indicator is equal to one for years after the 2012 tightening of AML enforcement. The sample is restricted to small banks in HIDTA counties and standard errors are clustered at the bank level. t-statistics are given in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Removal of Previously Sanctioned Banks

	Exit 1	Exit 2	Exit 3	Exit 4
AML C&D	0.432*	0.444*	0.556***	0.575***
	(1.88)	(1.87)	(4.80)	(4.76)
AML C&D × 2010	0.048	0.053		
	(0.16)	(0.17)		
AML C&D × 2011	0.281	0.296		
	(0.96)	(0.97)		
AML C&D × 2013	0.251	0.264		
	(0.83)	(0.84)		
AML C&D × 2014	0.422	0.443		
	(1.39)	(1.40)		
AML C&D × 2015	0.212	0.224		
	(0.67)	(0.68)		
AML C&D × 2016	0.075	0.082		
	(0.23)	(0.24)		
Post			0.247**	0.254**
			(2.22)	(2.22)
AML C&D × Post			0.125	0.132
			(0.80)	(0.80)
N	23,811	23,811	23,811	23,811
Model	Complementary log–log	Logit	Complementary log–log	Logit
Year FE	Yes	Yes	Yes	Yes