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# Unintended Consequences of Money-Laundering Regulations*

Fabrizio Colella[♯] Keith E. Maskus[♮] Alessandro Peri[§]

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**Abstract**

Tighter money-laundering regulations in offshore financial havens may inadvertently spur incentives to launder money domestically. Our study exploits regulations targeting financially based money laundering in Caribbean jurisdictions to uncover the creation of front companies in the United States. We find that counties exposed via offshore financial links to these jurisdictions experienced an increase in business activities after the tightening of anti-money-laundering regulations. The effect is more pronounced among small firms, in sectors at high risk of money laundering, and in regions with high intensities of drug trafficking. Our work provides the first empirical evidence of the real effects of policy-induced money-laundering leakage.

**Keywords**: Money laundering, money-laundering leakage, business establishments, offshore leaks, regulatory reforms, monopolistic competition.
**JEL Codes**: F30, K40, G28, H00, D58.

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*[W]hen governments take action against certain methods of money laundering [...], criminal activities tend to migrate to other methods.* Financial Action Task Force (2006, p. 1)

# 1 Introduction

In 2011, the United Nations Office on Drugs and Crime estimated that illicit proceeds worth 2.3-5.5% of global GDP are laundered every year, comparable to Germany's total annual output value (UNODC, 2011). The associated policy concerns have spurred an increase in both the number and scope of laws and regulations aimed at combating money laundering through the financial system, especially in suspected money-laundering havens. While these regulations have been shown to raise the cost of cleaning illicit profits in the regions where they are enforced, little is known about their effects on money-laundering practices elsewhere. Assessing the magnitude of money-laundering leakage is a foremost policy priority for understanding the effectiveness of unilateral policies, and the necessity of international coordination between surveillance authorities.

This paper exploits a policy shift in the strictness of regulations targeting financially based money laundering in Caribbean jurisdictions to uncover the creation of front companies in the United States.[1] We document that U.S. counties linked to these jurisdictions via offshore accounts experienced a more pronounced increase in business establishments following the policy, supporting the idea of leakage between money-laundering channels. We find the effect particularly marked in sectors deemed at high risk of money laundering (NAICS Association, 2014), in high-intensity drug trafficking areas (US Office of National Drug Control Policy, 2024), and among small firms (Associated Press, 2024). We also observe stronger impacts of the policy in counties with access to financial networks widely used for international money laundering (DEA, 2019). In addition, we show that exposed counties experienced an increase in the share of cash-based real-estate transactions, in line with the financially unconstrained

[1] Front companies are registered entities that produce legitimate goods and services (Financial Action Task Force and Egmont Group, 2020, p.18), and that are used to facilitate the cleaning of dirty money while concealing the identity of their owners (DOT, 2015, p. 43). When these entities are mainly focused on transferring illegal funds and not on production, they are termed shell companies. Since our data prevents us from clearly distinguishing between the two, we will refer to both types as front companies.

nature of money laundering. Overall, our analysis provides compelling indirect evidence of the real unintended consequences of anti-money-laundering (AML) regulations.

Our research design exploits a tightening in 2009 of AML regulations in Caribbean jurisdictions identified as money-laundering havens (UNODC, 1998). This policy shift was the result of a coordinated international initiative by the Caribbean Financial Action Task Force (CFATF) to combat money laundering in the financial sector. To guide our analysis, we build a theoretical framework that incorporates a money-laundering technology in a monopolistic-competition model similar to that in Parenti et al. (2017), in which criminals can launder illicit money via offshore accounts and by creating front companies. In this framework, tighter AML regulations targeting the financial channel shift money laundering into the creation of front companies. Our key analytical finding is that in the presence of pro-competitive effects of entry, an eventual increase in business establishments represents a lower bound to the unobserved effect on front companies.

We establish our empirical findings in four steps. First, we use information from the International Consortium of Investigative Journalists (2017) (ICIJ) to construct a time-invariant measure of the degree of exposure of each U.S. county to regulatory discipline abroad via financial links, created by 2004, to entities in reforming Caribbean jurisdictions.[2]

Second, we employ a two-way fixed effect event-study design to document the direct effect of county-level exposure to the Caribbean reforms on offshore links (*First Stage*) and on the total number of establishments in each U.S. county (*Reduced Form*). We show that these results are robust to alternative specifications and to the inclusion of a series of time-variant and non-parametric controls. We quantify the impact of offshore financial links on local business creation by estimating a two-stage least squares model and find an elasticity of establishments to the number of links between a U.S. county and offshore jusrisdictions of -0.2.

Third, we ease concerns about the fact that our findings are necessarily indirect evidence of the creation of front companies with additional empirical anal-

[2] The information comes from four databases: the Panama Papers, the Paradise Papers, the Bahamas Leaks, and Offshore Leaks. These were released by the ICIJ, a network of more than 200 investigative journalists and 100 media organizations in over 70 countries. These databases detail links between over 785,000 offshore entities and people or companies around the world.

yses. We show more pronounced leakage effects among sectors at high risk of money laundering. In line with the camouflaging nature of money laundering, we also find an increase in the creation of new and small businesses with relatively lower job-creation rates. These findings align with the hypothesis that these businesses function as fronts for money-laundering activities. We further show stronger impacts in U.S. counties that had access to ex-ante cheaper access to offshore money laundering via potentially illicit international networks through China and Hong Kong. Consistent with our assumption of illicit proceeds being laundered locally, we find more pronounced effects in high-intensity drug trafficking areas. We also document a significant increase in cash-based real-estate transactions in counties that are more exposed to regulatory reforms, in line with the financially unconstrained nature of money-laundering activities.

Fourth, we offer evidence that our findings do not reflect a potentially confounding mechanism associated with firms exploiting tax havens. Here, we find no evidence of money-laundering leakage when looking at the investment decisions of listed U.S. companies, which presumably are less likely to engage in illicit activities.

To the best of our knowledge, this is the first paper documenting, both analytically and empirically, the presence of meaningful substitution effects across alternative money-laundering channels. The policy relevance of our findings cannot be overstated: AML regulations designed to reduce financially based money laundering may force a share of criminal proceeds into other cleaning channels, a process we call *money-laundering leakage*. As a consequence, unilateral policies may be ineffective in reducing money laundering worldwide. Additionally, regulations targeting the financial sectors may have economically meaningful effects on the real economy. Our results, therefore, call for stronger coordination among authorities targeting different money-laundering channels.

Our study contributes to the literature on the identification and indirect measurement of unobserved economic activity. A few papers use data from the Panama Papers data release to analyze how linkages to secret offshore vehicles facilitate tax evasion and tax shifting (Alstadsæter et al., 2018; O'Donovan et al., 2019). Closely related to our work are prior studies of the impacts of anti-money laundering regulations. For example, Geiger and Wuensch (2007), in a comparison of Switzerland, Germany, and Singapore, noted that increased AML enforcement seemed to have little impact on underlying criminal offenses. One potential reason is that owners of illegitimate funds may find alternative channels to clean them, including front companies, in which case AML regulations may not effectively reach the predicate crimes.[3] Finally, there are a few studies of unintended consequences of AML policies. Slutzky et al. (2020) analyzed financial regulations in Colombia aimed at reducing the flow of money from drug trafficking into the financial system. They found that bank deposits declined most in municipalities with high drug trafficking, but this, in turn, reduced lending to small firms. Agca et al. (2021) showed that tighter AML regulations imposed by the United States in 2012 raised bank compliance costs in counties considered high drug-trafficking areas compared to others. However, this resulted in a higher share of large banks in those locations, generating a rise in small business establishments. While these papers are instructive, none addresses our question of how stronger regulatory actions aimed at reducing financially based money laundering may affect the growth of front companies through funds substitution.

## 2 Institutional Background and Conceptual Framework

Money laundering is the process of converting profits from criminal activities into seemingly legitimate incomes that obscure their illicit origin (Reuter and Truman, 2004, p. 1). In this context, illicit proceeds are defined as proceeds, often in cash, derived from one of five major crimes: "drug-trafficking, other "blue-collar" crimes, white-collar crimes, bribery and corruption, and terrorism." (Reuter and Truman, 2004, p. 4.).[4]

The laundering process involves three main stages (Board of Governors of the Federal Reserve System, 2002, p. 7), typically facilitated by professional money-laundering services (DOJ, 2015, Financial Action Task Force, 2018). The

[3]See also Masciandaro (1999) for a related finding in Italy.

[4]Tax evasion is typically excluded from estimates of money-laundering volumes because the underlying production revenues supporting it are generated by legal activities. In Section 6, we analyze proceeds generated by organized illicit drug trade by Transnational Criminal Organizations, a market estimated to be as much as 652 billion dollars annually (Mavrellis, 2017).

*placement* stage consists of converting illicit funds into forms that raise less suspicion and introducing them into the financial system or the retail economy. Next, the *layering* stage aims to dissociate these funds from their origins through complex transactions, often involving multiple intermediaries, to conceal their trail. Lastly, the *integration* stage involves reconstituting these funds as ostensibly legitimate proceeds from financial or commercial activities.

Dirty money may be cleaned in many ways, involving various financial instruments, offshore accounts, professional services, fraudulent invoicing of trade transactions, buying real estate, and acquiring front companies, which are cash-based enterprises selling goods and services. Each method involves varying costs and probabilities of detection, offering a menu of choices to sophisticated criminals seeking to maximize net returns from cleaning money. For example, financial enterprises offer services accepting placements and layering sources at costs ranging up to eight percent of proceeds (Reuter and Truman, 2004, p. 4). Purchasing or investing in domestic front companies involves both upfront and operating costs. Our primary point is that enhanced enforcement aimed at one channel alters these tradeoffs and induces shifts in cleaning flows among techniques as criminals reoptimize their allocations.

This paper focuses on money-laundering leakage between two of these major channels: *(i)* offshore financial accounts, and *(ii)* the creation of front companies in the United States. The reasons are the following. First, while the propensity for different criminal activities to use alternative laundering channels varies, drug trafficking (the major "blue collar" crime) stands out for its use of these two channels (Financial Action Task Force, 2004). Second, the two money-laundering channels that we consider fall under the purview of distinct regulatory bodies: the Caribbean financial authorities and U.S. national and sub-national government agencies, respectively. These authorities presumably impose different costs on the need to hide money laundering. Third, the leakage between the two channels can be estimated using publicly available data on U.S. establishments and financial connections between U.S. and offshore entities. Fourth, we can identify the relationship between the two channels by exploiting a major policy change that, in 2009, increased the cost of laundering money via financial offshore accounts in Caribbean jurisdictions deemed at high risk of money-laundering activity.

While we mainly focus on money-laundering leakage between the channels mentioned above, our work also acknowledges the versatility of criminal organizations in exploiting alternative laundering channels. This is further evidenced by our analysis of real-estate transactions in Section 6.2.

### 2.1 Policy Reform: Stricter AML regulation

Between 2008 and 2015, the Caribbean Financial Action Task Force (CFATF) orchestrated a comprehensive international initiative aimed at curbing financially based money laundering in the Caribbean region.[5] The initiative involved assessing existing regulatory regimes and proposing changes that led to actual legislative reforms, changes in enforcement strategies and oversight of suspicious activity. These policy shifts comprehensively made it harder to launder money via the financial system in those locations.

This institutional process offers a unique opportunity to study the unintended consequences of AML regulations. First, these policy efforts specifically targeted Caribbean jurisdictions long identified as money-laundering havens (UNODC, 1998): Anguilla (ANG), The Bahamas (BAH), Barbados (BRB), Bermuda (BER), British Virgin Islands (BVI), Cayman Islands (CAY), and Saint Kitts and Nevis (KNA). Second, these CFATF members have the largest amount of documented links to off-island agents, and, with the exception of Anguilla, all the selected jurisdictions are connected to U.S. counties via offshore financial links documented by the International Consortium of Investigative Journalists (2017).[6] Third, all CFATF jurisdictions undergo the same mutual evaluation process. This process entails a series of assessments conducted by a group of international examiners—lawyers, accountants, law enforcement professionals, and others—that document the evolution over time of the status of national regulatory compliance with anti-financial-based money-laundering recommendations.

To assess the *timing* of the policy change in terms of compliance with these

[5]See Appendix A for more information about the institutional history of the CFATF.

[6]We focus on Caribbean jurisdictions with more than 5000 worldwide links. Here are the approximate number of links, in thousands: British Virgin Islands (460), The Bahamas (274), Barbados (147), Bermuda (126), Saint Kitts and Nevis (71), the Cayman Islands (50) and Anguilla (7). Aruba (68) is excluded due to unreliable and less informative follow-up reports on compliance with CFATF regulations compared to the included countries.

recommendations, we build an index that proxies for the marginal cost of financially based money laundering. More precisely, the index is a hand-coded yearly measure of the degree of regulatory compliance with 49 AML recommendations, constructed with information retrieved from periodic reports released by the CFATF. The earliest publicly available data for all the selected jurisdictions are from the third round of *Mutual Evaluation Reports* and their associated *Follow-up Reports*. These field-based reports periodically assess the status of national regulatory compliance with each CFATF recommendation on a 4-tier scale: compliant, largely compliant, partially compliant, and non-compliant in accordance with the methodology set out by the central organization, the Financial Action Task Force.[7] We translate these ratings into numerical values by associating jurisdiction-specific yearly scores $S_{j,t}(r)$ from 3 (compliant) to 0 (non-compliant) for each rating.[8] We then sum the 49 scores for each jurisdiction $j$ and year $t$ and divide them by 147, the highest possible sum of scores. Thus, as shown in Eq. 1, the jurisdiction-specific annual Status of Compliance Index ($\text{SCI}_{j,t} \in [0, 100]$) reflects the percentage of all recommendations in compliance.

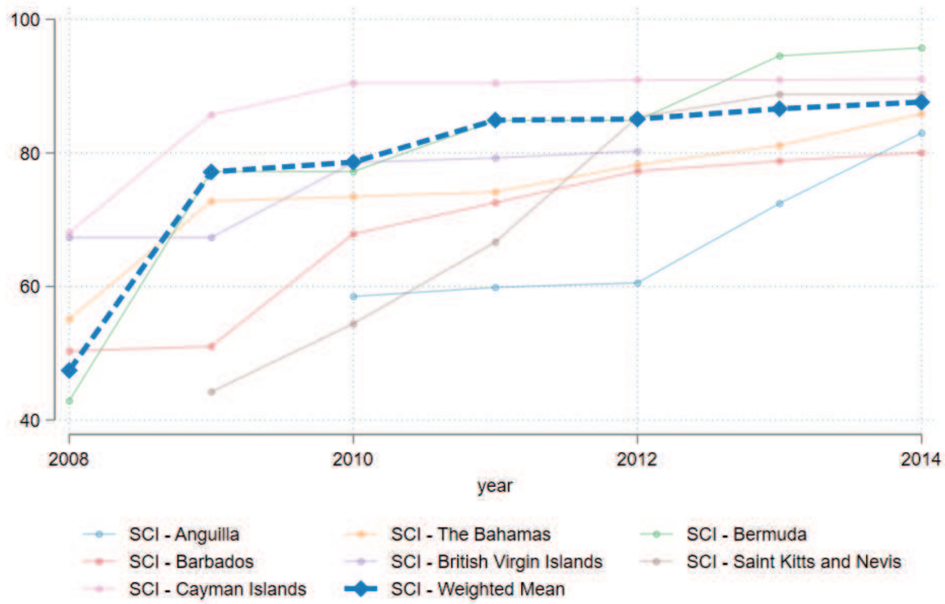
$$\text{SCI}_{j,t} = \frac{100}{147} \sum_{r=1}^{49} S_{j,t}(r) \tag{1}$$

Figure 1 illustrates the evolution over time of this index for the seven jurisdictions in our sample. The jurisdictions entered and completed the mutual evaluations and follow-up processes in different years. However, as illustrated by

[7] *Source:* http://www.fatf-gafi.org/publications/mutualevaluations/documents/fatf-methodology.html.

