Hiding Filthy Lucre in Plain Sight: Theory and Identification of Business-Based Money Laundering

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Abstract

Money laundering is the process of moving proceeds from illicit activities into the legal economy. We develop a monopolistic competition model incorporating a criminal enterprise which chooses between laundering through offshore financial investments or by acquiring legitimate establishments, called business-based money laundering (BBML). We use offshore accounts links to measure the exposure of U.S. counties to the evolution of anti-money-laundering regulations in Caribbean jurisdictions. We find that the number of business establishments grows significantly more in counties that are exposed to sharper financial scrutiny. Our theory implies that there must be greater growth in the number of BBML-established businesses. Overall, we provide the first empirical evidence of substitution between the two laundering channels.

Keywords: Money laundering, business establishment, Panama Papers, Offshore leaks, anti-money-laundering regulations, monopolistic competition.

JEL Codes: F30, K40, G28, H00, D58.

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1 Introduction[1]

Countries share considerable policy concerns about the mechanisms by which those engaged in illicit activities move the resulting profits into seemingly legitimate commerce. According to the widely-cited meta-analysis by the United Nations Office on Drugs and Crime, 2.3–5.5% of global GDP is laundered every year (UNODC, 2011). Recently leaked documents from the U.S. Treasury Department's Financial Crimes Enforcement Network (FinCEN) detailed over $2 trillion in suspicious financial activity over the period 2000-2017.[2] Although estimates of the extent of money laundering vary, the general consensus on its scale makes it a primary policy challenge.

Proceeds from illicit activities percolate into the legal economy through several money-laundering channels. In this paper we focus on two main ones. Illicit funds may be placed by investing in a legitimate business, the ownership of which disguises the source of the money, in a process we call business-based money laundering (BBML). Alternatively, they may be channeled through financial institutions using hidden bank accounts, anonymous trusts, and intermediaries located in different countries, a technique labeled financial-based money laundering (FBML).[3] With money laundering comes the potential for criminality and corruption, the ultimate targets of financial regulations and law enforcement. However, as such economic activity is deliberately obscure, it is hard to detect and quantify. We propose a theory-based approach that uses publicly available data to estimate changes in BBML due to regulatory changes affecting the marginal cost of FBML.

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[2]"See Eight Things You Need to Know about the Dark Side of the World's Biggest Banks, As Revealed in the FinCEN Files" BuzzFeed News, posted 25 September 2020, at https://www.buzzfeednews.com/article/jasonleopold/fincen-files-8-big-takeaways, last visited 24 January 2021.

[3]For more details see e.g., Bloomberg (2019).

First, in Section 2, we construct and analyze a monopolistic-competition model, featuring a criminal enterprise that seeks a placement for the money it must clean.[4] To do so, the criminal enterprise chooses between purchasing a legitimate business (BBLM) or hiding the money in the financial system (FBML). Each channel is costly, and the optimal placement of funds requires redirecting more into BBML if FBML becomes more expensive due to stricter regulations. Total business activity and the equilibrium number of varieties increase due to such rerouting. Crucially, the associated entry of firms established through BBML crowds out legally formed enterprises. We use this equilibrium insight to derive our key testable prediction: stricter regulations targeting FBML cause an increase in *observed* business activity which—as a result of the crowding-out effect—provides a *lower bound* on the *unobserved* rise in BBML.[5]

Second, we empirically test this prediction by adopting an exposure-based research design approach (e.g., Autor et al., 2013). We start by constructing an index that measures the exposure of all U.S. counties to changes in financial regulations targeting FBML abroad. The index has two components. First, we quantify the status of compliance of selected Caribbean countries—widely suspected to host offshore vehicles used for money laundering—with recommended standards for combating FBML issued by the Caribbean Financial Action Task Force (CFATF) over the period 2008-2015. Second, we construct a time-invariant measure of the degree of relative exposure of each U.S. county to regulatory discipline abroad via their offshore accounts in those jurisdictions created before 2008.[6] Combining the two, we construct our key treatment vari-

[4]The model is based on Parenti et al. (2017), who generalize the monopolistic competition framework of Krugman (1979).

[5]The results rest on empirically supported assumptions about the (non-constant) elasticity of substitution between varieties, as in Parenti et al. (2017), while incorporating some general-equilibrium effects.

[6]The information comes from the Offshore Leaks database, released by the International Consortium of Investigative Journalists (ICIJ), a network of more than 200 investigative journalists and 100 media organizations in over 70 countries. Their releases include three other publicly available databases, the Panama Papers, the Paradise Papers, and the Bahamas Leaks, and the four together detail links between over 785,000 offshore entities and people or companies around the world. See International Consortium of Investigative

able: a county-year index of exposure to financial regulations targeting FBML abroad.

We use our index to estimate the *contemporaneous* and *intertemporal* impact of stronger anti-money-laundering (AML) regulations targeting FBML[7] on the growth in the number of establishments in U.S. counties linked to these countries via offshore accounts. An appealing feature of our research design is that it relies on publicly available micro-data to identify BBML, a phenomenon that is difficult for authorities to detect in the absence of detailed transactions data.