[8] If jurisdictions were subject to more than one follow-up evaluation per year, we use end-of-year reports. While encoding ratings from the mutual evaluation reports is straightforward, working with follow-up report assessments requires more careful reading. Our numerical ratings are mainly based on the conclusions of each such report while incorporating the details provided in the body of those documents. For example, the Bahamas' 5th follow-up report (Oct 12, 2012) states: "The Bahamas has also achieved full compliance with Recommendations 19 and 30." In this case, we code recommendations 19 and 30 as compliant, and they receive a score of 3 each. Some recommended standards cover multiple areas of legal reforms or enforcement norms, and, in a small number of cases, the reports assessed some sub-components differently, saying either partially compliant or largely compliant. In those instances, we assigned scores in increments of 0.25 to the specific recommendation, which could be ranked as 2.5, for example. *Source*: https://www.cfatf-gafic.org/documents/cfatf-follow-up-reports/the-bahamas/878-the-bahamas-5th-follow-up-report/file. See Appendix A for more information on the institutional framework and for a detailed list of the CFATF recommendations.

Figure 1: The Status of Compliance Index




*Notes:* Level of the Status of Compliance Indexes for each of the seven jurisdictions in the Caribbean (fainting solid lines) and an average of all the indexes weighted by the number of links between each jurisdiction and the United States in 2004. *Source:* Constructed by authors from information in reports by the Caribbean Financial Action Task Force (CFATF).

the dashed line in Figure 1, when we consider the importance of each jurisdiction in offshore activities, it becomes apparent that the bulk of the policy changes happened in 2009.[9] This year witnessed the robust enforcement of new AML regulations in Bermuda and the Cayman Islands, which together account for 94% of the financial offshore links between the U.S. and all Caribbean jurisdictions. Therefore, for the purposes of our analysis, we identify 2009 as the pivotal year for the policy shift.

[9]Most jurisdictions started the process in 2008. The only exceptions are Saint Kitts and Nevis and Anguilla, which started in 2009 and 2010, respectively. As noted in Section 3.2, this is not a concern, since offshore financial links to these jurisdictions account only for a small share (less than 0.05%) of the total number of links (Table D5).

### 2.2 Money-Laundering Leakage: A Conceptual Framework

Tighter money-laundering regulations in offshore financial havens (Section 2.1) are likely to incentivize domestic laundering through alternative channels, such as front companies. This section outlines a formal model of this money-laundering leakage. A comprehensive description and characterization of this model are in Appendix B.

Suppose a criminal enterprise has access to two money-laundering channels to clean its illicit profits, $E$: financially based money laundering or creation of front companies.[10] Assume the former technology is linear, such that for every dollar channeled in the financial system, the criminal enterprise obtains $0 < \alpha < 1$ cleaned dollars in a legitimate offshore account, say 75¢. Alternatively, the criminal enterprise can use $z \leq E$ dirty dollars to cover the investment or acquisition cost $f$ and operating cost $c\bar{q}$ of each of $M = \frac{z}{f+c\bar{q}}$ front companies in the official sector. In essence, the criminal enterprise pays these costs to workers but earns the resulting, and equal, market revenues. Thus, there are zero profits, but the returned revenues consist of cleaned funds.

These acquisitions may attract scrutiny by enforcement authorities. In particular, we assume that the likelihood of being detected increases with the relative weight of front companies, $\frac{M}{N}$, in the total number of businesses $N = M + n$, where $n$ is the mass of firms created in the legitimate sector).[11] Accordingly, the marginal cost of acquiring front companies increases with the volume of investment, $z$. The acquisition of front companies returns the revenues of the firms that are not confiscated, $V(z) = \left(1 - \frac{M}{N}\right) M\bar{p}\bar{q}$, where $\bar{p}$ is the price of the goods sold in the official sector.

Thus, the criminal enterprise maximizes the output of clean money by al-

[10] As mentioned above, there are multiple channels of money laundering. Our focus on these two channels rests on two justifications. First, drug trafficking, a primary source of illegal funds, stands out for its use of both financial instruments and front companies (Financial Action Task Force, 2004). Second, this approach is appropriate as long as other streams of illicit profits enter linearly in the portfolio choice, rendering the sub-production structure in the two inputs strongly separable from the rest. In this case, the substitution elasticity between them is invariant to the use of other inputs. We retain this assumption in the model.

[11] This assumption can be violated in case dirty money fully corrupts legal and enforcement agencies. This scenario is of limited relevance since we focus our empirical analysis on the United States.

locating the illicit funds, $E$, across the two channels, which we assume to be substitutes (Financial Action Task Force, 2006):

$$\max_{0\leq z\leq E} \underbrace{\alpha(\varphi)[E-z]}_{\text{Financially based}} + \underbrace{V(z)}_{\text{Front Companies}} \tag{2}$$

$$V(z) = \left(1-\frac{M}{N}\right)M\bar{p}\bar{q}, \quad M = \frac{z}{f+\bar{q}c} \tag{3}$$

The parameter $\alpha$ determines the unobserved marginal cost of laundering money in the financial sector, $1-\alpha$, and it is directly affected by the observed strictness of AML regulations, $\varphi$: $\alpha'(\varphi) < 0$. Intuitively, the tighter AML regulations focused on financially based activities, as discussed above, increase the marginal cost of laundering money via offshore accounts, making relatively more attractive the creation of front companies in the United States.

# 3 Data

This section describes our data and then explains how we construct our measure of exposure of U.S. counties to the aforementioned regulatory changes in the CFATF jurisdictions.

## 3.1 Data and Descriptive Statistics

Our primary data are compiled from several sources. We use the four data releases from the International Consortium of Investigative Journalists (2017) to identify financial linkages between U.S. counties and Caribbean locations. The ICIJ releases detailed links between thousands of U.S. entities and offshore vehicles, permitting aggregation to the U.S. county level. We use this information to construct: *(i)* the county-year number of offshore financial links connecting U.S. counties to the Caribbean jurisdictions; and *(ii)* the time-invariant exposure of U.S. counties to the Caribbean policy reforms detailed in Section 2.1.

We collect information on the sector-county-year level of business establishments over 2004-2015 from the United States Bureau of Labor Statistics (2015) (BLS). We collapse this information at the county-year level to construct our main dependent variable: the natural logarithm of the annual establishment counts for a given year by county. We also use this information to construct the share of establishments in sectors more vulnerable to money-laundering activities, according to the U.S. Bank Secrecy Act's Anti-Money-Laundering board's business risk criteria (NAICS Association, 2014).

Information pertaining to establishment size, entry, and job creation is sourced from the Business Dynamics Statistics Datasets, United States Census Bureau (2016a). We use this information to explore business characteristics indicative of money laundering through front companies.

Next, we follow the US Office of National Drug Control Policy (2024)'s classification to flag, with a dummy variable, counties in high-intensity drug-trafficking areas (HIDTAs). In the US Office of National Drug Control Policy system, there are 33 regional headquarters covering all U.S. states, tribal areas, and territories. In this context, more than 600 U.S. counties (excluding territories) are designated as HIDTAs. We use this information to explore effects in areas with potentially larger amounts of money to be laundered.

We gather real-estate transaction data in the United States from ATTOM (2023), an online platform with more than 70 billion transaction-level entries. We aggregate transaction-level data at the county level to construct an annual measure of the share of cash-based real-estate transactions. A transaction is classified as cash-based if it lacks a corresponding mortgage report. We use this information to explore alternative money-laundering leakage channels.

Last, we collect data for a wide range of economic and demographic variables at the county level for use as regression controls. In particular, we source data at a yearly frequency from several sources, including BLS, the Bureau of Economic Analysis, the Census Bureau's Population Division database, and the Census Bureau's Small Area Income and Poverty Estimates (SAIPE). Appendix Table C4 contains the details. As recommended by the Census Bureau,[12] we adjust nominal variables for inflation by using the All Items CPI-U-R (CPI Research series). Real variables are expressed in 2010 U.S. dollars.

Panel A of Table 1 offers descriptive statistics for our primary variables and controls. On average, there are about 2500 establishments in a county over our

[12] *Source*: https://www.psc.isr.umich.edu/dis/acs/handouts/Compass_Appendix.pdf.

sample period, with no counties with less than five establishments. This panel also indicates considerable variations in size and economic conditions across U.S. counties. To account for this heterogeneity, we control for population, income, and unemployment rates in our analysis both in a linear and in a non-parametric fashion.

Table 1: Descriptive Statistics

| **Variable** | **N** (1) | **Mean** (2) | **Std. Dev.** (3) | **Min.** (4) | **Max.** (5) |
|---|---|---|---|---|---|
| *Panel (a): Main Variables* | | | | | |
| Number of Establishments | 36960 | 2556.64 | 10327.32 | 5 | 441987.5 |
| Population in Thousands | 36960 | 98.65 | 315.77 | .06 | 10085.42 |
| Real Personal Income | 36960 | 4094.63 | 14867.97 | 2.21 | 513740.2 |
| Real Median Household Income | 36960 | 43.58 | 10.97 | 18.37 | 119.08 |
| Unemployment Rate | 36960 | 6.76 | 2.89 | 0 | 28.9 |
| *Panel (b): Links and Exposure* | | | | | |
| Offshore Financial Links | 36960 | 11.95 | 123.44 | 0 | 5167 |
| Offshore Financial Links to Bermuda | 36960 | 10.12 | 119.49 | 0 | 4402 |
| Exposure Variable | 36960 | .62 | 1.2 | 0 | 8.5 |
| *Panel (c): Outcomes in 2008* | | | | | |
| Logarithm of Links + 1 ($\times$100) | 3080 | 65.06 | 121.13 | 0 | 849.17 |
| Logarithm of Establishments ($\times$100) | 3080 | 648.87 | 147.73 | 207.94 | 1291.86 |

*Notes:* Descriptive statistics for the main variables of interest used in the analysis. *Data Sources:* ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period:* 2005-2015.

### 3.2 Links and Exposure to Anti-Money-Laundering Regulations

We use data compiled by the International Consortium of Investigative Journalists (2017) (ICIJ) to isolate the offshore financial *links* connecting U.S. counties to Caribbean jurisdictions.

The ICIJ database details financial connections between thousands of U.S. stakeholders and various entities such as shell companies, trusts, and offshore vehicles in the Caribbean jurisdictions, some of which have been shown to involve the transfer of illicit funds.[13] The database categorizes links between three distinct groups of agents. The first group includes all the *entities*, i.e., the firms, corporations, and trusts with an associated offshore jurisdiction, which determines the laws and regulations to which they are subject. The second group refers to *officers*. These are owners, beneficiaries, and shareholders of the entities. The third group encompasses the *intermediaries*, who are individuals or institutions that assist in setting up the entities.

We select from the database all the entities in jurisdictions subject to the CFATF regulations that either have a registered address in the United States or have an associated officer with a U.S. mailing address. As suggested in the CFATF reports, these entities may include financial establishments that provide money-laundering services to U.S. individuals.

We define a link as a connection between a registered address in a U.S. county and an entity in the Caribbean jurisdictions. Using the information on financial links' start and end dates, we then create our link variable $L_{cjt}$, which reports the number of active links, connecting county $c$ to jurisdiction $j$ in a particular year, $t$.[14]

We then construct a measure of U.S. county exposure to AML regulations. As illustrated in Eq. 4, the exposure measure is defined as an increasing function $f(\cdot)$ of the cumulative sum of the county ($c$) jurisdiction ($j$) links created through 2004 ($t \leq 2004$).

$$\mathrm{Exp}_c = f\left(\sum_{t\leq 2004}\sum_{j\in\mathbf{J}} L_{cjt}\right) \tag{4}$$

In our baseline analysis we adopt the following measure $\mathrm{Exp}_c = log(1 + \sum_{t\leq 2004}\sum_{j\in\mathbf{J}} L_{cjt})$. We also show that our results are robust to different choices of the function $f(\cdot)$. If a county has no links created through 2004, the exposure measure is zero.

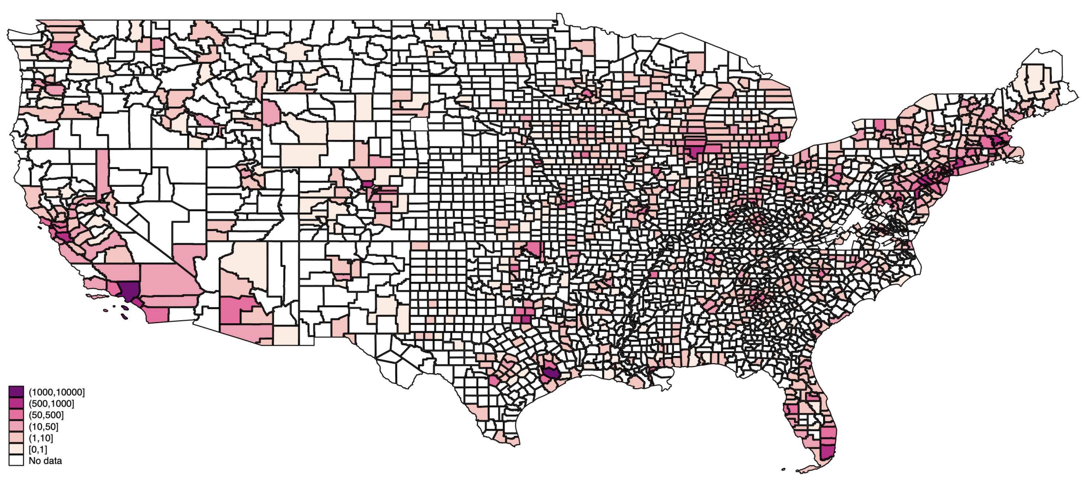
[13]For example, The Panama Papers refers to the release by Panamanian law firm Mossack Fonseca of 11.5 million documents detailing how shell companies have been used to transfer funds across borders, much of it for illicit purposes.

[14]Please refer to Appendix D for a detailed description of the procedure we followed to identify links

As shown in Panel B of Table 1, there are, on average, 12 offshore financial links connecting a U.S. county to Caribbean jurisdictions. The majority of links are with Bermuda (85%), suggesting a considerable concentration in the distribution of links. The next largest jurisdictions in terms of links are the British Virgin Islands and the Cayman Islands. Our exposure measure has an average of 0.62 and a considerable spatial variation, as indicated by a standard deviation of 1.2. Panel C of Table 1 reports descriptive statistics for the two main outcome variables used in our analysis for our reference year. We will use these statistics in our quantification exercise (Section 4.3).

Figure 2 highlights significant geographical variation, with a high density of links in metropolitan areas. The maximum number of links is recorded in Manhattan, New York.

Figure 2: County Exposure to AML regulations




*Notes:* Time-invariant cumulative sum of county-jurisdiction links created through 2004, $\sum_{t\leq 2004}\sum_{j\in \mathbf{J}} L_{cjt}$. *Data Source*: ICIJ.

## 4 Effects of Anti-money-laundering Regulations

In this section, we estimate the money-laundering leakage in the United States resulting from the Caribbean policy reforms. We employ a standard event-study design to show that regulatory changes in the treated Caribbean jurisdictions significantly reduced the volume of links with U.S. counties. We also study the evolution of business creation in the United States for different levels of county-specific exposure to the reforms. We then quantify the positive effect of the destruction of an offshore link on county business establishments by estimating a two-stage least squares (2SLS) model.

We start by analyzing two main county-level outcomes: the number of links between the United States and the Caribbean jurisdictions and the number of business establishments in the United States each year in relation to our measure of exposure. Let $Y_{ct}$ represent an outcome associated with the county $c$ at year $t$. Then, we fit a model of the form:

$$Y_{ct} = \gamma_c + \lambda_{st} + \delta X_{ct} + \sum_{k=2004}^{2015} \beta_k \text{Exp}_c \times \underline{d}_{t=k} + \varepsilon_{ct} \tag{5}$$

Here, $\underline{d}_{t=k}$ is the year-$k$ dummy variable, and $\text{Exp}_c$ is our time-invariant county-specific exposure variable, which is constructed with information on links up to 2004. The model includes county fixed effects ($\gamma_c$), state-year fixed effects ($\lambda_{st}$), and time-variant county-year controls, such as population and average income ($X_{ct}$). This last component also incorporates quantiles of county-specific pre-2004 characteristics that are interacted with time dummies to control for potential confounding factors in the evolution of the outcomes variables across different levels of the pre-period characteristics.

We estimate the model for the period 2005-2015 and take as the reference year 2008, which is the year before the enforcement of the regulations in most of the Caribbean jurisdictions.[15] The coefficient $\beta_k$ measures the impact of our exposure measure on the changes in outcome $Y_{ct}$ at each year.[16]

### 4.1 First Stage: How informative is our exposure measure?

Panel (a) of Figure 3 presents estimates of the $\beta_k$ coefficient in Eq. 5, where the dependent variable is the logarithm of the yearly number of existing links between U.S. counties and the offshore jurisdictions in the sample (multiplied by

[15] Section 2.1 explains why we pick 2009 as the pivotal year for the policy shift.