We estimate these effects using a linear causal-regression model and the intertemporal treatment-effects estimators developed by De Chaisemartin and d'Haultfœuille (2021) (hereafter CH). In our analysis we address multiple identification threats, which still arise after controlling for time-invariant county characteristics, state-specific trends and county yearly income controls. First, we conduct an event study to alleviate concerns that business activity may have trended differently in exposed versus non-exposed counties and to exclude anticipation effects. In this context, the CH estimators allow us to test for a more general common-trends assumption, holding over several (rather than two) consecutive periods. Second, we replace the weighted index of county-level exposure to offshore AML regulations in all reforming jurisdictions with exposure to each country's individual index of regulatory compliance, verifying that the results remain intact. This exercise addresses two potential concerns. It shows that the results are robust to alternative measures of AML regulations, indicating that potential measurement error in the weighted index is not driving the findings. It also varies the treatment and control groups, in terms of both time windows and exposed counties, easing concerns about selection bias. We address selection issues further by restricting the estimation samples to exposed counties and comparing results. Third, we show that our results are robust to the addition of an array of county-year controls relating to wealth, income, and demographics. Finally, we demonstrate that our findings are

Journalists (2017).

[7] In what follows we refer to them simply as AML regulations.

robust to expanding the units of analysis to county-sector-year observations, deploying additional fixed effects, and different levels of clustering.

Using the linear causal regression model, we find that the increasing rigor of AML regulations in the Caribbean islands over the period 2008-2015 caused on average *at least* a 1.7% increase in the number of establishments due to BBML in exposed counties, conditional on state-year and county fixed effects, plus other controls. Further, we show that the impact varies by production sector. Specifically, the effect is strongest in retail trade and other services, but absent in manufacturing. Finally, we find evidence that this business activity is tied to the presence of illicit global financial networks.

Using the intertemporal treatment-effects estimators, we find that the effects of AML regulatory changes gradually built over time, peaking to 2.6% after 6 years from the first switch. This result is consistent with delays in either restructuring the money-laundering network or enforcing AML regulations.

We conclude by conducting two experiments to provide further external validity to our analysis. First, we find that stricter AML regulations are associated with a reduction in the yearly number of offshore financial vehicles in selected Caribbean countries. This suggestive evidence is consistent with our modelling assumption that tighter regulations reduce the yield of FBML. Second, we investigate whether stricter AML regulations against FBML influence the decisions of publicly listed firms to change their assets. We find no significant effects of this type, easing concerns that our results on BBML may be spurious in the sense that regulatory compliance may also have influenced the behavior of legitimate enterprises. The fact that investments by publicly listed firms are insensitive to regulatory reforms suggests that our results identify shady behavior.

Our research belongs to a developing literature on identifying unobserved economic activity.[8] Tax evasion and asset hiding are important outcomes of the access criminal organizations have to tax havens and secret offshore vehi-

[8] See Medina and Schneider (2018) for a survey. Prior papers using ICIJ-leaked databases include Alstadsæter et al. (2018) ,O'Donovan et al. (2019), Bayer et al. (2020), all of which studied different questions than ours.

cles, but no papers to date explicitly address the impacts of money laundering. To our knowledge, we are the first to pose this question and to isolate how organizations seeking to disguise illicit profits shift into establishing or acquiring legitimate businesses in the wake of greater enforcement. Overall, our analysis provides the first evidence of an increase in money laundering through the business sector in the wake of regulatory reforms that raise the costs of operating through financial channels.

2 Theoretical and Institutional Background

This section contains the model, which includes a novel stylized description of the money-laundering technology. The analysis of factors affecting the symmetric equilibrium of the model yields a testable hypothesis. The summary of anti-money laundering regulations presented thereafter guides our data construction described in the following section.

2.1 Theoretical Framework

We extend the monopolistic competition model by Parenti et al. (2017) to include money-laundering activities. We add a criminal enterprise, which operates largely outside the local economy, except for selling illicit goods and engaging in money laundering.

2.1.1 The Model

The economy contains L identical consumers, a continuum of firms in the official sector, and a criminal enterprise. In the empirical analysis that follows we interpret an economy to be a representative county.

Firms in the official sector and consumers are modelled as in Parenti et al. (2017). The economy is characterized by a symmetric equilibrium where firms maximize profit and consumers maximize utility for a given mass of varieties N, which is determined by the free-entry condition.

The official sector is a monopolistic-competition environment with a continuum of firms. There are no economies of scale for producing several 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 is symmetric and has a unique solution, so each firm produces the same amount, $q_i = \bar{q}$ and charges the same markup-inclusive price,

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

where: $\bar{x}$ is the symmetric equilibrium demand for each variety, and $\sigma(\bar{x}, N)$ is the demand elasticity for any variety as defined in Parenti et al. (2017)). This implies that the profit $\pi_i = \bar{\pi} = (\bar{p} - c)\bar{q}$ is the same for all firms.

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, as 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-for-variety property; *(ii)* the Inada conditions; and *(iii)* the decreasing-marginal-revenue property.[9]

Besides official goods, consumers also buy illicit goods. For simplicity we assume that the total expenditure on illicit goods by regular consumers, $E > 0$, is fixed.[10] For our purposes, it is sufficient to assume that E is affected neither

[9] A consumption profile $x \geq 0$ is a Lebesgue-measurable mapping from the space of potential varieties $[0, \mathcal{N}]$ to $\mathbb{R}_+$ such that for $i \in]N, \mathcal{N}]$, $x_i = 0$, 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 $[0, \mathcal{N}]$. 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. Strictly speaking, the marginal-revenue property requires existence of the third derivative of the utility function.

[10] One justification for fixing E is that the value of aggregate demand for some illegal

by the way the money is laundered nor by the range of varieties and prices of the official goods. 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—the only productive resource in this economy—to produce services that benefit the criminal enterprise, which owns the illicit good.[11]

The criminal enterprise (CE) is a large entity as compared to the local economy. It produces illicit goods beyond its boundaries, sells them to local consumers and spends the laundered proceeds elsewhere. We assume that the production and consumption decisions of this large enterprise are independent of its money-laundering allocation. The latter is the only reason why the CE may decide to purchase and operate some firms in the official sector.