[16] We acknowledge that excluding alternative money-laundering channels from the analysis, as discussed in footnote 10 above, could potentially influence the outcome variables through general-equilibrium effects. Thus, our estimates in this section might be biased downward.

100).[17]

As expected, after controlling for state-year and county fixed effects and for a battery of time-variant county-specific controls, a higher exposure value has no effect on the number of links with the offshore jurisdictions before the policy change. We can, at most, observe a small and insignificant increasing trend, which could be due to a residual correlation between the exposure measure and the evolution of the links that our controls do not take into account. This trend inverts dramatically once the regulations from the Caribbean Financial Action Task Force (CFATF) kick in. From 2009 onwards, the coefficient becomes increasingly negative and significant. This suggests there was a sharp decrease in the number of links between the more exposed U.S. counties and the offshore jurisdictions, signaling that regulatory compliance with the CFATF policies generated a negative impact on financially based money laundering. Further, this effect grew over time. This may be due to the fact that agents need time to terminate their business abroad, as well as to time lags in increasing enforcement and achieving greater policy salience. The average treatment effect in the two years after the policy change is -2.51, meaning that a unitary change in the exposure variable implies a 2.51 percent reduction in the number of links. Therefore, a one-standard-deviation increase in exposure generates a reduction of the number of links of 3 percent.

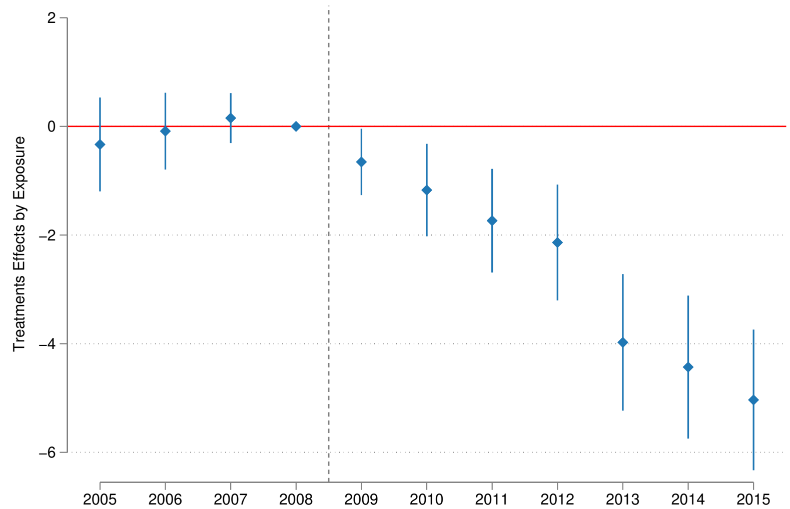
Table E7 in the Appendix shows how the inclusion of controls impacts the estimated coefficients. The positive pre-trend becomes more marked but is almost never significant when non-parametric controls are excluded from the regression. However, the main result remains stable across all specifications, including in a more demanding case where we add non-parametric demographic controls.

## 4.2 Reduced Form: Effect on Business Establishments

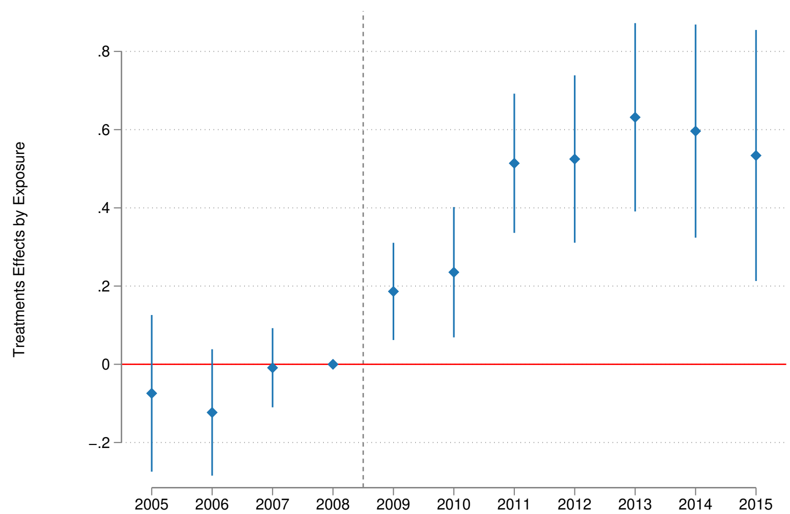
Next, we turn to evaluating the effect of the policy change on business activity. We estimate the model in Eq. (5) using as a dependent variable the logarithm of

[17]Given the significant number of county-year pairs with no links, our dependent variable is the logarithm of one plus the number of links between a county and any jurisdiction in a given year. We multiply this number by 100 to achieve coefficients that are easier to distinguish in Figure 3 and associated Appendix tables.

Figure 3: Event Study




(a) First stage




(b) Reduced Form

*Notes:* OLS estimates of the interactions between county exposure measure ($\mathrm{Exp}_c$) and year dummies ($\underline{d}_{t=k}$) for two dependent variables: (a) logarithm of (one plus) the number of county offshore links; and (b) logarithm of the number of establishments. Both variables are multiplied by 100 to ease the reading of the Figure. Reference year: 2008. Diamonds represent point estimates, and vertical bars show 95% confidence intervals. All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Standard errors are clustered at the county level. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

the yearly number of business establishments in each county, again multiplied by 100. Estimates for the $\beta_k$ coefficient for our preferred specification are reported in Panel (b) of Figure 3, while Table E8 in the Appendix shows how estimates react to the inclusion of different controls.

As in the previous analysis, there is no significant impact of the time-interacted exposure measure on business activity before 2008. However, the coefficients turn positive and significant just after the policy change, ranging from 0.25 in the first two years to 0.6 in the following years. On average, a unitary change in the exposure measure translates into a 0.5 percent increase in the number of establishments in one county. This means that a one-standard-deviation increase in the exposure measure triggers a 0.6 percent increase in business activity. Relating this outcome to our model suggests that this estimated elasticity of establishment growth serves as a lower bound for the increase in front companies. In Section 5, we provide extensive evidence that much of this growth comes in establishments with characteristics that are consistent with recognized descriptions of front companies.

### 4.3 Quantification

To further investigate the relationship between a link destroyed and the creation of business activity, and to combine the two results presented in Figure 3, we estimate a two-stage least squares model. Specifically, in the first stage, we instrument the number of links with the interaction between the exposure measure and a dummy for post-policy change, $\underline{d}_{post}$.[18] This instrumented effect is then used in a second-stage estimation of the effects of links destroyed on county business establishments. In practice, we fit the following equations:

$$Z_{ct} = \gamma_{2,c} + \lambda_{2,st} + \delta_2 X_{ct} + \beta_2 \mathrm{Exp_c} \times \underline{d}_{post} + \varepsilon_{2,cst} \tag{6}$$

$$Y_{ct} = \gamma_{3,c} + \lambda_{3,st} + \delta_3 X_{ct} + \beta_3 \widehat{Z_{ct}} + \varepsilon_{3,cst} \tag{7}$$

Where $Z_{ct}$ is the yearly number of existing links between U.S. counties and

[18] The values 0 and 1 of $\underline{d}_{post}$ proxy empirically for the lower ($\varphi_L$) and higher ($\varphi_H$) stringency levels of AML regulation in the model, with $\varphi_L < \varphi_H$.

offshore jurisdictions, and $Y_{ct}$ is the logarithm of the yearly number of business establishments in each county, both multiplied by 100. Eq. 6 is, therefore, the difference-in-difference version of the model estimated in Section 4.1.

The coefficient of interest is $\beta_3$, which represents the percentage change in the number of establishments generated by a one-percent increase in the number of links. This is the elasticity of total business activity with respect to links with offshore jurisdictions. This model is based on the assumption that the destruction of links is the substitution channel through which the different values of exposure translate into the creation of business establishments after the policy change. Column (3) of Table 2 presents the estimated OLS coefficient, while the estimated second-stage results are presented in column (4). For completeness, we also include the first-stage and the second-stage post-reform coefficients in Table 2, which were discussed in the two previous subsections.

Table 2: Quantification

| **OLS Estimation** | | | | |
|---|---|---|---|---|
| Model: | First Stage | Red. Form | OLS | 2SLS |
| Dependent Variable: | *Log links* | *Log estab.* | *Log estab.* | *Log estab.* |
| | (1) | (2) | (3) | (4) |
| $\text{Exp}_c \times \underline{d}_{post}$ | -2.511*** | 0.497*** | | |
| | (0.519) | (0.120) | | |
| Log number of links$_c$ | | | 0.001 | -0.198*** |
| | | | (0.002) | (0.064) |
| Baseline Controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | ✓ | ✓ | ✓ | ✓ |
| Observations | 33,869 | 33,869 | 33,869 | 33,869 |

*Notes:* Columns 1-2: OLS estimates of the interactions between county exposure measure ($\text{Exp}_c$) and a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$). Column 3: OLS estimates of logarithm of (one plus) the number of county offshore links. Column 4: 2SLS estimates of logarithm of (one plus) the number of county offshore links instrumented using the interactions between county exposure measure ($\text{Exp}_c$) and a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$). The dependent variables are the logarithm of (one plus) the number of county offshore links in column 1 and the logarithm of the number of establishments in columns 2-4. All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Standard errors clustered at the county level. *** significant at 1%, **significant at 5%, * significant at 10%. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

As shown in column (3), once we include the fixed effects and the linear and non-parametric controls in the specification, there is no residual correlation between the exposure measure and the number of establishments in a county. However, the two-stage least squares coefficient in column (4) is negative and significant, signaling an elasticity of establishments to the number of links of about -0.2. Therefore, a 1-percent decrease in the number of links generated by the policy change is associated with a 0.2 percent rise in the total number of business establishments in the average county.

To provide a more concrete estimate of the magnitude of money-laundering leakage, we compute the effect of the policy reforms for a hypothetical county with the average exposure (0.62) and the average number of establishments (2,557) as of 2008. The first-stage estimate indicates that 1.56 percent $(0.62 \cdot 0.0251)$ of the links are destroyed as a result of the policy reforms in the average county. The second-stage coefficient implies that for every one percent of links destroyed, the number of establishments increases by 5.06 units $(2,557 \cdot 0.00198)$. Multiplying these two figures, we obtain that the number of active establishments in the average county increased by 8 units as a result of the Caribbean policy reforms.

This estimate allows us to make a back-of-the-envelope calculation about the amount of money-laundering leakage resulting from the CFATF AML regulations. Assume that the average value of one establishment is $295,000 in 2023 dollars.[19] Then our estimates imply an increase in money laundering via front companies of approximately $2.4 million in 2023 dollars in the average county. To speculate further, this county-average leakage amounts to approximately $7 billion in 2023 dollars across the United States over the period 2008-2015, or approximately 5 percent of the average annual U.S. market size for illicit drugs in 2023 dollars (Burns et al., 2014).

[19] This was the median sale price of an establishment in 2017 in the United States. *Source:* https://www.bizbuysell.com/insight-report/. The CPI was 103.42 in 2017 and 128.56 in 2023. *Source:* https://fred.stlouisfed.org/series/CPALTT01USA661S.

## 5 Tracing the Footprints of Front Companies

A potential concern about our research design is that our empirical findings are necessarily indirect evidence of creation of front companies. We address this concern both theoretically and empirically.

First, we incorporate our money-laundering technology (Section 2.2) in the monopolistic-competition model by Parenti et al. (2017) in Appendix B. There, we derive under very weak assumptions on the functional form of the consumer preferences the following proposition:[20]

**Proposition 1.** *Under pro-competitive effects of entry, tighter AML regulations cause the unobservable relative increase in front companies to be at least as large as the relative increase in observable business activity in the new equilibrium.*

Consequently, the estimated effect on legitimate businesses in Section 4 is in equilibrium a conservative estimate (lower bound) of the actual, albeit unobserved, impact on front companies.

We then address this concern empirically. In the next sections, we look at characteristics that align with the hypothesis of these businesses functioning as front companies for money-laundering activities. Section 5.1 documents a stronger effect in sectors deemed by official authorities at high risk of money laundering. Section 5.2 then shows a relatively more pronounced increase in the share of small firms in exposed counties, reflecting the camouflaging tactics inherent in money-laundering practices. Here, we also observe a relatively lower job creation in small firms upon entry, consistent with the shell nature of these companies. Last, we demonstrate in Section 5.3 that counties with ex-ante cheaper access to offshore money-laundering services experienced a more significant re-channeling of funds into front companies after the policy change.

### 5.1 Effect in Sectors at High Risk of Money Laundering

Authorities have identified 50 specific sectors, that are more vulnerable to money-laundering activities, according to the U.S. Bank Secrecy Act's Anti-Money-

[20]We are grateful to an anonymous referee for clarifying the crucial role of the pro-competitive effect of entry in driving this finding and for recognizing its generality under a wide range of consumer preferences.

Laundering board's business risk criteria (NAICS Association, 2014). This categorization includes cash-intensive businesses (32 six-digit NAICS sectors), high-risk businesses (11 sectors), money-services businesses (4 sectors), and non-bank financial institutions (3 sectors). Examples of the first group are convenience retailers, florists, restaurants, and parking garages. Some high-risk sectors are used-car dealers, casinos, and automotive repair. Money-service businesses include consumer lending, credit intermediation, and related services. Finally, non-bank financial institutions are exemplified by jewelry wholesalers and retailers and international non-depository credit intermediation services.

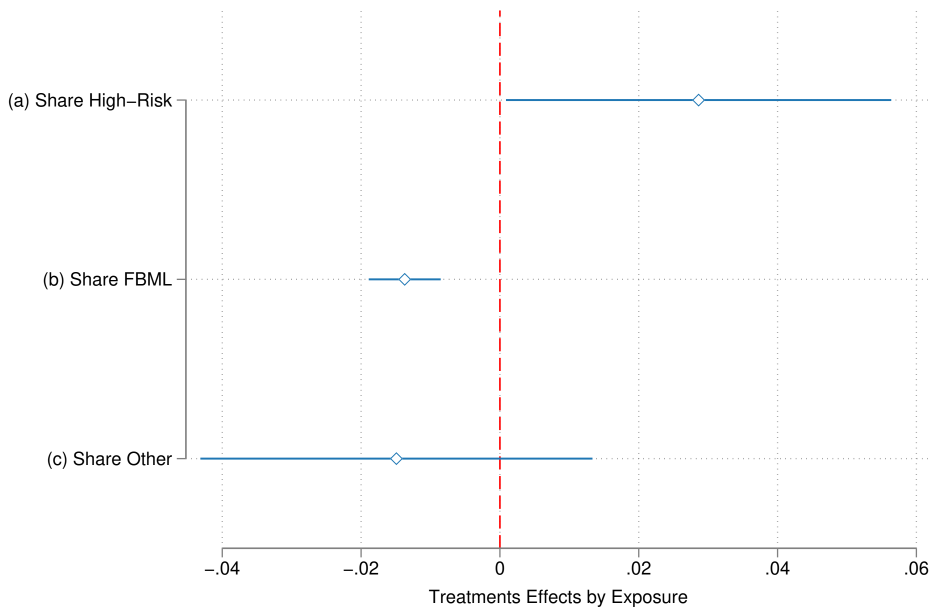
Again, these industries are flagged as those most vulnerable to money laundering. Accordingly, if our analysis truly captures a domestic shift in money laundering in response to offshore financial regulations, we should expect a stronger creation of front companies in these sectors. We test this hypothesis by computing the shares of business establishments for three groups of firms: firms in high-risk and cash-intensive sectors, those in the two financial aggregates, which we label FBML here, and all other sectors. We then estimate the model in Eq. (6) for each of the three outcomes and display the results in Figure 4.

Estimates of the $\beta_2$ coefficient reveal a strongly positive response of establishments in sectors at high risk of money laundering and cash-intensive businesses (*High-risk*). Conversely, the effect on sectors at lower risk of money laundering (*Other*) is negative (though insignificant), easing concerns that our previous findings in Section 4 were picking up some confounding trends. Interestingly, Money Services Businesses and Non-Bank Financial Institutions (*FBML*) respond negatively to the shock. This is consistent with the idea that stronger AML regulations in offshore jurisdictions make it harder to launder money via the financial system. These results lend further credence to the claim that we are uncovering evidence of the formation of front companies.