The CE has to decide how to launder E dollars of illicit proceeds. It has access to a **money-laundering (ML) technology**, which consists of two channels. The first is financial-based money laundering. The FBML technology is linear: 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, as explained in Section 2.2. Thus, α stands for the yield earned in FBML, or alternatively $1-\alpha$ can be interpreted as the *marginal cost* of FBML. The value of α is not observable in the data, however we expect the yield to depend on the relevant anti-money-laundering regulations, which are publicly observable and can be quantified. Let φ be a measure of the strictness of AML regulations targeting FBML. In order to relate our theoretical predictions to

activities (such as illicit drugs) appears to be unaffected by recent AML measures. While there is no general consensus regarding the prices of illicit drugs in recent years, their consumption has slightly increased. According to the UNODC World Drug Report 2020, "Drug use around the world has been on the rise, in terms of both overall numbers and the proportion of the world's population that uses drugs. In 2009, the estimated 210 million users represented 4.8 per cent of global population aged 15-64, compared with the estimated 269 million users in 2018, or 5.3 per cent of the population". *Source*: United Nations Office on Drugs and Crime (2020).

[11]The nature of these services is unspecified, though they could be construed in part as labor used to facilitate local connections to FBML, for example. The value of these services is denominated in units of productive labor, which is the numeraire in this model. See Appendix A.1 for details.

observable variables, we make the following assumption.

Assumption 1. The yield of FBML, α, is a smooth decreasing function of the strictness of AML regulations targeting the financial sector, φ: $\alpha'(\varphi) < 0$.

The second channel is business-based money laundering. The illicit enterprise can exercise this option by using dirty money to acquire and run a legitimate firm in the local economy. Note that the enterprise may have sufficient illegally gained funds to establish multiple legitimate firms. Let z be the amount of dirty money invested in BBML to acquire and operate $M = \frac{z}{f+c\bar{q}}$ firms for money laundering, and let $N = M + n$ be the total mass of firms consisting of BBML and clean ones, respectively. It is likely that such acquisitions attract scrutiny by enforcement authorities. Thus, we assume that the business sector is monitored and a fraction $\frac{M}{N}$ of the BBML firms' assets are confiscated by enforcement authorities. The key idea we capture with this assumption is that the higher the relative weight of businesses purchased with dirty money in the locality, the easier it is to detect and punish criminal activity.[12] As a result, the marginal cost of BBML increases with the volume of investment by the criminal enterprise in the official sector. The clean output of BBML equals the revenues of the firms that are not confiscated.

To sum up, the problem of the CE is to maximize the output of clean money by allocating the illicit funds, E, across the two channels:

$$\max_{0\leq z\leq E} \underbrace{\alpha(\varphi)[E-z]}_{\text{FBML}} + \underbrace{V(z)}_{\text{BBML}} \tag{2}$$

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

where $V(z)$ denotes the clean output of BBML. We assume that the CE does not take into account the potential effect of its decision on consumers' demand for the official goods and on the total mass of firms, and hence on the profits of firms in the official sector. Thus, the profits of all firms, whether established

[12]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.

legitimately or by BBML, are determined by the free-entry condition, exactly as in Parenti et al. (2017). The solution of the problem is presented in Lemma 1 in Appendix A.1.

Equilibrium Definition. An equilibrium is an allocation of final consumption by individuals, a total mass of production firms N and BBML firms 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 BBML and FBML; and *(v)* all markets clear.

Equilibrium Description is in Appendix A.1, containing an implicit characterization of the symmetric equilibrium and the proofs of Propositions 1 and 2.

2.1.2 Results and Testable Implications

We illustrate the effect of stricter AML regulations on BBML in three steps. First, we use the equilibrium analysis to detect when the effect should be present. Second, we define the sign of the effect of AML regulations on total business activity, N, in Proposition 1. Third, we show in Proposition 2 that this effect is relatively stronger for BBML.

First, the equilibrium mass of firms, N, is not affected by stricter regulations, φ, if no dirty money is invested in FBML (see Appendix A.1). This happens if rerouting all illicit revenues, E, into BBML generates a marginal yield which is higher than that of FBML, $V'(E) \geq \alpha$. In this case, all the dirty money is routed into the BBML channel and all proceeds from the illicit activities flow back into the official sector in the form of labor income expended for BBML firms. Thus, the model predicts that some localities may not be engaged in FBML, either because the yield of FBML, α, 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 FBML. Conversely, if the yield to FBML is sufficiently high, $V'(E) < \alpha$, it is worthwhile for the criminal enterprise to use the FBML channel.

Second, we focus on localities where the effect of stricter regulations on BBML should be present, which, we argue, are those with higher spending on illicit goods, E, and lower marginal cost of FBML, $1 - \alpha$. To derive the effect of the regulations on the total mass of firms, we impose commonly used assumptions on the elasticity of demand (e.g., Tirole, 1988; Anderson et al., 1995; Parenti et al., 2017).

Assumption 2. The elasticity of demand 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 $\frac{\partial \sigma(\bar{q}, N)}{\partial q} \leq 0$.

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

Third, we turn to the response of BBML to stricter AML regulations. Although this effect cannot be measured directly in publicly available data, since we do not observe the mass of BBML firms, the next proposition provides a characterization leading to its indirect identification. In particular, we find that BBML effectively crowds out legitimate business investment, as the criminal enterprise buys some of the commercial firms that would have been financed by legitimate investors otherwise.