### 5.2 Effect on Newly Established Businesses

This section examines whether newly established businesses in exposed counties exhibit characteristics that align with the hypothesis of their functioning as front companies for money-laundering activities. To address this question, we

Figure 4: Reduced Form Results by Sector




*Notes:* OLS estimates of the interactions between county exposure measure ($\text{Exp}_c$) and a dummy taking value 1 for observations post-2008 ($\underline{d}_{year>2008}$) for two dependent variables: (a) share of high-risk and cash-intensive establishments; (b) share of money services businesses and non-bank financial institutions (FBML); (c) share of establishments not in the previous categories (Other). Reference year: 2008. Diamonds represent point estimates, and vertical bars show 95% confidence intervals. All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Standard Errors are clustered at the county level. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

exploit information on newly created establishments and establishment size at the county level from the Business Dynamics Statistics databases (BDS), United States Census Bureau (2016a).

In UNODC (1998), the International Money Laundering Information Network states on page 13: “While in principle there is no limit to the fronts through which and forms in which money can be laundered, in practice, launderers try to make their choices reflect as closely as possible the profile of normal business in the area and jurisdiction in which they are operating.” To reduce the probability of detection, money launderers are likely to invest in small businesses, which constitute the vast majority of county businesses (more than 70% of establishments in our sample have up to 19 employees). Accordingly, we expect a stronger response in terms of entry among small businesses. Additionally, we expect these businesses to reveal traits of shell companies with low employment rates, primarily serving as conduits for laundering illicit profits.

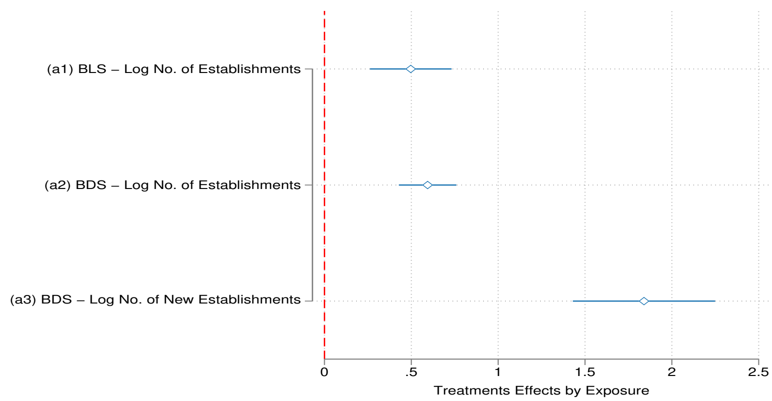
We test these hypotheses using the difference-in-differences model outlined in Eq. (6). The coefficient of interest remains the one associated with the interaction term, $\text{Exp}_c \times \underline{d}_{t=post}$.

We begin by addressing potential concerns that our findings may be artifacts of transitioning from the BLS to BDS database. Figure 5a confirms the similarity between the estimates of $\beta_2$ derived by regressing the natural logarithm of establishments imputed by BLS (first row) and BDS (second row).

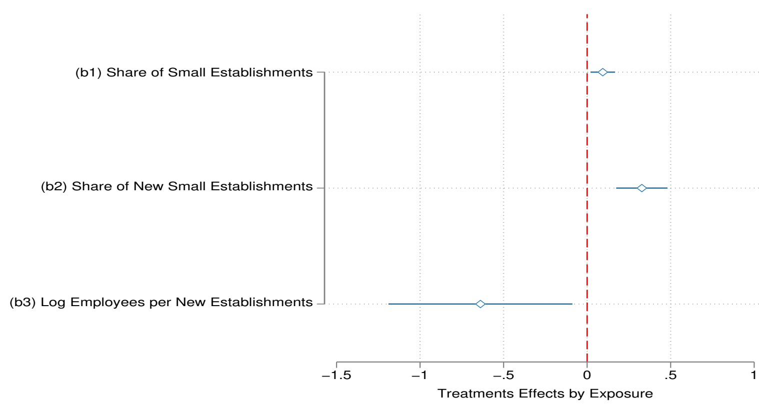
We then examine the influence of exposure to Caribbean policy reforms on the formation of new establishments. The result in the last row of Figure 5a reveals that the effect on new establishments is three times as large as the one on the total number of establishments (row 2). This finding indicates a heightened concentration of money-laundering leakage at the *extensive margin*, likely due to illicit funds being channeled into the establishment of new businesses.

Figure 5b next reveals the effect of the policy shift to be particularly concentrated among small firms. Consistent with the camouflaging nature of money-laundering activities, we estimate a positive increase in the share of establishments with less than 19 employees, particularly concentrated among small firms at entry. This result provides additional indirect evidence on the compositional effects of money-laundering leakage.

Figure 5: Reduced Form Results for New Establishments




(a) Stock vs New Establishments




(b) Establishment Size

*Notes:* OLS estimates of the interactions between county exposure measure ($\text{Exp}_c$) and a dummy taking value 1 for observations post-2008 ($\underline{d}_{year>2008}$) for different county-level dependent variables: (a1) logarithm of the number of establishmentsin the BLS database, (a2) logarithm of the number of establishments in the BDS database (a3) logarithm of the number of new establishments, (b1) share of establishments with less than 20 employees, (b2) share of establishments with less than 20 employees among new establishments, (b3) logarithm of (one plus) the number of employees per each new establishment. Reference year: 2008. Diamonds represent point estimates, vertical bars show 95% confidence intervals. All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Standard Errors are clustered at the county level. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

We then delve deeper and investigate whether the hiring practices of newly created establishments resemble those typically observed in front companies established for non-production-related purposes. We address this question by estimating Eq. (6), with the dependent variable being jobs created by new establishments. The last row of Figure 5b documents lower job-creation rates among the newly established businesses in exposed counties.

Taken together, the results of this section suggest that newly created businesses present characteristics consistent with those of front companies, both at the extensive and intensive margins.

### 5.3 Cheaper Laundering: the East Asian Channel

The 2019 National Drug Threat Assessment underscores the key role of Asian Transnational Criminal Organizations (TCOs) in providing cost-effective money-laundering services to the Mexican, Colombian, and Dominican TCOs.[21] Importantly, the assessment points to international money-laundering networks as a key connection between the East Asian TCOs and the U.S.-Caribbean links analyzed above (p. 108): "Money-laundering tactics employed by Asian TCOs generally involve the transfer of funds between China and Hong Kong, using front companies to facilitate international money movement." This report suggests that the geographic variation of links could be used as a proxy for the variations in the marginal cost of financially based money laundering, $1 - \alpha$ in Eq. (2).

In this section, we exploit this variation by isolating the subnetwork of direct and indirect links between U.S. and the Caribbean jurisdictions with connections via China and Hong Kong in the ICIJ database.[22] Using these links, we construct our exposure variable in Eq. (4) to account for both counties exposed to the East Asian subnetwork and those without such connections.

[21] The report cites: "Asian Money Laundering Organizations have emerged within the last few years as leaders within the money-laundering networks, due to a combination of charging *lower fees* and the efficiency of the services they provide." (p. 122).

[22] Indirect links are all the unique connections between officers with a U.S. address that includes zip code and entities in CFATF jurisdictions that are either associated with the China or Hong Kong country codes or are connected to intermediaries with registered addresses in those countries. Direct links are all the entities in CFATF jurisdictions with a U.S. address that includes a zip code, and are either associated with a China or Hong Kong country code or are connected to intermediaries from those places.

Table 3: The East Asian Money Laundering Channel

| **OLS Estimation** | | | | |
|---|---|---|---|---|
| Dependent Variable: *Logarithm of the number of establishments in a County* | | | | |
| | (1) | (2) | (3) | (4) |
| $\text{Exp}_c \times \underline{d}_{post}$ | 0.497*** | | | |
| | (0.120) | | | |
| $\text{Exp-No-Asian}_c \times \underline{d}_{post}$ | | 0.493*** | | 0.282** |
| | | (0.120) | | (0.122) |
| $\text{Exp-Asian}_c \times \underline{d}_{post}$ | | | 1.553*** | 1.159*** |
| | | | (0.274) | (0.260) |
| Baseline Controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | ✓ | ✓ | ✓ | ✓ |
| Observations | 33,869 | 33,869 | 33,869 | 33,869 |

*Notes:* OLS estimates obtained by interacting a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$) with alternative measures of county exposure: baseline exposure, $\text{Exp}_c$ (Column 1); exposure excluding links in the East-Asian Network, $\text{Exp-No-Asian}_c$ (Column 2); exposure including only links within the East-Asian Network $\text{Exp-Asian}_c$ (Column 3); and both the last two exposure measures (Column 4). The dependent variable is the logarithm of the number of establishments in columns. All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Standard errors clustered at the county level. *** significant at 1%, **significant at 5%, * significant at 10%. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

Table 3 reports reduced-form estimates of the effects of these subnetworks. The coefficients for all exposed counties and those exposed but unlinked to the East Asian subnetwork are quite close, as shown in columns (1) and (2). Yet, the coefficient for counties with connections to the East Asian subnetwork is significantly larger, as detailed in column (3). Including both exposure metrics into the regression within a horse-race framework (column 4) reveals that the coefficient associated with East Asian linkages is fourfold greater than that for other connections. This result supports the idea that counties exposed to the the AML reform via linkages with China and Hong Kong are considerably more sensitive than the others. This analysis, therefore, is consistent with our model and indicates a stronger creation of front companies in counties with access to more affordable money-laundering services, where illicit proceeds are more likely to be rerouted to offshore accounts.

# 6 Robustness

In this section, we present further evidence corroborating the presence of money-laundering leakage. First, we show that the policy's effect on business activity is more pronounced in areas that presumably have higher volumes of illicit profits (High-Intensity Drug Trafficking Areas), suggesting that these proceeds are being laundered locally. Second, we observe a notable increase in cash-based real-estate transactions in exposed counties, aligning with the cash-intensive nature of money-laundering activities. Third, we document that investment by publicly listed firms is not positively affected by these regulations, easing concerns about potential confounding effects due to unobserved correlations between anti-money laundering and profit-shifting regulations in these tax havens. Fourth, we demonstrate that our findings are robust to incorporating links to other prominent offshore financial centers, reinforcing the validity of focusing on the AML policy change within the CFATF Caribbean jurisdictions. Lastly, we show that our results are robust to alternative estimation methods, measures of exposure, and sample restrictions.

### 6.1 Effect in High-Intensity Drug Trafficking Areas

A key identification assumption of our econometric model is that criminal proceeds must be laundered locally. This local laundering mechanism might stem from the higher costs and complexities associated with establishing front companies at a distance or from the increased risk of detection by enforcement agencies when moving illicit funds across borders. Still, it may be that some money laundering involves acquiring front companies in other counties. We do not observe these geographical spillovers, making it challenging to address this issue. Should such spillovers exist, the coefficients we have estimated in the previous sections would represent a conservative estimate of the overall effect of substituting illicit activities. Consequently, the actual impact of international anti-money laundering regulations on the formation of front companies could be more pronounced than our findings suggest.

However, we can assess this localization assumption by leveraging variations in the intensity of drug trafficking across different geographic regions in the United States. Drug trafficking is a major "blue collar" crime and stands out for its use of both financial instruments and front companies for money laundering (Financial Action Task Force, 2004). In our context, counties with a high degree of illicit drug sales have higher amounts of money to clean. If it is costly to move illegal funds across regions, we should expect a stronger creation of front companies in such localities.

To operationalize this idea we use information from the US Office of National Drug Control Policy (2024), which classifies certain counties as high-intensity drug-trafficking areas (HIDTAs). Hence, we augment Eq. (6) by including a dummy indicating a county being classified as a high-intensity drug-trafficking area ($\text{HIDTA}_c$) interacted with the post-period dummy $\underline{d}_{t=post}$ and a triple interaction among $\text{Exp}_c$, $\text{HIDTA}_c$, and $\underline{d}_{t=post}$.

$$
\begin{aligned}
Y_{ct} = {} & \gamma_{3,c} + \lambda_{3,st} + \delta_3 X_{ct} + \beta_1 \text{Exp}_c \times \underline{d}_{t=post} + \beta_2 \text{HIDTA}_c \times \underline{d}_{t=post} \\
& + \beta_3 \text{Exp}_c \times \text{HIDTA}_c \times \underline{d}_{t=post} + \varepsilon_{ct}
\end{aligned} \tag{8}
$$

The model in Eq. (8) compares counties with similar characteristics and similar exposure to AML regulations but with different values of drug-trafficking intensity. The first three columns of Panel (a) of Table 4 report the estimated coefficients of interest, $\beta_3$, for three outcomes: logarithm of all establishments, the logarithm of new establishments, and the share of small firms among all establishments. The triple interaction coefficient is positive and significant for all three outcomes, meaning that the main effects highlighted in the previous sections are more prominent in areas with high-intensity drug trafficking.

These findings are consistent with the presence of geographical frictions in the money-laundering network that increase the cost of laundering criminal profits at longer geographical distances, supporting our assumption that front companies are established locally.

### 6.2 Cash-Based Real-Estate Transactions

Real-estate transactions are considered by authorities to be susceptible to money laundering. For example, someone seeking to clean criminal proceeds may purchase a home and quickly resell it for a markedly different price. It is documented that the greatest red flag is the use of cash to buy a property at closing or not to have a mortgage.[23]

Consequently, county real-estate markets may constitute an additional channel of money-laundering leakage resulting from Caribbean policy reforms. If this is the case, we can test the validity of our empirical analysis and our exposure measure by exploring the impact of the policy change on the propensity to buy properties with liquid assets. We expect to observe a relatively more pronounced increase in cash transactions in exposed counties in response to the foreign AML regulatory changes.

To test this hypothesis, we construct an annual measure of the share of cash-based real-estate transactions in all real-estate deals at the county level using data provided by ATTOM (2023), a service tracking all real-estate transactions in the United States. We then re-estimate the model in Eq. (6), using this

[23] See National Association of Realtors, "Anti-Money-Laundering Voluntary Guidelines for Real Estate Professionals," 16 February 2024, at https://www.narfocus.com/billdatabase/clientfiles/172/4/1695.pdf.

Table 4: Drug Areas, Cash Based Transactions, and Firms' Investiments

**OLS Estimation**

Panel (a): Drug Areas and Cash Based Transactions

| Dependent Variable: | *Log estab.* | *L. New estab.* | *Share Small* | *Share Cash* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Exp_c \times \underline{d}_{post}$ | $0.264^{***}$ | 0.531 | 0.023 | $0.010^{***}$ |
| | (0.094) | (0.407) | (0.035) | (0.003) |
| $Exp_c \times HIDTA_c$ | 0.003 | $-1.854^{**}$ | $-0.451^{***}$ | |
| | (0.194) | (0.838) | (0.071) | |
| $Exp_c \times HIDTA_c \times \underline{d}_{post}$ | $0.306^{***}$ | $2.046^{***}$ | $0.171^{***}$ | |
| | (0.108) | (0.469) | (0.040) | |
| Baseline Controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | ✓ | ✓ | ✓ | ✓ |
| Observations | 33,869 | 33,869 | 33,854 | 29,953 |

Panel (b): Investment of Publicly listed firms

Dependent Variable: *Logarithm of Property Plant and Equipement*

| Sample: | *All* | *1st Quartile* | *2nd Quartile* | *3rd Quartile* | *4th Quartile* |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $Exp_c \times \underline{d}_{post}$ | -0.013 | -0.140 | 0.034 | $-0.037^{*}$ | 0.013 |
| | (0.018) | (0.108) | (0.050) | (0.019) | (0.016) |
| Baseline Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Firms FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | ✓ | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 7,957 | 1,383 | 1,930 | 2,049 | 2,190 |

*Notes:* Panel (a), Columns 1-3: OLS estimates of the interactions between county exposure measure ($Exp_c$) and a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$), the interactions between county exposure measure ($Exp_c$) and a dummy taking value 1 for counties with High Intensity Drug Trafficking Areas ($HIDTA_c$) and a triple interaction, $Exp_c$ x $HIDTA_c$ x $\underline{d}_{post}$. The dependent variable is the logarithm of the number of establishments in columns in Column 1, logarithm of the number of new establishments in Column 2, and the share of establishments with less than 20 employees in Column 3. Panel (a), Columns 4: OLS estimates of the interactions between county exposure measure ($Exp_c$) and a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$). The dependent variable is the share of real-estate transactions in cash over all the transactions in the real-estate market in a county in a given year. Panel (b): OLS estimates of the interactions between county exposure measure ($Exp_c$) and a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$). The dependent variable is the firm-year logarithm of property plant and equipment and the database is Compustat. Column (1) reports estimates on the entire Compustat sample. Columns (2)-(5) report estimates when the sample is restricted to the firms with values of property plant and equipement belonging to their respective quartile of the distribution in 2005. Firm entry and exit account for differences in sample sizes. All regressions in both panels include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Standard errors clustered at the county level. *** significant at 1%, **significant at 5%, * significant at 10%. Compustat, CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

variable as an outcome, and report the result in Column (4) of Panel (a) of Table 4. The positive and significant coefficient documents a stronger increase in cash-based real-estate transactions in counties more exposed to Caribbean policy reforms. This finding is consistent with the financially unconstrained nature of money-laundering activities.

### 6.3 Effect on Investment Decisions of Large Firms

The selected Caribbean jurisdictions are strongly considered by the International Money Laundering Information Network to be financial havens, not only for money laundering but also as tax havens (UNODC, 1998). One may be concerned that our estimates may reflect potential shifts in tax regulations correlated with the AML regulations. This concern may be relevant in light of the finding in Suárez Serrato (2018) that a U.S. law targeting the ability of multinational firms to shift profits abroad reduced those firms' investments and employment in U.S. counties.

To exclude this confounding mechanism, we follow Suárez Serrato (2018) in looking for investment impacts of the CFATF policy changes on measurable real investments in the United States. Specifically, we test whether AML regulations affect the asset decisions of publicly listed firms. Using the geographical information in the Compustat Database (Historical Segment), we restrict the sample to publicly listed firms with reported assets in the United States. Assets are defined as property, plant, and equipment, which is the closest analog to establishments in Compustat. We attribute these assets to the county where the headquarters of the publicly listed firm is located. We regress the log value of firm-level assets on our exposure measure interacted with the post-policy dummy and the usual controls, as in equation (6), with the addition of firm-specific fixed effects.

The coefficient of $\text{Exp}_c \times \underline{d}_{t=post}$ in Column (1) in Panel (b) of Table 4 is close to zero and not significant, indicating that the real investment decisions of Compustat firms are not affected by stronger AML regulations in Caribbean countries. The result still holds when we run our regression for the different quartiles of the asset size distribution in the year 2005 as reported in Columns (2)-(5). This eases concerns that attribution of assets to the headquarters county may be mismeasured, as larger firms in the data may have their establishments spread across the United States.[24]

The fact that the volume of physical assets owned by listed firms is insensitive to AML regulations is relevant for two reasons. First, it suggests that the confounding mechanism that may arise from the correlation of AML regulations with profit-shifting regulations is not relevant for the firms that are most likely to take advantage of it (Suárez Serrato, 2018). Second, it indirectly supports the idea that our approach captures shady behavior, as the effect does not appear among firms that are subject to more intense financial scrutiny.

### 6.4 Alternative Offshore Financial Centers

By focusing on AML reforms in seven Caribbean locations, our analysis potentially overlooks regulatory changes in other offshore financial havens.[25] This omission might bias our estimates if: *(i)* significant AML reforms occurred in the excluded jurisdictions during our sample period, and *(ii)* there was a strong correlation between U.S. county exposure to these jurisdictions and the included Caribbean ones.

To address these concerns, we exploit the ICIJ database to gauge exposure to other prominent offshore financial havens. Excluding our sample, the only jurisdictions with over 10,000 global connections are Malta, Panama, Samoa, Seychelles, The Cook Islands, Niue, Isle of Man, and Jersey, cumulatively accounting for more than 500,000 links in the releases. Notably, when focusing on offshore links with U.S. addresses created up to the year 2004, only 4,162 links remain, predominantly with The Cook Islands. The limited exposure to these offshore financial centers ease concerns regarding the potential bias from excluding these jurisdictions in our analysis.

Furthermore, all these offshore financial centers display characteristics reducing concern about their AML regulatory implementations. Some began mutual evaluation processes after our study period (Panama, The Isle of Man, and Jer-

[24]For firms in the third quartile, we find a mildly significant negative effect, which is not a concern since it goes in the opposite direction of money laundering leakage.

[25]The International Monetary Fund identified 46 offshore financial centers in 2007, which encompasses the seven Caribbean jurisdictions included in our study (Zorome, 2007). Offshore financial centers are defined as "...a country or jurisdiction that provides financial services to nonresidents on a scale that is incommensurate with the size and the financing of its domestic economy." (Zorome, 2007, p. 7).

sey). The rest lacked follow-up reports post-evaluation, suggesting minimal reform implementation during our analysis timeframe.[26]

We mitigate concerns regarding a potential bias due to the exclusion of these no-CFATF jurisdictions as follows. We estimate the *direct* effect of alternative measures of exposure on offshore links to Caribbean jurisdictions. Columns (1)-(2) in Panel (a) of Appendix Table E6 shows that the estimates barely change when we replace our baseline exposure measure with one that incorporates *both* pre-existing links to CFATF and no-CFATF jurisdictions. Conversely, we find no impact on these links when we use an exposure measure that considers *only* pre-existent links to these omitted jurisdictions (Columns (3) in Panel (a) of Appendix Table E6). These findings carry through in our two-stage least square estimates (Panel (b) of Appendix Table E6). Notably, we detect no evidence of money laundering leakage due to exposure to these additional jurisdictions.

These considerations suggest that our focus on Caribbean jurisdictions is not only well-founded on relevance and harmonization grounds (as discussed in Section 2.1), but is also unlikely to suffer significant bias from excluding other major offshore financial centers from the sample.

### 6.5 Alternative controls, exposure measures, methods, and samples

Our findings are robust to additional considerations regarding exposure measures, estimation methods, and sample restrictions.

We start by analyzing how the inclusion of controls impacts our estimates in section 4. Tables E7 and E8 in the Appendix replicate the main analysis for the first-stage and the reduced-form analysis, respectively, with different levels of controls. The estimates show that our main results remain stable across the inclusion of controls and are robust to the inclusion of additional demographic

[26] Malta, a member of MONEYVAL, received a MER in 2007 with no follow-up reports until 2019. Panama, a member of the Financial Action Task Force of Latin America, received its first MER in 2018, after our sample period. Samoa, in the Asia/Pacific Group (APG), received a MER in 2007, and no follow-up reports until 2015. In the same group, The Cook Islands received a MER in 2009, but no follow-up reports until 2018. Similarly, Niue in the APG performed a MER in 2012, with no additional reports to date. Seychelles, in the Eastern and Southern Africa Anti-Money Laundering Group, received a MER in 2008 but no follow-up reports before 2018. The Isle of Man and Jersey are in MONEYVAL and received a MER only in 2017.

controls.

We then move to the exposure. Our measure is constructed using only offshore-financial links in the ICIJ database, which may not include existent but undocumented financial connections. To account for this source of uncertainty, we re-estimate all our main results in Section 4 by bootstrapping the standard errors. Appendix Figure E2 and Table E11 shows that all results still hold.

Next, we observe that our exposure is specified as the logarithm of one plus the total number of links of a county through 2004. To show that this functional form does not impact the results, we substitute the function $f(\cdot)$ in Eq. 4 with an inverse hyperbolic sine transformation. Columns (1)-(4) in Appendix Table E9 show that the estimate $\beta_2$ from Eq. (6) for the reduced-form and first-stage outcomes barely change when we replace our baseline exposure measure with this alternative one. This robustness also addresses concerns regarding the treatment of counties with zero exposure in our sample.

We continue by considering our outcome variable for the first stage: the logarithm of one plus the number of links in a county. We replace this variable with a simple counting of the yearly number of links between a county and an offshore jurisdiction, and, given the abundance of "zeros" in the outcome, we estimate the model employing a Poisson Pseudo-likelihood estimator. The estimated coefficient reported in Column (5) of Appendix Table E9 is $(e^{-0.03} - 1) * 100 = -2.96$ and does not statistically differ from its OLS counterpart. This result holds true even when controlling for a different exposure measure (inverse hyperbolic sine transformation) in Column (6). This analysis alleviates concerns regarding our handling of counties with no time-varying financial links, in the first stage.

Lastly, we perform two subsample analyses. The first exercise explores the fact that Nevada and Delaware have secrecy laws that may facilitate domestic financially based money laundering, potentially reducing the necessity for offshore alternatives. Accordingly, we expect a stronger response by dropping these states. Column (2) of Appendix Table E10 shows that this is the case, albeit not statistically significant, due to the fact that these states jointly account for just 20 counties. The second exercise accounts for the fact that there is considerable variation in the number of establishments across U.S. counties (Table 1). In Column (3) Appendix Table E10, we show that our findings are robust to dropping counties with fewer establishments, defined as those with an establishment count in 2004 below the first quartile of that year's national distribution.

## 7 Conclusions

In 2009, several members of the Caribbean Financial Action Task Force implemented a comprehensive regulatory initiative to curb money-laundering activities through the financial sector in the Caribbean region. This paper documents economically meaningful unintended ramifications of these stricter money-laundering regulations for the formation of front companies in the U.S.

First, we incorporate a money-laundering technology into a monopolistic-competition model to illustrate the main substitution mechanism between financially based money laundering and the creation of front companies. In this context, we show that in the presence of pro-competitive effects of entry, the growth in business activity observed in the data provides a conservative estimate of the creation of front companies.

Using offshore financial links compiled in multiple releases by the International Consortium of Investigative Journalists (2017), we then construct a measure of exposure of U.S. counties to the Caribbean regulatory changes. We find that counties exposed to tighter regulations abroad observe a more pronounced increase in business establishments. This impact is greatest in sectors deemed at high risk of money laundering and among small firms, which tend to hire fewer workers. We also find the effect to be more pronounced in high-intensity drug trafficking areas and for counties with links to international financial money-laundering networks. Further, exposed counties also experience an increase in cash-based real-estate transactions, aligning with the financially unconstrained nature of money-laundering activities.

Our study reveals that money-laundering leakage can render unilateral policies less effective at mitigating global money laundering. Accordingly, it underscores the need for collaborative efforts between international financial bodies, such as the Financial Action Task Force, and local audit and enforcement authorities to effectively combat money laundering.

A money-laundering process that we have not investigated directly is commingling, or the mixing of criminal and legitimate financial resources in order to disguise the former. Our model could be extended to account for the use of front companies in this process. Testing the resulting theoretical implications would require access to confidential administrative data, which we plan to explore in future research.

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# Appendix

## A Institutional Framework

This section provides additional information regarding the institutional background of our analysis. For convenience, we report here the list of acronyms used in the paper. In this context we exclude acronyms for: widely used U.S. databases; widely used methodologies,

Table A1: **List of Acronyms**

| | |
|---|---|
| AML | Anti-money-laundering |
| CFATF | Caribbean Financial Action Task Force |
| FATF | Financial Action Task Force |
| HIDTAs | Counties at high-intensity drug-trafficking areas |
| ICIJ | International Consortium of Investigative Journalists |
| MER | Mutual Evaluation Report |
| NAICS | North American Industry Classification System |
| SCI | Caribbean Jurisdictions Status of Compliance Index |
| TCOs | Transnational Criminal Organizations |
| UNODC | United Nations Office on Drugs and Crime |

### A.1 Institutional History of FATF and CFATF

In response to the largely undocumented yet mounting volumes of transactions involving illegal activities and the related threat to the banking system and financial institutions, in 1989, the G-7 countries, in cooperation with the European Commission and eight other countries, created a new international organization, called the Financial Action Task Force. Its role was to develop recommendations to "further protect the integrity of the financial system by providing governments with stronger tools to take action against financial crime" and to assess the effectiveness of anti-money-laundering and counter-terrorist financing tools in the member states. The FATF evaluates, through a series of reports, the compliance of each country's financial regulations with the standards it has promulgated. Its ambit was extended in 2001 to address terrorism financing.[27] Over time, a global network of nine regional bodies has emerged to promote these recommendations and issue reports, with over 200 jurisdictions committing to meet these recommendations. Within this network, 98 countries since 2007 have been publicly

[27]Information in this paragraph was taken from https://www.fatf-gafi.org/en/home.html.

listed as problematic and 72 of these have adopted sufficient reforms to come into compliance, removing them from the listings. One such regional body is the Caribbean Financial Action Task Force.

## A.2 The Status of Compliance Index

Table A2 reports the 40 (standard) + 9 (special) recommendations of the CFATF. We refer the reader to the FATF website for detailed explanations and definitions of the terms used below.[28]

Table A2: The 40+9 CFATF recommendations

| | | |
|---|---|---|
| **Anti-Money Laundering and Countering the Financing of Terrorism Policies and Coordination.** | | |
| R.1 | Assessing Risks and Applying a Risk-Based Approach | Core |
| R.2 | National cooperation and coordination | |
| **Money Laundering and Confiscation.** | | |
| R.3 | Money laundering offense | Key |
| R.4 | Confiscation and provisional measures | Key |
| **Terrorist Financing and Financing of Proliferation.** | | |
| R.5 | Terrorist financing offense | Core |
| R.6 | Targeted financial sanctions related to terrorism & terrorist financing | |
| R.7 | Targeted financial sanctions related to proliferation | |
| R.8 | Non-profit organisations | |
| **Preventive Measures.** | | |
| R.9 | Financial institution secrecy laws | |
| R.10 | Customer due diligence | Core |
| R.11 | Record keeping | |
| R.12 | Politically exposed persons | |
| R.13 | Correspondent banking | Core |
| R.14 | Money or value transfer services | |
| R.15 | New technologies | |
| R.16 | Wire transfers | |
| R.17 | Reliance on third parties | |
| R.18 | Internal controls and foreign branches and subsidiaries | |
| R.19 | Higher-risk countries | |
| R.20 | Reporting of suspicious transactions | |
| R.21 | Tipping-off and confidentiality | |
| R.22 | Designated Non-Financial Businesses and Professions (DNFBP): Customer due diligence | |
| R.23 | DNFBPs: Other measures | Key |
| **Transparency and Beneficial Ownership of Legal Persons and Arrangements.** | | |
| R.24 | Transparency and beneficial ownership of legal persons | |
| R.25 | Transparency and beneficial ownership of legal arrangements | |

[28]The definition of the 40 FATF recommendations can be found at https://www.cfatf-gafic.org/documents/fatf-40r. The definition of the 9 special recommendations can be found at https://www.fatf-gafi.org/publications/fatfrecommendations/documents/ixspecialrecommendations.html.

Table A2 – *Continued from the previous page*

| | | |
|---|---|---|
| **Powers and Responsibilities of Competent Authorities and Other Institutional Measures.** | | |
| R.26 | Regulation and supervision of financial institutions | Key |
| R.27 | Powers of supervisors | |
| R.28 | Regulation and supervision of DNFBPs | |
| R.29 | Financial intelligence units | |
| R.30 | Responsibilities of law enforcement and investigative authorities | |
| R.31 | Powers of law enforcement and investigative authorities | |
| R.32 | Cash couriers | |
| R.33 | Statistics | |
| R.34 | Guidance and feedback | |
| R.35 | Sanctions | Key |
| R.36 | International instruments | Key |
| R.37 | Mutual legal assistance | |
| R.38 | Mutual legal assistance: freezing and confiscation | |
| R.39 | Extradition | |
| R.40 | Other forms of international cooperation | Key |
| **The 9 special recommendations by FATF** | | |
| I. | Ratification and implementation of UN instruments | Key |
| II. | Criminalising the financing of terrorism and associated money laundering | Core |
| III. | Freezing and confiscating terrorist assets | Key |
| IV. | Reporting suspicious transactions related to terrorism | Core |
| V. | International co-operation | Key |
| VI. | Alternative remittance | |
| VII. | Wire transfers | |
| VIII. | Non-profit organisations | |
| IX. | Cash couriers | |

Table A3: The Status of Compliance by Jurisdiction - Descriptives

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| SCI - Anguilla | 6 | 69.671 | 11.709 | 58.503 | 83.673 |
| SCI - The Bahamas | 9 | 73.677 | 11.728 | 55.102 | 87.245 |
| SCI - Bermuda | 7 | 79.616 | 17.802 | 42.857 | 95.748 |
| SCI - Barbados | 9 | 71.191 | 12.448 | 50.34 | 82.599 |
| SCI - British Virgin Islands | 5 | 74.558 | 6.61 | 67.347 | 80.272 |
| SCI - Saint Kitts and Nevis | 6 | 71.372 | 19.228 | 44.218 | 88.776 |
| SCI - Cayman Islands | 8 | 84.464 | 10.298 | 68.027 | 91.088 |

*Data Source*: Constructed by authors from CFATF reports. *Sample period*: 2005-2015.