Proposition 2 (Crowding-out effect)**.** *Under the assumptions of Proposition 1, the semi-elasticity of legitimate business activity with respect to strictness of AML regulations is lower than the that of BBML:*

$$0 \leq \frac{dN}{d\varphi}\frac{1}{N} \leq \frac{dM}{d\varphi}\frac{1}{M}. \tag{4}$$

The economic intuition for the crowding-out effect is that it works through both supply and demand effects. First, the supply impact is that stricter AML regulations in the financial sector cause the illicit enterprise to reroute its funds into the official sector, increasing the mass of BBML-established firms, M.

Note that this increase raises competitive pressure on established local firms financed by legitimate funds, implying that their mass, n, could fall. Second, local demand increases because regular consumers receive greater income due to working for these new BBML firms. This demand impact boosts both n and M, resulting in a larger total mass of produced varieties, $N = n + M$. Intuitively, both the supply and demand effects raise M, while only the latter expands n, which may be lower or higher in equilibrium. However, we know that there is some crowding out because the model predicts that the share M/N of BBML firms in the overall business activity increases. That is, even if n rises, the proportion of total firms created through BBML goes up, implying that BBML-financed firms replace some of the legitimately funded firms, at least in relative terms.

Proposition 2 summarizes the testable implication of our model. Tighter AML regulations targeting the financial sector cause a relative increase in *unobservable* BBML which is at least as large as the relative increase in *observable* business activity.

2.2 Institutional Background

To clarify our data construction and research design, we provide a brief review of the basics of financial-based money laundering, along with AML regulations designed to reduce it.[13]

Money laundering via the financial channel consists of three main stages: placement, layering, and integration. Placement refers to mechanisms by which illicit funds are placed through financial institutions. Layering involves financial agents combining proceeds from illicit activities received from a multitude of depositors. Original depositors pay fees for these activities, after which they own offshore accounts. Integration is the final establishment of these cleaned accounts.

As this description suggests, FBML is conducted via professional money-laundering services. These services manage shell companies, trusts, and pas-

[13] For a detailed description see Financial Action Task Force, *Professional Money Laundering*, Paris, 2018, and DOJ (2015).

sive private holdings, often hosted in offshore havens. The key service often is to obscure the identity of the ultimate owners and depositors of illicit funds. Although these companies can promote legitimate investments, they may also facilitate money layering, wherein they receive wire transfers from many accounts, some of which may contain proceeds from illicit activities. After paying fees to such professional services, the original depositors own offshore accounts, which can be used to purchase and transfer legitimate assets.

The series of data leaks made by the ICIJ in recent years provides a rare opportunity to identify links between various stakeholders and thousands of such shell companies, trusts, and other offshore vehicles, located in various countries where weak financial regulations were, at the time, fertile grounds for money laundering.[14] Although the identity of the owners in these leaks is often obscured, the registered addresses of the financial entities or of their owners allow us to associate such entities with a particular locale elsewhere in the world. We focus on the links between U.S. counties and financial entities in the Caribbean. Some links are a part of a bigger network, involving, for example, addresses in Mexico, China, and Hong Kong. We make use of this information in Section 6.1, where we illustrate potential forces driving our results.

Our approach requires that we measure changes in AML regulations aimed at combating FBML. For this purpose, we rely on the regulatory efforts led by the Caribbean Financial Action Task Force (CFATF). For some time, there was growing concern worldwide about largely undocumented yet mounting volumes of transactions involving illegal activities, and the related threat to the banking system and financial institutions. In response, 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 (FATF). It now includes 39 member-states. Its role is to develop recommendations to "further protect the integrity of the financial system by

[14] 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.

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. These regulations are designed to raise barriers to money laundering, primarily in the financial sector. For example, the identity of a new company owner is to be verified through an elaborate due diligence process, while similar procedures are to be followed by financial institutions opening a new account for a client. Somewhat later, a related organization, the Caribbean Financial Action Task Force (CFATF) was created to undertake these processes in Caribbean economies. We use the CFATF national evaluation reports to quantify the evolution and strengthening of the resulting regulatory rules to reduce FBML in Caribbean jurisdictions that have been widely perceived as offshore financial centers attracting money laundering a decade ago.

3 Data and Construction of the Regulation Index

Our sample consists of three data sources. We use the first two sources to construct our main explanatory variable, which measures the strictness of offshore AML regulations faced by economic agents located in the Unites States. The last group of variables measures variations in business activity, economic conditions, and demographics by county.

First, we consult periodic reports released by the Caribbean Financial Action Task Force to assess the status of regulatory compliance of selected countries and territories in the Caribbean region with its recommended standards over the period 2008-2015. In this context, we construct a hand-coded measure of yearly changes in AML regulations in seven countries (jurisdictions) reputed to be havens for money laundering. Second, we use the Offshore Leaks database by the International Consortium of Investigative Journalists to measure the exposure of U.S. counties to regulatory changes in these jurisdictions. This source lists U.S. entities linked to offshore activities in the Caribbean nations, permitting aggregation of these links to the county level. Third, we collect information on the county-year level of business establishments from the Bureau of Labor Statistics (BLS). Our final database consists of 24,656 county-year observations from 2008 to 2015.