## B Conceptual Framework

We build a model to formalize the money-laundering leakage channel discuss in the paper. In this context, we derive a lower-bound on the effect of AML regulations on the creation of front companies, testable and quantifiable in publicly available business data.

Our theoretical framework extends the monopolistic-competition model by Parenti et al. (2017) to introduce a novel money-laundering technology.[29]

The economy contains $L$ identical consumers, a continuum of firms in the official sector producing differentiated varieties, and a criminal enterprise. Each consumer is endowed with $y$ units of productive labor, co-owns the production firms and enjoys a variety of consumption goods produced in the official sector. There is no disutility from work, so the aggregate supply of official labor is $yL$. We focus on the equilibrium with positive wages, which are normalized to one. Thus, $y$ can also be interpreted as personal income. Following Parenti et al. (2017) we assume that consumers' preferences over the set of official goods are additive, symmetric in varieties, and satisfy: *(i)* the love-of-variety property; *(ii)* the Inada conditions; and *(iii)* the decreasing-marginal-revenue property.[30]

The official sector is monopolistically competitive with a continuum of firms. There are no cost advantages in producing multiple varieties, so each firm picks a single variety. In order to produce $q_i$ units of its variety, firm $i$ needs $f + cq_i$ units of labor, which is the only input. Firm $i$ chooses the quantity $q_i$ that maximizes its operating profit, $\pi(q_i) = (p_i - c)q_i$. The firms' profit-maximization problem has a unique solution.

In the unique symmetric equilibrium, each firm produces the same amount, $\bar{q}$, of its own variety and charges the markup-inclusive price, $\bar{p}$,

$$\bar{p} = c\frac{\sigma(L\bar{x}, N)}{\sigma(L\bar{x}, N) - 1} \tag{B1}$$

where $\bar{x}$ is the symmetric equilibrium demand for each variety, and $\sigma(\bar{x}, N)$ is the demand elasticity for any variety. This price maximizes operating profits.

Utility-maximizing consumers co-own the legitimate firms, supply a fixed amount of labor (the numeraire) and have preferences (with a non-constant elasticity of substitution) over the variety of official goods. Differently from Parenti

[29] In our empirical analysis we interpret an economy to be a U.S. county.

[30] A consumption profile $x \geq 0$ is a Lebesgue-measurable mapping from the space of potential varieties $[0, \mathscr{N}]$ to $\mathbb{R}_+$ such that for $i \in ]N, \mathscr{N}]$, $x_i = 0$, where $x_i$ is the consumption of variety $i$. The utility representation is assumed to be Fréchet differentiable on the space of square integrable functions on $[0, \mathscr{N}]$. For the formulation and use of the Inada conditions, see Parenti et al. (2017, Lemma 1), while see Caplin et al. (1991) for a definition of the marginal-revenue property, which requires existence of the third derivative of the utility function.

et al. (2017), consumers also spend a fixed amount $E > 0$ on illicit goods.[31] To cover consumption of illicit goods, total income must be larger than the amount spent on them, $Ly > E$. In addition, to purchase these goods, income-balancing requires that local consumers dedicate part of their labor to produce services that benefit the criminal enterprise, which owns the illicit good.[32]

The criminal enterprise is a large entity that produces these illicit goods outside the economy, sells them to local consumers and spends the laundered proceeds elsewhere. We assume that the production and consumption decisions of this enterprise are independent of its money-laundering allocation.

The criminal enterprise uses a money-laundering technology to launder its illicit profits, $E$. The technology consists of two channels. The first is financially based money laundering, which is linear, in that for every dollar of input, $0 < \alpha < 1$ dollars come out clean and enter a valid bank account. The rest is used to obscure the origins of the proceeds. Thus, $\alpha$ stands for the yield earned in financially based money-laundering, or alternatively $1 - \alpha$ can be interpreted as the *marginal cost* of using this channel. Since the value of $\alpha$ is not observable in the data, in order to relate our theoretical predictions to observable variables, we make the following assumption.

*Assumption* 1. The unobserved yield of financially based money-laundering, $\alpha$, is a smooth decreasing function of the observable strictness of AML regulations, $\varphi$: $\alpha'(\varphi) < 0$.[33]

The second channel is the use of front companies. The criminal enterprise can exercise this option by using $z$ units of dirty money to create or acquire $M = \frac{z}{f + c\bar{q}}$ firms in the official sector of the local economy and run them as front companies.[34] The official sector is monitored and it is likely that such acquisitions attract scrutiny by enforcement authorities. We assume that the likelihood of being detected increases with the the share of businesses purchased for money-laundering purposes in the locality, $\frac{M}{N}$, where $N = M + n$, is the total mass of front companies, $M$, and clean firms financed by legitimate funds, $n$.[35] As a re-

[31] One justification for fixing $E$ is that the value of aggregate demand for some illegal activities (such as illicit drugs) appears to be unaffected by recent anti-money-laundering measures in the financial realm. While there is no general consensus regarding the prices of illicit drugs in recent years, their consumption has slightly increased (United Nations Office of Drug Control, 2020). For our purposes, it is sufficient to assume that $E$ is affected neither by the way the money is laundered nor by the range of varieties and prices of the official goods.

[32] The nature of these services is unspecified, though they could be construed in part as labor used to facilitate local connections to financially based money laundering, for example. The value of these services is denominated in units of productive labor.

[33] By observable, we mean by an econometrician.

[34] This is the only reason why the criminal enterprise may decide to purchase and operate firms in the official sector.

[35] This assumption can be violated in case dirty money fully corrupts legal and enforcement

sult, the marginal cost of laundering through front companeis increases with the volume of investment by the criminal enterprise in the official sector. The cleaned money via this channel equals the revenues of the firms that are not confiscated, $V(z) = \left(1 - \frac{M}{N}\right) M\bar{p}\bar{q}$.

The criminal enterprise maximizes the output of clean money by allocating the illicit funds, $E$, across the two channels, which we assume to be substitutes, as mentioned by (Financial Action Task Force, 2006):

$$\max_{0\leq z\leq E} \underbrace{\alpha(\varphi)[E-z]}_{\text{Financially based}} + \underbrace{V(z)}_{\text{Front Companies}} \tag{B2}$$

$$V(z) = \left(1 - \frac{M}{N}\right) M\bar{p}\bar{q}, \quad M = \frac{z}{f + \bar{q}c} \tag{B3}$$

The criminal enterprise does not take into account the potential effect of its decision on consumers' demand for the official goods or on the total mass of firms, and hence on firms' profits. Thus, the profits of legitimate firms and front companies are determined by the free-entry condition, as in Parenti et al. (2017). Among other variables, the masses of all firms, $N$, and of front companies, $M$, are determined in equilibrium, where all agents are price-takers and markets clear.

**Equilibrium Definition.** An equilibrium is an allocation of final consumption by individuals, a total mass of production firms $N$ and front companies $M$, as well as prices of all consumption goods such that: *(i)* consumers choose the best affordable bundle taking prices as given; *(ii)* a firm selling legitimate consumer goods of any variety maximizes its profits; *(iii)* the mass of production firms is such that no additional firm can earn a profit above the entry fee; *(iv)* the criminal enterprise chooses an optimal allocation of funds to launder across the two channels; and *(v)* all markets clear.

### B.1 Testable implication: $\Delta N/N < \Delta M/M$

To derive our testable prediction, we make the following common assumption on the elasticity of substitution (see Tirole, 1988; Anderson et al., 1995; Parenti et al., 2017).

*Assumption* 2. The elasticity of substitution between varieties is non-decreasing in the mass of varieties produced $\frac{\partial\sigma(\bar{q},N)}{\partial N} \geq 0$ and non-increasing in the average volume of per-variety production $\frac{\partial\sigma(\bar{q},N)}{\partial q} \leq 0$.

agencies. This scenario is of limited relevance, since we focus our empirical analysis on the United States.

Consistent with empirical findings, Assumption 2 guarantees a procompetitive effect resulting from the entry of firms. As in standard models of monopolistic competition, entry displaces some legitimate establishments due to strategic complementarity in pricing, generating a relatively larger growth in front companies.[36] We establish this point in the following proposition, also reported in the body of the paper.

**Proposition 1.** *Under Assumptions 1, 2, and if $\alpha < 1$, the equilibrium semi-elasticity of legitimate business activity with respect to strictness of AML regulations is lower than that of front companies:*

$$0 \leq \frac{dN}{d\varphi}\frac{1}{N} \leq \frac{dM}{d\varphi}\frac{1}{M}. \tag{B4}$$

For greater intuition, Proposition 1 may be explained as follows. On one hand, stricter AML regulations cause the criminal enterprise to reroute its funds into the official sector, increasing the mass of front companies, $M$. This increase puts competitive pressure on legitimate firms, implying that their mass, $n$, could fall. On the other hand, local demand increases because regular consumers receive greater income, boosting both $n$ and $M$ and raising the total mass of produced varieties, $N = n + M$. Both factors raise $M$, while only the latter expands $n$, which may be lower or higher in equilibrium. The model predicts that the share $M/N$ of front companies in the overall business activity increases, a result that might be termed a crowding-out effect of money laundering. Specifically, even if $n$ rises, the proportion front companies goes up, implying that the latter displace some of the former, at least in relative terms.

While the substitution between financially based money laundering and creation of front companies due to tighter AML regulations is intuitive, both the resulting increase in the overall business activity and the crowding-out effect are not. These results hinge on the equilibrium interplay of market forces.

Proposition 1 summarizes the main testable implication of our model. Tighter AML regulations aimed at combatting FBML cause a relative increase in *unobservable* front companies that is at least as large as the relative increase in *observable* business activity.

[36] Assumption 2 implies existence of this procompetitive impact as a higher number of total firms raises the elasticity of substitution and cuts firm-level markups. Further, Assumption 2 is both necessary and sufficient for strategic pricing under a wide range of flexible demand systems used in the literature, including directly additive preferences (Dhingra and Morrow, 2019), indirectly additive preferences (Bertoletti and Etro, 2017), and homothetic demands with either a single aggregator (Matsuyama and Ushchev, 2017) or Kimball's flexible aggregator (Kimball, 1995). We are grateful to an anonymous referee for making this point.

### B.2 Equilibrium Characterization and Proofs

Solution to the optimization problem of the criminal enterprise is summarized in the following Lemma.

**Lemma 1.** *Let $\gamma = \frac{M}{N}$ be the fraction of criminal enterprise's financed firms. If $V'(E) \geq \alpha$, then the criminal enterprise invests in front companies only and so $\gamma^* = \frac{E}{(f+c\bar{q})N}$, which is independent of $\varphi$ for any fixed $N$. Otherwise, the criminal enterprise uses both money-laundering channels and the optimal fraction $\gamma^*$ increases in $\varphi$,*

$$\gamma^* = \frac{1}{2}(1 - \alpha(\varphi)\frac{f + c\bar{q}}{\bar{p}\bar{q}})$$

*Proof.* Recall that the optimization problem of the criminal enterprise is

$$\max_{0 \leq z \leq E} \alpha(\varphi)[E - z] + V(z)$$
$$V(z) = \left(1 - \frac{M}{N}\right) M\bar{p}\bar{q}, \quad M = \frac{z}{f + \bar{q}c}$$

By definition, $\gamma(z) = \frac{z}{(f+c\bar{q})N}$. Then, $V(z) = N\bar{p}\bar{q}(1 - \gamma(z))\gamma(z)$. It is easy to check that $V'(0) > \alpha$ if the operating profit equals the entry cost, $\bar{\pi} = f$, so the optimal investment in front companies, $z$, is strictly positive. If $V'(E) \geq \alpha$, the criminal enterprise invests only in front companies, $z = E$. Otherwise, there is an interior optimum, where $V'(z) = \alpha$, since $V$ is increasing and strictly concave. The optimality condition implies

$$(1 - 2\gamma(z))\gamma'(z)N\bar{p}\bar{q} = \alpha(\varphi) \implies$$
$$(1 - 2\gamma^*)\frac{\bar{p}\bar{q}}{f + c\bar{q}} = \alpha(\varphi) \implies \frac{1}{2}(1 - \alpha(\varphi)\frac{f + c\bar{q}}{\bar{p}\bar{q}}) = \gamma^*$$

It is easy to see that in this case an increase in $\varphi$ decreases $\alpha$ by Assumption 1, which increases $\gamma^*$.[37] □

**Equilibrium Characterization.** In the previous section we provided a partial description of a symmetric equilibrium where all the production firms choose the same quantity of output. Here we complete the characterization.

The criminal enterprise purchases labor services to operate and run legitimate production of varieties, as any other firm. It extends a payment of $z = M(f + c\bar{q})$

[37] This monotonicity result relies on a few key features of the functions involved. We could work with $V(z) = Nv(\gamma(z))$, where $v$ is differentiable, concave in $\gamma$ and satisfies $Nv'(0) > \alpha$. In the case above $v(\gamma) = (1 - \gamma)\gamma\bar{p}\bar{q}$.

to local workers. This payment effectively reduces the amount that the local consumers owe to the criminal enterprise for illicit goods. By working in criminal enterprise's owned firms they produce both additional varieties and the "clean revenues" for the criminal enterprise. In other words, the productive resources in this economy, $Ly$, have three uses. First, consumers work to produce local goods in firms that they own: $nf + cn\bar{q}$. Second they work for the front companies owned by the criminal enterprise, expending $cM\bar{q} + fM$ units of labor there. Third, they dedicate some of the resources to repay the rest of the illicit goods, $E - z$.[38]

$$nf + nc\bar{q} + cM\bar{q} + fM = Ly - (E - z)$$

Therefore, we can solve for the level of output of each firm:

$$\bar{q} = \frac{Ly - E}{c(N - M)} - \frac{f}{c} \tag{B5}$$

Further, in a symmetric equilibrium the income of a consumer available for purchases, $\bar{p}\bar{x}$ of local varieties is $y - \frac{(E-z)}{L} + \frac{\bar{\pi}n - fn}{L}$. Thus, we have a full specification of the budget constraint and preferences that determine consumer demand and hence the elasticity of substitution used for firms' optimal pricing decisions.[39]

Combining the definition of $\bar{\pi}$ and firms' pricing decisions from Equation (B1), we get the free-entry condition,

$$c\bar{q} = f(\sigma(\bar{q}, N) - 1)$$

Substituting the equilibrium quantity $\bar{q}$ produced by each firm from Equation B5, we get

$$\sigma(\bar{q}, N)(N - M) = \frac{Ly - E}{f}$$

By the free-entry condition, $f + c\bar{q} = \bar{p}\bar{q}$. If $V'(E) \leq \alpha(\varphi)$, or, equivalently, $1 - \frac{2E}{N(f+c\bar{q})} \geq \alpha$, then, by Lemma 1, the criminal enterprise will choose to purchase $M^* = N\gamma^*(\varphi)$ front companies, where $\gamma^*(\varphi) = \frac{1}{2}(1 - \alpha(\varphi))$.

To sum up, the equilibrium satisfies the following conditions.

[38] As we mentioned before, we do not specify the exact mechanism for such repayment. For our purposes, it is sufficient to denominate this payment in terms of local labor.

[39] Summing over all the budget constraints, and using the market clearing, $L\bar{x} = \bar{q}$, we get condition $\bar{p}\bar{q} = yL - (E - z) + \bar{\pi}n - fn$, which is consistent with the above reasoning, given free entry: $\bar{\pi} = f$.