3.1 Constructing the AML Financial Regulations Index

The goal of this section is to construct a county-year proxy of the strictness of AML regulations, φ. Regional changes in AML regulations in the United States may arise endogenously as a policy response to the distribution and volume of local money-laundering activities. Such regulations are national or state responsibilities, obviating the worry about county-level regulatory responses. Still, county-level enforcement efforts, which are unobserved in our data, could vary with local money laundering. To overcome this problem, we construct a Bartik index that uses changes in relevant international AML regulations.

This approach requires quantifying two sources of variation: (i) time-series yearly evolution in the compliance of selected Caribbean countries with recommended AML standards covering the period from 2008 to 2015; and (ii) time-invariant cross-sectional exposure of U.S. counties to these offshore regulations.

As a first step, we select a subset $\mathbf{J}$ of seven CFATF jurisdictions: Anguilla (ANG), The Bahamas (BAH), Barbados (BRB), Bermuda (BER), British Virgin Islands (BVI), Cayman Islands (CAY), and Saint Kitts and Nevis (KNA). We focus on the mutual-evaluation process of CFATF members for two reasons. First, these are the countries in the ICIJ database (Panama Papers, Paradise Papers, Offshore Leaks and Bahamas Leaks) with the largest amount of documented links to off-island agents.[15] Second, they go through the same CFATF

[15] 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). We omit Aruba (68) from the list since its followup reports on the degree

evaluation process. All selected jurisdictions have links to U.S. counties.

To quantify the two required sources of variation, we construct two variables, the status-of-compliance index $\mathrm{SCI}_{j,t}$ and exposure-share $w_{c,j}$, as explained in the following two subsections.

3.1.1 The Status-of-Compliance Index

Our constructed variable $\mathrm{SCI}_{j,t}$ measures the degree of compliance of each selected Caribbean jurisdiction with the list of 49 AML standard recommendations issued by CFATF. Among these, [C]FATF identified its "core" standards, which include criminalization of money laundering and terrorist financing, customer due diligence and record keeping, and suspicious-transaction reporting.[16]

The countries went through a series of assessments summarized in reports prepared by a group of international examiners (lawyers, accountants, law enforcement professionals, and others). There are two types of reports. First, the field-based *Mutual Evaluation Reports* (MER) assessed the status of national regulatory compliance with each CFATF AML recommendation on a 4-tier scale: compliant (C), largely compliant (LC), partially compliant (PC), and non-compliant (NC) in accordance with FATF methodology.[17] We translate these ratings into numerical values by associating scores, from 3 (C) to 0 (NC) for each rating. Second, *Follow-up Reports* (FUR) document each jurisdiction's progress towards meeting specific requirements from the MER necessary to comply with each of the 49 recommendations. These requirements range from changes in the legal system to observable indicators of law enforcement. When jurisdictions were subject to more than one followup evaluation per year, we use end-of-year reports.

The earliest publicly available data for all the jurisdictions in our sample are from the third round of the MER. While encoding the ratings from the

of compliance with CFATF regulations were unreliably dated and were considerably less informative than reports about the included countries.

[16] See Appendix D.1 for the list of core and key recommendations.

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

MER is a straightforward task, working with assessments in FUR requires more careful reading. Our numerical ratings are mainly based on the conclusions of each FUR, while incorporating the details provided in the body of those documents.[18] For example, the 5th *Follow-up* report of the Bahamas (Oct, 12, 2012)[19] states: "The Bahamas has also achieved full compliance with Recommendations 19 and 30." In this case, we code recommendations 19 and 30 as compliant (C) 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, say either PC or LC. In those instances, we assigned scores in increments of 0.25 to the specific recommendation, which could be ranked as 2.5, for example.

Finally, to construct the $\mathrm{SCI}_{j,t}$ we sum the 49 scores $S_{j,t}(r)$ for each jurisdiction j and year t (based on MER and FUR) and divide them by 147, the highest possible sum of scores. Thus, $\mathrm{SCI}_{j,t} \in [0, 100]$ reflects the percentage of all recommendations in compliance:

$$\mathrm{SCI}_{j,t} = \frac{100}{147} \sum_{r=1}^{49} S_{j,t}(r) \tag{5}$$

Figure 1 illustrates the evolution of the status-of-compliance index over time for the jurisdictions in our sample. The jurisdictions entered and completed the mutual evaluation and followup process in different years. To achieve a balanced panel for our index, we add missing values for all the years from 2008 to 2015, using a constant extrapolation backward and forward in time. In the robustness checks, we complement this analysis with alternative formulations of the index. In particular, in Appendix G.1 we analyze the impact of $\mathrm{SCI}_{j,t}$ for each jurisdiction separately, thus using the original data only, as presented in Figure 1.

This figure also shows that four of the seven jurisdictions started the evalu-

[18] Our supplementary material, available in an online data summary, links each assessment we made of a change in compliance to the corresponding part in the official report.

[19] See https://www.cfatf-gafic.org/documents/cfatf-follow-up-reports/the-bahamas/878-the-bahamas-5th-follow-up-report/file