If $1 - \frac{2E}{N(f+c\bar{q})} \geq \alpha(\varphi)$, then

$$N\sigma(\bar{q}, N)(1-\gamma^*(\varphi)) = \frac{Ly-E}{f}, \text{ where}$$
$$\bar{q} = \frac{Ly-E}{cN(1-\gamma^*(\varphi))} - \frac{f}{c}$$

Otherwise, none of the equilibrium variables depend on $\varphi$:

$$\sigma(\bar{q}, N)(N - \frac{E}{f+c\bar{q}}) = \frac{Ly-E}{f}, \text{ where}$$
$$\bar{q} = \frac{Ly-E}{c(N-\frac{E}{f+c\bar{q}})} - \frac{f}{c}$$

Note that the inequality distinguishing the two cases can be formulated using a well-defined threshold $\alpha_0$, because the equilibrium value of $N$ and parameter $\alpha$ are negatively related, as we show in Lemma 2. As a result, the left-hand side of the inequality decreases in $\alpha$.

To sum up, the equilibrium mass of firms, $N$, is not affected by stricter regulations, $\varphi$, if no dirty money is invested in financially based money laundering. This happens if rerouting all illicit revenues, $E$, into front companies generates a marginal yield which is higher than that of financially based money laundering, $V'(E) \geq \alpha$. In this case, all the dirty money is routed into front companies and all proceeds from the illicit activities flow back into the official sector in the form of labor income. Thus, *the model predicts that some localities may not be engaged in financially based money laundering, either because the yield of financially based money laundering, $\alpha$, is perceived to be small or because there is not much dirty money to launder, $E$.* In either case, these locations would experience no effect on business activity $N$ of policy changes that decrease the yield to financially based money laundering. Conversely, if the yield to financially based money laundering is sufficiently high, $V'(E) < \alpha$, it is worthwhile for the criminal enterprise to use that channel.

**Lemma 2.** *Under Assumptions 1 and 2 and assuming that $\alpha < 1$, the total equilibrium mass of firms, $N$, increases in the strictness of AML regulations, $\varphi$: $\frac{dN}{d\varphi} \geq 0$.*

*Proof of Lemma 2.* If $V'(E) < \alpha$, that is, if

$$1 - 2\frac{E}{N(f+c\bar{q})} < \alpha \tag{B6}$$

then the equilibrium is characterized by the following equation:

$$F(N,\varphi)=\frac{1}{2}\sigma(q(N,\alpha(\varphi)),N)N(1+\alpha(\varphi))-\frac{Ly-E}{f}=0$$

where $q(N,\alpha(\varphi))=\frac{2(Ly-E)}{cN(1+\alpha(\varphi))}-\frac{f}{c}$. We evaluate the derivative of $N$ with respect to $\varphi$ at a given equilibrium point,[40] using the implicit function theorem,

$$\frac{dN}{d\varphi}|_{N,\varphi}=-\frac{\frac{\partial F(N,\varphi)}{\partial\varphi}}{\frac{\partial F(N,\varphi)}{\partial N}}$$

The derivatives evaluated at the equilibrium are as follows.

$$\begin{aligned}\frac{\partial F}{\partial\varphi}=&\frac{N}{2}\sigma(\cdot)\alpha'(\varphi)+\frac{\partial\sigma(\cdot)}{\partial q}\frac{\partial q(\cdot)}{\partial\alpha}\alpha'(\varphi)\frac{N}{2}(1+\alpha(\varphi))\\ \frac{\partial F}{\partial N}=&\frac{1}{2}(1+\alpha(\varphi))\sigma(\cdot)+\big(\frac{\partial\sigma(\cdot)}{\partial N}+\frac{\partial\sigma(\cdot)}{\partial q}\frac{\partial q(\cdot)}{\partial N}\big)\frac{N}{2}(1+\alpha(\varphi))\end{aligned}$$

By Assumption 2, $\frac{\partial\sigma(\cdot)}{\partial q}\leq 0$. Direct computation shows that $\frac{\partial q(\cdot)}{\partial\alpha}<0$. By Assumption 1, $\alpha'(\varphi)<0$. This implies that $\frac{\partial F}{\partial\varphi}<0$. Further, by Assumption 2, $\frac{\partial\sigma(\cdot)}{\partial N}\geq 0$. Direct computation implies $\frac{\partial q(\cdot)}{\partial N}<0$. Therefore, $\frac{\partial F}{\partial N}>0$.

Hence $\frac{dN}{d\varphi}>0$.

If $\alpha$ is sufficiently low that inequality (B6) is violated, then $\alpha$ and hence, $\varphi$ have no effect on the equilibrium $N$. □

*Proof of Proposition 1 in Section B.1.* By Lemma 1, if $V'(E)<\alpha$ then $M(\varphi)=\gamma^*(\varphi)N(\varphi)$ in equilibrium. Hence,

$$\frac{M'(\varphi)}{M}=\gamma^*(\varphi)\frac{N'(\varphi)}{M}+(\gamma^*)'(\varphi)\frac{N}{M}$$

By the same lemma, $(\gamma^*)'(\varphi)>0$, so

$$\frac{M'(\varphi)}{M}=\gamma^*(\varphi)\frac{N'(\varphi)}{M}+(\gamma^*)'(\varphi)\frac{N}{M}>(\gamma^*)(\varphi)\frac{N'(\varphi)}{M}=\frac{N'(\varphi)}{N}\tag{B7}$$

By Lemma 2, the last ratio is non-negative. If $V'(E)\geq\alpha$ , then neither $N$ nor $M$ is affected by $\varphi$. □

[40] The reference to the equilibrium point will be dropped hereafter.

# C Variables Description and Data Sources

Table C4: Main Variables

| Variable | Description |
|---|---|
| Establishments | Annual average number of quarterly establishments for a given year by county. According to BLS, an establishment is a single physical location where one predominant activity occurs (Source Link).<br>*Units:* County-year counts.<br>*Source:* United States Bureau of Labor Statistics (2015). |
| Population | Total number of residents for a given year by county.<br>*Units:* County-year residents in thousands.<br>*Source:* United States Census Bureau, Population Division (2010) and United States Census Bureau, Population Division (2019). |
| Real Personal Income | Personal income received by, or on behalf of all persons resident in the county, from all sources, including from participation as laborers in production, from owning a home or business, from the ownership of financial assets, and from government and business in the form of transfers.[41] The variable is computed by multiplying population (in thousands) by personal income per capita (in thousands of U.S. dollars). Nominal figures are expressed in 2010 dollars using CPI.<br>*Units:* County-year personal income in millions of 2010 U.S. dollars.<br>*Source:* United States Census Bureau, Population Division (2010), United States Census Bureau, Population Division (2019), United States Bureau of Economic Analysis (2020). |
| Real Median Household Income | Median household income expressed in 2010 dollars using CPI for a given year by county.<br>*Units:* County-year, in thousands of 2010 U.S. dollars.<br>*Source:* United States Census Bureau (2016b).[42] |
| Unemployment Rate | Unemployment rate for a given year by county.<br>*Units:* County-year in percent.<br>*Source:* United States Bureau of Labor Statistics (2016). |
| Offshore Financial Links | Annual number of links to Caribbean jurisdictions by county. See Section 3.2.<br>*Units:* County-year counts. *Source:* International Consortium of Investigative Journalists (2017). |
| Offshore Financial Links to Bermuda | Annual number of links to Bermuda by county. See Section 3.2.<br>*Units:* County-year counts. *Source:* International Consortium of Investigative Journalists (2017). |
| $\text{Exp}_c$ | Exposure to offshore financial regulations, see Section 3.2.<br>*Units:* County counts. *Source:* International Consortium of Investigative Journalists (2017). |
| SCI | Status of Compliance Index for a given year and Caribbean jurisdiction (Equation (1)). See Section 2.1 for details.<br>*Units:* Jurisdiction-year index in $[0, 100]$. *Source:* CFATF. |

[41] https://www.bea.gov/resources/methodologies/local-area-personal-income-employment.
[42] https://www.census.gov/programs-surveys/saipe.html

# D Details on Links and the Exposure Measure

To construct our measure of county-year offshore financial links and associated exposure measure to Caribbean policy reforms ((3.2)) we use the Bahamas Leaks, Offshore Leaks, Panama Papers, and Paradise Papers from the Offshore Leaks database compiled by the International Consortium of Investigative Journalists (2017). The database distinguishes and provides links between three types of agents. The first are *entities*, which are firms, corporations, and trusts with an associated offshore jurisdiction, which determines the laws and regulations to which they are subject. The second are *officers*, who are owners, beneficiaries, and shareholders of the entities. The third group are *intermediaries*, who assist in setting up the entities.

We select from the database entities in jurisdictions subject to the CFATF regulations that either have a registered address in the U.S. or have an associated officer with a U.S. mailing address. Information about the intermediaries is not used in the construction of our baseline exposure measure, $\text{Exp}_c$. However, we use this information to assess the role of international money-laundering networks in Section 5.3.

To construct the links of U.S. counties to offshore jurisdictions, we proceed as follows. We start by consolidating the data. First, we reclassify a small fraction of officers (0.15%) that are also assigned the role of intermediaries, by designating them solely as intermediaries. Second, officers may be connected to entities via multiple links. For example, the same officer might appear both as an "owner" and a "beneficiary" of an entity as indicated by the gray arrows in Figure D1. We classify such multiple links as a single connection. Second, the database records start and end dates for these connections. We assume a link persists if its end-date is missing, unless the entity to which this connection lead has ceased, at which point we use the entity's exit date. Conversely, if a start-date is absent, we presume the connection exists throughout our period of analysis, unless we have data indicating the formation date of the related entity, which we then adopt as the start-date.

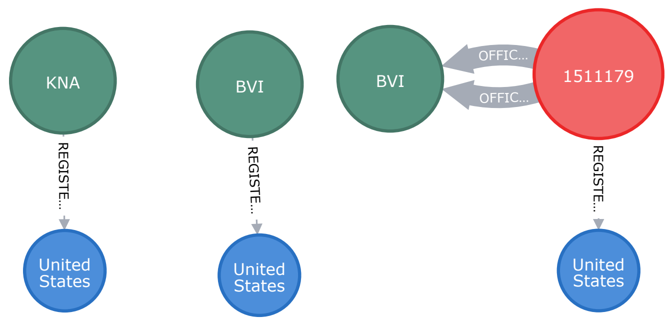
Next, we identify direct and indirect links as follows. *Direct links* comprise all entities in a Caribbean jurisdiction that have one U.S. zip code. Each zip-jurisdiction connection counts as a separate link. *Indirect links* consist of all unique connections between officers with a U.S. address, including zip code, and entities in the Caribbean jurisdictions, where these entities are not already counted as direct links. See Figure D1 illustrating both types of links for a Florida county.

Thus, we create a list of all U.S. addresses linked to the Caribbean jurisdictions. Next, we assign each address in the list to a county, based on the zip code, using USPS county-zip crosswalks (United States Department of Housing and

Urban Development, 2020).

Finally, we calculate the distribution of links by U.S. county and jurisdiction. For each county we count the number of direct and indirect links from that county to all entities in each of the offshore jurisdictions. We denote this number by $L_{c,j,t}$. Figure D1 illustrates the calculation.

Figure D1: Illustration of the computation of offshore links for a Florida county.




*Notes:* Officers are depicted as the largest (red) circles (their names are replaced by the internal id numbers), entities are smaller green circles, links are the gray arrows, registered addresses are the smallest blue circles. This county has three links. Two of them are direct: to St. Kitts and Nevis (KNA) and to the British Virgin islands (BVI). The third one is an indirect link to the BVI via officer 1511179 whose registered address is in the county. Accordingly, we have $L_{c,BVI} = 2$, and $L_{c,KNA} = 1$. *Source*: Generated by authors using *Neo4jDesktop for ICIJ* database.

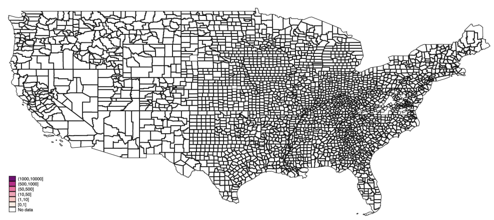
Table D5: Descriptive Statistics - U.S. Links to Caribbean Jurisdictions

| **Variable** | **N** (1) | **Mean** (2) | **Std. Dev.** (3) | **Min.** (4) | **Max.** (5) |
|---|---|---|---|---|---|
| Offshore financial links (Total) | 36960 | 11.95 | 123.44 | 0 | 5167 |
| Offshore financial links to The Bahamas | 36960 | .02 | .31 | 0 | 10 |
| Offshore financial links to Bermuda | 36960 | 10.12 | 119.49 | 0 | 4402 |
| Offshore financial links to Barbados | 36960 | .06 | 1.01 | 0 | 48 |
| Offshore financial links to British Virgin Islands | 36960 | .99 | 18.51 | 0 | 622 |
| Offshore financial links to Saint Kitts and Nevis | 36960 | 0 | .08 | 0 | 3 |
| Offshore financial links to The Cayman Islands | 36960 | 1.28 | 17.98 | 0 | 840 |
| Offshore financial links to Anguilla | 36960 | 0 | 0 | 0 | 0 |

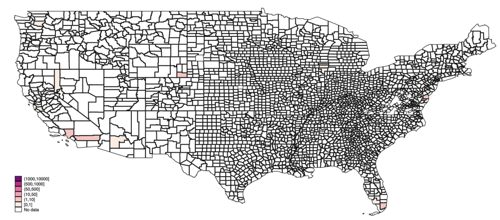
*Notes:* Descriptive statistics for the average number of links by jurisdiction. *Data Sources:* ICIJ. *Sample period:* 2005-2015.

Figure D2: County Exposure to AML regulations, by Jurisdiction

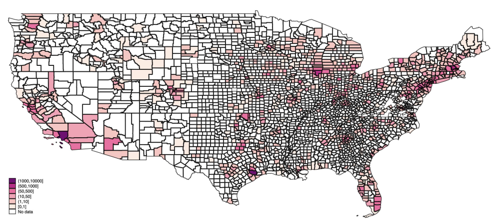
(a) Anguilla



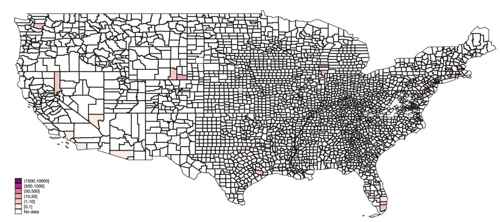
(b) The Bahamas



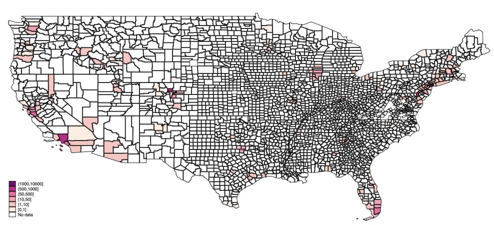
(c) Bermuda



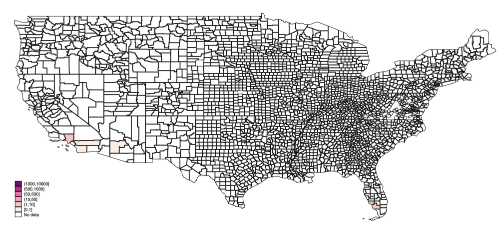
(d) Barbados



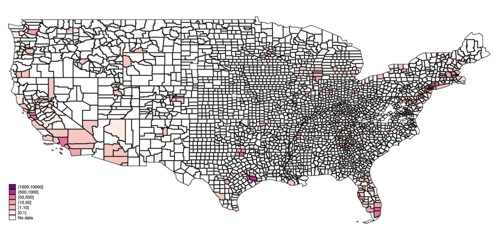
(e) British Virgin Islands



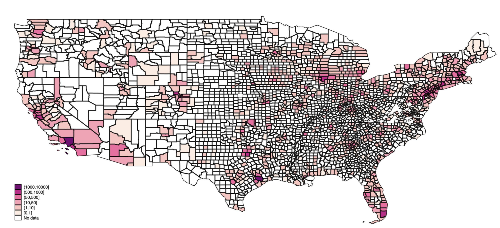
(f) Saint Kitts and Nevis



(g) Cayman Islands



(h) All jurisdictions



*Notes:* Time-invariant cumulative sum of county-jurisdiction links created through 2004, $\sum_{t\leq 2004} L_{cjt}$, by jurisdiction and county. *Data Source*: ICIJ.