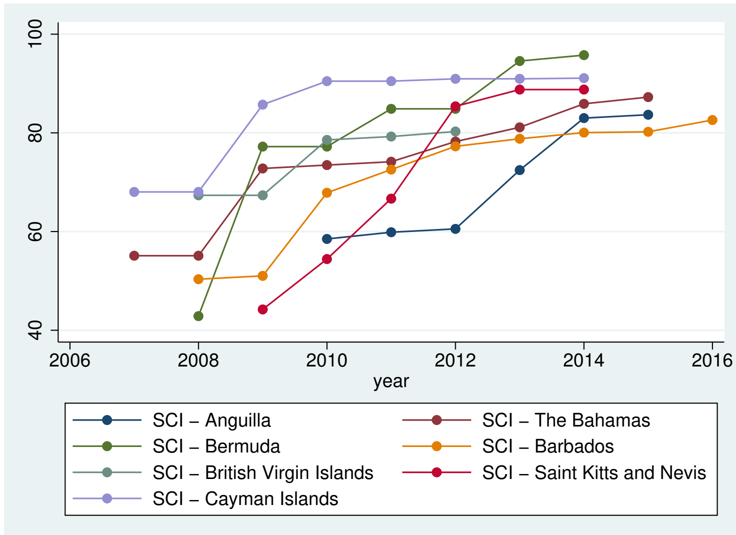

Figure 1: **The status-of-compliance index by jurisdiction**. *Source:* Constructed by authors from information in reports by Caribbean Financial Action Task Force (CFATF).

ation process in 2008, with Cayman Islands and the Bahamas beginning a year earlier. However, the first effective policy changes were implemented in 2009, after these countries received the evaluation reports.[20] Thus, for the purposes of our analysis, we take 2009 to be the year of the initial policy change.

3.1.2 Exposure Shares

The variable $w_{c,j}$ measures the relative exposure of county c to AML regulatory changes in Caribbean jurisdiction j. This share is based on the number of links ($L_{c,j}$) between legal agents in a U.S. county and entities in a specific Caribbean jurisdiction, as documented in the ICIJ database. The variable $w_{c,j}$ is the ratio of the number of such links to the total number of connections between that county and all the included Caribbean jurisdictions as of 2008.

[20]The only exception are Saint Kitts and Nevis and Anguilla, which started in 2009 and 2010, respectively, and they account on average for 0.02% of the total share of exposure, as reported in Table 1.

The exposure shares are zero if a county has no offshore links at all.

$$w_{c,j} = \begin{cases} \frac{L_{c,j}}{\sum_{k \in \mathbf{J}} L_{c,k}} & \text{if } \sum_{k \in \mathbf{J}} L_{c,k} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

To construct the exposure shares, we use the Bahamas Leaks, Offshore Leaks, Panama Papers, and Paradise Papers from the Offshore Leaks database compiled by the ICIJ.[21] 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 established before 2008 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. As suggested in the CFATF reports, these entities may include financial establishments that provide FBML services to U.S. individuals.

Information about the intermediaries is not used in the construction of our basic set of exposure shares. However, we use it in Section 6.1 to assess the role of international money-laundering networks.

To construct the links of U.S. counties to offshore jurisdictions, we proceed as follows. We start by consolidating the data. First, a small fraction of officers are also assigned the role of intermediaries.[22] We classify them 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 2. We classify such multiple links as a single connection.

Next, we identify direct (1,492) and indirect (51,388) links as follows. *Direct links* comprise all entities in a Caribbean jurisdiction that have one U.S. zip

[21] *Source*: International Consortium of Investigative Journalists (2017).

[22] They constitute 0.16% of officers present solely in the Offshore Leaks database.

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 2 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 the 2010-1Q USPS county-zip crosswalk.[23] Where zip codes are associated with multiple counties, we allocate them using the business ratio, which reports the share of businesses in a zip code located within those counties.

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 $L_{c,j}$. Then, we use Equation (6) to compute the associated exposure shares $w_{c,j}$. Figure 2 illustrates the calculation.

Panel A of Table 1 reports descriptive statistics for total county-jurisdiction linkages and an indicator of overall exposure. More than a third of U.S. counties are exposed to changes in AML regulations via pre-2008 connections to offshore Caribbean entities, providing substantial cross-sectional variation.[24] Panel B shows the degree of exposure of those counties to each jurisdiction. The majority of links of an average county are with Bermuda, suggesting a considerable concentration in the distribution of shares. The British Virgin Islands and the Cayman Islands also are prominent.

Figure 3 illustrates substantial geographical variation in the intensity of exposure to offshore entities. As is evident from the map, major metropolitan areas have a relatively higher density of links.

The corresponding jurisdiction-specific heat maps in Figure 9 in Appendix E point to cross-sectional variation that could help identify the impacts of

[23]In order to improve the matching we also use the 2012-4Q cross-walk. *Source*: United States Department of Housing and Urban Development (2020).

[24]The maximum number of links is recorded in Manhattan, New York.

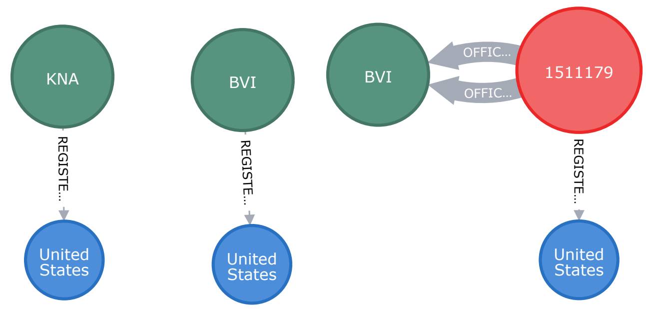

Figure 2: **Illustration of the computation of offshore links for a Florida county.** Officers are depicted as the largest (red) circles (their names are replaced by the internal id numbers), entities are smaller green circles, links are the gray arrows, registered addresses are the smallest blue circles. 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 $L_{c,BVI} = 2$, $L_{c,KNA} = 1$, $w_{c,BVI} = 2/3$, and $w_{c,KNA} = 1/3$. *Source*: Generated by authors using *Neo4jDesktop for ICIJ* database.