# E Additional Results and Robustness

## E.1 Alternative Offshore Financial Centers

Table E6: Other Offshore Financial Centers

**OLS and 2SLS Estimations**

Panel (a): First Stage Results

Dependent Variable: *Logarithm of the number of links in a County*

| Exposure Measure: | *Baseline (CFATF)* | *CFATF + Others* | *Only Others* |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\text{Exp}_c \times \underline{d}_{post}$ | -2.511*** | -2.178*** | 0.901 |
| | (0.519) | (0.499) | (0.767) |
| Baseline Controls | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | ✓ | ✓ | ✓ |
| Observations | 33,869 | 33,869 | 33,869 |

Panel (b): Second Stage Results

Dependent Variable: *Logarithm of the number of establishments in a County*

| Exposure in the IV: | *Baseline (CFATF)* | *CFATF + Others* | *Only Others* |
|---|---|---|---|
| | (1) | (2) | (3) |
| Log number of links$_c$ | -0.198*** | -0.222*** | 1.070 |
| | (0.064) | (0.076) | (0.952) |
| Baseline Controls | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | ✓ | ✓ | ✓ |
| Observations | 33,869 | 33,869 | 33,869 |

*Notes:* Panel (a): First Stage OLS estimates of the interaction between a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$) with different measures of exposure ($\text{Exp}_c$) which consider links to: CFATF jurisdictions (Baseline) in Column (1); CFATF plus Other jurisdictions in Column (2); Other jurisdictions only in Column (3). The dependent variable is the logarithm of (one plus) the number of county offshore links to CFATF jurisdictions in a county in a given year. Panel (b), 2SLS estimates of the logarithm of (one plus) the number of county offshore links instrumented using the interactions between a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$) with different measures of exposure ($\text{Exp}_c$) which consider links to: CFATF jurisdictions (Baseline) in Column (1); CFATF plus Other jurisdictions in Column (2); Other jurisdictions only in Column (3). The dependent variable is the ogarithm of the number of establishments in a county in a given year. All regressions in both panels include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Standard errors clustered at the county level. *** significant at 1%, **significant at 5%, * significant at 10%. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

## E.2 The Impact of Controls

Table E7: First Stage

**OLS Estimation**

Dependent Variable: *Logarithm of the number of links in a County*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\text{Exp}_c \times 2005$ | -1.138*** | -0.407 | -0.332 | -0.332 | 1.771*** |
| | (0.399) | (0.445) | (0.447) | (0.441) | (0.643) |
| $\text{Exp}_c \times 2006$ | -0.726* | -0.123 | -0.088 | -0.088 | 0.963* |
| | (0.397) | (0.445) | (0.446) | (0.361) | (0.506) |
| $\text{Exp}_c \times 2007$ | -0.105 | 0.158 | 0.153 | 0.153 | 0.265 |
| | (0.396) | (0.444) | (0.446) | (0.235) | (0.299) |
| $\text{Exp}_c \times 2008$ | omitted | omitted | omitted | omitted | omitted |
| $\text{Exp}_c \times 2009$ | -0.618 | -0.685 | -0.654 | -0.654** | -0.839** |
| | (0.399) | (0.446) | (0.447) | (0.312) | (0.426) |
| $\text{Exp}_c \times 2010$ | -0.751* | -1.195*** | -1.172*** | -1.172*** | -1.928*** |
| | (0.400) | (0.446) | (0.448) | (0.434) | (0.602) |
| $\text{Exp}_c \times 2011$ | -1.291*** | -1.746*** | -1.736*** | -1.736*** | -2.496*** |
| | (0.402) | (0.446) | (0.448) | (0.487) | (0.668) |
| $\text{Exp}_c \times 2012$ | -1.685*** | -2.139*** | -2.137*** | -2.137*** | -3.229*** |
| | (0.404) | (0.448) | (0.449) | (0.544) | (0.734) |
| $\text{Exp}_c \times 2013$ | -3.464*** | -3.978*** | -3.975*** | -3.975*** | -5.686*** |
| | (0.406) | (0.449) | (0.451) | (0.641) | (0.881) |
| $\text{Exp}_c \times 2014$ | -3.873*** | -4.439*** | -4.430*** | -4.430*** | -5.686*** |
| | (0.409) | (0.451) | (0.453) | (0.671) | (0.903) |
| $\text{Exp}_c \times 2015$ | -4.892*** | -5.077*** | -5.035*** | -5.035*** | -5.761*** |
| | (0.414) | (0.455) | (0.456) | (0.660) | (0.878) |
| Baseline Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | | | ✓ | ✓ | ✓ |
| Non-parametric Controls Demographics | | | | | ✓ |
| Observations | 33,869 | 33,869 | 33,869 | 33,869 | 33,869 |

*Notes:* OLS estimates of the interactions between county exposure measure ($\text{Exp}_c$) and year dummies ($\underline{d}_{t=k}$). All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares. Non-parametric Controls Income refers to county-level deciles of median household income in 2004 interacted with year dummies. Non-parametric Controls Unemployment refers to county-level deciles of unemployment rate in 2004 interacted with year dummies. Non-parametric Controls Demographics refers to county level deciles of population density and urban dummy in 2004, both interacted with year dummies. Heteroskedasticity-Robust Standard errors in columns 1-3. Standard errors clustered at the county level in columns 4-5. *** significant at 1%, **significant at 5%, * significant at 10%. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

Table E8: Reduced Form

| OLS Estimation | | | | | |
|---|---|---|---|---|---|
| Dependent Variable: *Logarithm of the number of establishments in a County* | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| $\text{Exp}_c \times 2005$ | -0.342*** | -0.083 | -0.074 | -0.074 | -0.041 |
| | (0.114) | (0.128) | (0.128) | (0.102) | (0.106) |
| $\text{Exp}_c \times 2006$ | -0.342*** | -0.133 | -0.123 | -0.123 | -0.080 |
| | (0.114) | (0.128) | (0.128) | (0.082) | (0.090) |
| $\text{Exp}_c \times 2007$ | -0.120 | -0.005 | -0.009 | -0.009 | -0.005 |
| | (0.113) | (0.128) | (0.128) | (0.052) | (0.056) |
| $\text{Exp}_c \times 2008$ | omitted | omitted | omitted | omitted | omitted |
| $\text{Exp}_c \times 2009$ | 0.183 | 0.168 | 0.186 | 0.186*** | 0.149** |
| | (0.114) | (0.128) | (0.128) | (0.063) | (0.065) |
| $\text{Exp}_c \times 2010$ | 0.254** | 0.230* | 0.235* | 0.235*** | 0.224** |
| | (0.115) | (0.128) | (0.128) | (0.085) | (0.087) |
| $\text{Exp}_c \times 2011$ | 0.524*** | 0.514*** | 0.514*** | 0.514*** | 0.312*** |
| | (0.115) | (0.128) | (0.129) | (0.091) | (0.100) |
| $\text{Exp}_c \times 2012$ | 0.477*** | 0.525*** | 0.525*** | 0.525*** | 0.323*** |
| | (0.116) | (0.128) | (0.129) | (0.109) | (0.119) |
| $\text{Exp}_c \times 2013$ | 0.583*** | 0.619*** | 0.632*** | 0.632*** | 0.402*** |
| | (0.116) | (0.129) | (0.129) | (0.123) | (0.129) |
| $\text{Exp}_c \times 2014$ | 0.563*** | 0.571*** | 0.596*** | 0.596*** | 0.320** |
| | (0.117) | (0.129) | (0.130) | (0.139) | (0.144) |
| $\text{Exp}_c \times 2015$ | 0.566*** | 0.502*** | 0.534*** | 0.534*** | 0.289* |
| | (0.119) | (0.131) | (0.131) | (0.164) | (0.163) |
| Baseline Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | | | ✓ | ✓ | ✓ |
| Non-parametric Controls Demographics | | | | | ✓ |
| Observations | 33,869 | 33,869 | 33,869 | 33,869 | 33,869 |

*Notes:* OLS estimates of the interactions between county exposure measure ($\text{Exp}_c$) and year dummies ($\underline{d}_{t=k}$). All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares. Non-parametric Controls Income refers to county-level deciles of median household income in 2004 interacted with year dummies. Non-parametric Controls Unemployment refers to county-level deciles of unemployment rate in 2004 interacted with year dummies. Non-parametric Controls Demographics refers to county level deciles of population density and urban dummy in 2004, both interacted with year dummies. Heteroskedasticity-Robust Standard errors in columns 1-3. Standard errors clustered at the county level in columns 4-5. *** significant at 1%, **significant at 5%, * significant at 10%. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

## E.3 Alternative Exposures, Methods, and Samples

Table E9: Alternative Exposure Measures and Estimation Methods

| **OLS and PPML Estimation** | | | | | | |
|---|---|---|---|---|---|---|
| Regression Method: | *OLS* | | | | *Poisson Pseudo-Likelihood* | |
| Dependent Variable: | *Logarithm of establishments* | | *Log(1+Links)* | | *Links* | |
| Exposure Measure | Baseline | IHST | Baseline | IHST | Baseline | IHST |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\text{Exp}_c \times \underline{d}_{post}$ | 0.497*** | | -2.511*** | | -0.030*** | |
| | (0.120) | | (0.519) | | (0.007) | |
| $\text{Exp}_c^{IST} \times \underline{d}_{post}$ | | 0.406*** | | -2.173*** | | -0.030*** |
| | | (0.102) | | (0.448) | | (0.007) |
| Baseline Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 33,869 | 33,869 | 33,869 | 33,869 | 13,123 | 13,123 |

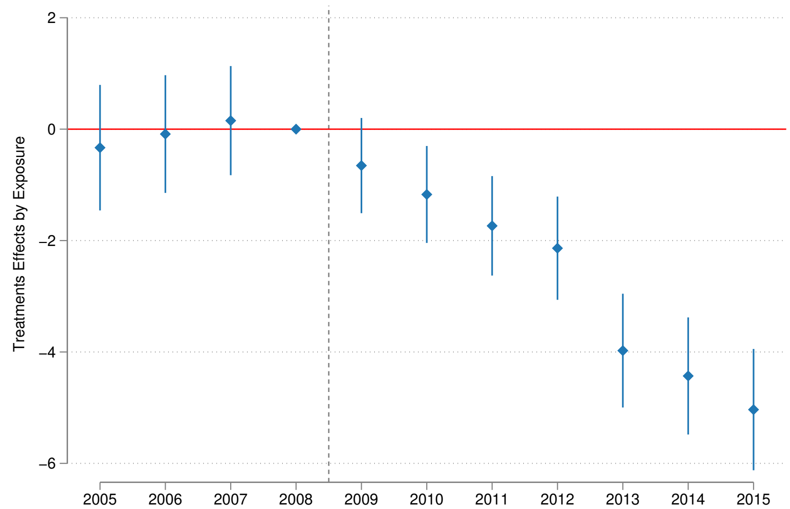
*Notes:* OLS estimates and PPML estimates of the interactions between county exposure measure and a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$). The dependent variables are: the logarithm of the number of county-year establishments in Columns (1)-(2); the logarithm of one plus the number of county-year links in Column (3)-(4); the number of county-year links in Column (5)-(6). Coefficients in Columns (1)-(4) are estimated using OLS. Coefficients in Columns (5)-(6) are estimated using the Poisson Pseudo-Likelihood method. Columns (1), (3) and (5) use our baseline exposure measure, $\text{Exp}_c$. Columns (2), (4) and (6) replace our baseline exposure measure with its inverse hyperbolic sine transformation (IHST), $\text{Exp}_c^{IHST} = \log\left(L + \sqrt{L^2+1}\right)$, where $L$ is the time-invariant cumulative sum of all links created through 2004. All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Standard errors clustered at the county level. *** significant at 1%, **significant at 5%, * significant at 10%. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

Table E10: Alternative Samples

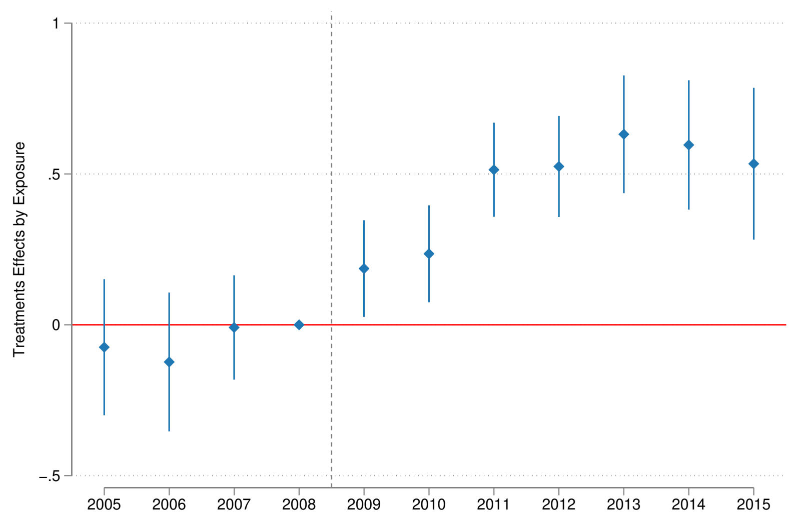
| **OLS Estimation** | | | |
|---|---|---|---|
| Dependent Variable: *Logarithm of the number of establishments in a County* | | | |
| Sample: | All | W/o Nevada-Delaware | W/o Counties with Few Estab. |
| | (1) | (2) | (3) |
| $\text{Exp}_c \times \underline{d}_{post}$ | 0.497*** | 0.524*** | 0.385*** |
| | (0.120) | (0.120) | (0.095) |
| Baseline Controls | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | ✓ | ✓ | ✓ |
| Observations | 33,869 | 33,649 | 25,377 |

*Notes:* OLS estimates of the interactions between county exposure measure ($\text{Exp}_c$) and a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$). The dependent variable is the logarithm of the number of establishments. All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Columns differ in the sample. Column 1 reports estimates for the entire sample; Column 2 drops the states of Nevada and Delaware; Column 3 drops counties in the first quartile of the establishments distribution in 2004. Standard errors clustered at the county level. *** significant at 1%, **significant at 5%, * significant at 10%. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

Figure E2: Event Study - Bootstrap




(a) First stage




(b) Reduced Form

*Notes:* Estimates of the interactions between county exposure measure ($\text{Exp}_c$) and year dummies ($\underline{d}_{t=k}$) for two dependent variables: (a) logarithm of (one plus) the number of county offshore links; (b) logarithm of the number of establishments. Reference year: 2008. Diamonds represent point estimates, vertical bars show 95% confidence intervals. All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Standard Errors are Bootstrapped (1000 replications). *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.

Table E11: Quantification - Bootstrap

| **Estimation with Bootstrapped Standard Errors** | | | | |
|---|---|---|---|---|
| Model: | First Stage | Red. Form | OLS | 2SLS |
| Dependent Variable: | *Log links* | *Log estab.* | *Log estab.* | *Log estab.* |
| | (1) | (2) | (3) | (4) |
| $\text{Exp}_c \times \underline{d}_{post}$ | -2.511*** | 0.497*** | | |
| | (0.279) | (0.067) | | |
| Log number of $\text{links}_c$ | | | 0.001 | -0.198*** |
| | | | (0.001) | (0.036) |
| Baseline Controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| State x Year FE | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Income | ✓ | ✓ | ✓ | ✓ |
| Non-parametric Controls Unemployment | ✓ | ✓ | ✓ | ✓ |
| Observations | 33,869 | 33,869 | 33,869 | 33,869 |

*Notes:* Columns 1-2: Estimates of the interactions between county exposure measure ($\text{Exp}_c$) and a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$). Column 3: Estimates of logarithm of (one plus) the number of county offshore links. Column 4: Estimates of logarithm of (one plus) the number of county offshore links instrumented using the interactions between county exposure measure ($\text{Exp}_c$) and a dummy taking value 1 for observations post 2008 ($\underline{d}_{post}$). The dependent variables are the logarithm of (one plus) the number of county offshore links in column 1 and the logarithm of the number of establishments in columns 2-4. All regressions include: county and state-year fixed effects, county-level logarithms of population, median household income, and average individual expenditure and their squares, county level deciles of median household income and unemployment rate in 2004, both interacted with year dummies. Bootstrapped Standard errors in parenthesis (500 replications). *** significant at 1%, **significant at 5%, * significant at 10%. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2005-2015.