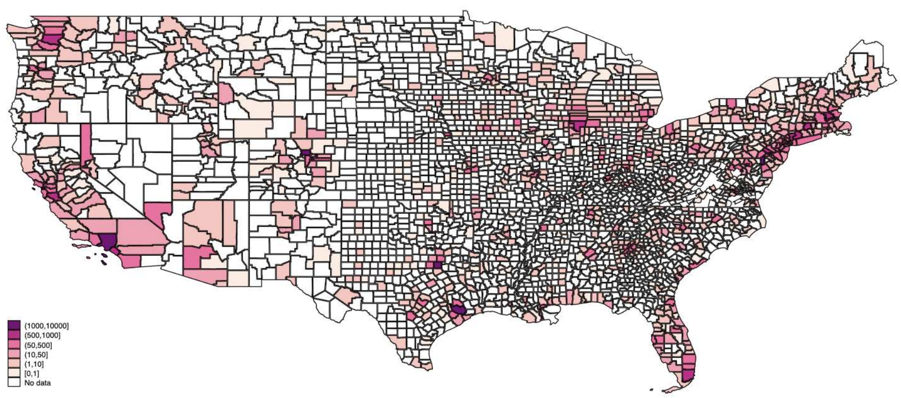

Figure 3: **Intensity of the counties' exposure to all jurisdictions, $\sum_{j \in \mathbf{J}} L_{c,j}$.** *Data Source*: ICIJ.

AML regulations. For example, the British Virgin Islands (BVI) and the Cayman Islands (CAY) both account for around 12 percent of pre-2008 linkages. Counties in the Pacific Northwest of the United States appear more exposed to BVI than to CAY, while counties in southern Texas exhibit the opposite pattern. In general, as we show later, it is not possible to claim that the exposure shares are randomly assigned across counties. Rather, some county features

Table 1: Descriptive Statistics for $L_{c,j}, w_{c,j}$, cf. Equation (6).

Panel A: Unconditional Descriptive Statistics					
	Counties	Mean	Std	Min	Max
Total Links	3082	16.74	201.68	0.00	6960
Exposure Dummy	3082	0.34	0.47	0.00	1
Panel B: Descriptive Statistics for Exposed Counties ($\sum_{j \in \mathbf{J}} L_{c,j} > 0$)					
	Counties	Mean	Std	Min	Max
Total Links	1046	49.33	343.97	0.00	6960
Share of Links to ANG	1046	0.01	0.27	0.00	7
Share of Links to BAH	1046	0.84	7.62	0.00	100
Share of Links to BER	1046	74.41	36.30	0.00	100
Share of Links to BRB	1046	0.57	5.76	0.00	100
Share of Links to BVI	1046	12.19	27.50	0.00	100
Share of Links to KNA	1046	0.02	0.54	0.00	17
Share of Links to CAY	1046	11.94	26.19	0.00	100

Note. **Panel A** reports the sample descriptive statistics for: *(i)* the total number of links $L_{c,j}$; and *(ii)* the indicator of exposure ($\sum_{j \in \mathbf{J}} L_{c,j} > 0$), that takes the value of 1 when the county's total number of links is positive and 0 otherwise. **Panel B** reports the descriptive statistics for the restricted sample of exposed counties, where the exposure dummy takes the value of 1. The reported share of links, $w_{c,j}$, is multiplied by 100 to be expressed in percentage terms. *Data Source*: ICIJ.

might affect the intensity of exposure, which is the reason for introducing county fixed effects in our baseline specification, as explained in Section 4.

3.1.3 Offshore Financial Regulations Index

We combine the exposure-share and the status-of-compliance index in computing our AML financial regulations index, Offshore-FRI$_{c,t}$, as a weighted average of the status-of-compliance index for each U.S. county and year, where the weights, $w_{c,j}$ are the corresponding exposure shares.

$$\text{Offshore-FRI}_{c,t} = \sum_{j \in \mathbf{J}} w_{c,j} \cdot \text{SCI}_{j,t} \tag{7}$$

The variable Offshore-FRI$_{c,t}$ is Bartik in nature (Goldsmith-Pinkham et al., 2020, p. 2592; Bartik, 1991). Its first component, $w_{c,j}$ is time-invariant and the second component, SCI$_{j,t}$, is location-independent as regards U.S. counties. Our index, Offshore-FRI$_{c,t}$, provides an empirical proxy for φ and measures the time-varying county exposure to stringency in foreign AML financial regulations and constitutes our treatment.

3.2 Outcome and Control Variables

We collect U.S. county-level information on economic activity at yearly frequency from the Bureau of Labor Statistics (BLS) database. Our main dependent variable is the natural logarithm of the annual average of quarterly establishment counts for a given year by county, ln N$_{c,t}$. We collect U.S. county demographic and economic information at 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 Program (SAIPE). Table 8 in Appendix B contains the details. As recommended by the Census Bureau,[25] 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.

4 Exposure-Based Research Design

Our goal is to assess the impact of anti-FBML regulations on the *observed* level of establishments across U.S. counties, which we showed in Section 2.1.2 to be a lower bound of the impact on the *unobserved* level of BBML. An ideal experiment would randomly assign regulations of different strictness to the relevant U.S. counties. In the absence of such an experiment, we rely on an *exposure-based research design* (e.g. Autor et al., 2013) that uses the index Offshore-FRI$_{c,t}$ constructed in Section 3.1 as a treatment. This approach generates a staggered-adoption design (where counties that are treated do not

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

switch out of treatment) with continuous and weakly increasing treatment.

4.1 Econometric Models

We use three econometric models to study different aspects of this empirical question. First, in Section 5 we estimate the linear constant-effects causal relationship

$$\ln \mathrm{N}_{c,t} = \beta_0 + \beta_1 \cdot \text{Offshore-FRI}_{c,t} + \underline{d}_c + \underline{d}_{s,t} + X'_{c,t-1}\gamma + \varepsilon_{c,t} \tag{8}$$

between the natural logarithm of county-year number of establishments, $\ln \mathrm{N}_{c,t}$, and the index of exposure to offshore financial regulations (Offshore-FRI$_{c,t}$, Equation (7)), conditional on county fixed effects ($\underline{d}_c$), state-year fixed effects ($\underline{d}_{s,t}$), and a vector $X_{c,t-1}$ consisting of the lagged county-year natural logarithm of personal income and its interaction with the dummy variable for exposure. Henceforth, we will refer to these covariates as *baseline controls*. The key estimate of our analysis is β_1, which measures the effect of AML regulations on business activity and, indirectly, on BBML.

Second, in Section 6 we explore heterogenous effects that may arise from county characteristics that affect the relative yield of FBML versus BBML. To do so, we estimate the following interaction model:

$$\begin{aligned} \ln \mathrm{N}_{c,t} =& \beta_0 + \beta_1 \cdot \text{Offshore-FRI}_{c,t} + \beta_2 \cdot \text{Offshore-FRI}_{c,t} \cdot \text{Characteristic}_{c,t} \\ &+ \beta_3 \cdot \text{Characteristic}_{c,t} + \underline{d}_c + \underline{d}_{s,t} + X'_{c,t-1}\gamma + \varepsilon_{c,t} \end{aligned} \tag{9}$$

The additional element in this regression involves county-specific characteristics. The key coefficient in this case is β_2, which measures the impact of a change in the interaction term on county-level business activity.

Third, in Section 7 we use the intertemporal treatment-effects estimators developed in De Chaisemartin and d'Haultfœuille (CH, 2021) to estimate how the effect of regulatory changes may have gradually built up over time. This approach allows us to estimate how tighter AML regulations affect the logarithm of county-year number of establishments in the first period of treatment (switch) and in later periods.

To operationalize this approach, we need first to adjust our treatment variable. The index Offshore-FRI$_{c,t}$ measures the county-year *level* of exposure to AML financial regulations aimed at reducing FBML. This exposure varies across counties in 2008, the beginning of the mutual-evaluation process. To correctly interpret the intertemporal CH estimator results we need to measure the *tightening* of these regulations in the CFATF followup process. Thus, as a first step we take the difference between the level of Offshore-FRI$_{c,t}$ in a given year (from 2009 to 2016) and its value at the base year, 2008. To save notation, let $t \in \{1, \dots, T\}$ with $T = 8$ denote the periods associated with years $\{2008, \dots, 2015\}$.

In order to construct the intertemporal estimators, we need appropriately sized control and "switchers" groups for each level of treatment. Since the explanatory variable Offshore-FRI$_{c,t}$ takes a wide range of values, we create a discretized version Offshore-FRI$^{D}_{c,t}$, of the first difference of Offshore-FRI$_{c,t}$. This variable defines the break-down of the sample into subgroups indexed by the treatement level $r \in \{0, 20, 22.5, 25, 27.5 \dots, 50, 52.5, 55\}$.[26] For example, Offshore-FRI$^{D}_{c,t} = 25$ for county c that faced an increase of at least 25 but less than 27.5 points in the stringency of the offshore regulations by period t compared to the initial level in 2008. The correlation between the original and discretized index is 0.89.

For each level of treatment r, we illustrate the intertemporal difference-in-differences estimators developed in De Chaisemartin and d'Haultfœuille

[26] In our analysis we experiment with finer grids of each two-unit increase in treatment, and coarser grids of every five-unit or ten-unit increase, with no change in the results. The range for the first group is chosen to be the smallest level of treatment, which permits computing the maximal number of long-difference CH placebo tests.

(2021).[27]

$$DiD^{X,+}_{r,t,l} = \sum_{c:F_{c,\neq r}=t-l, I_{c,r}=1} \frac{(\ln \mathrm{N}_{c,t} - \ln \mathrm{N}_{c,t-l-1} - (X_{c,t} - X_{c,t-l-1})'\hat{\gamma})}{O^{\neq r,+}_{t,l}} - \sum_{c:F_{c,\neq r}>t} \frac{(\ln \mathrm{N}_{c,t} - \ln \mathrm{N}_{c,t-l-1} - (X_{c,t} - X_{c,t-l-1})'\hat{\gamma})}{O^{=r}_{t}} \tag{10}$$

$$DiD^{X,-}_{r,t,l} = \sum_{c:F_{c,\neq r}>t} \frac{(\ln \mathrm{N}_{c,t} - \ln \mathrm{N}_{c,t-l-1} - (X_{c,t} - X_{c,t-l-1})'\hat{\gamma})}{O^{=r}_{t}} - \sum_{c:F_{c,\neq r}=t-l, I_{c,r}=0} \frac{(\ln \mathrm{N}_{c,t} - \ln \mathrm{N}_{c,t-l-1} - (X_{c,t} - X_{c,t-l-1})'\hat{\gamma})}{O^{\neq r,-}_{t,l}}. \tag{11}$$

where $O^{\neq r,+}_{t,l}$ denotes the number of counties switching to face stricter regulations than r at period t , $O^{=r}_{t}$ stands for the number of counties with treatment r up to period t and $O^{\neq r,-}$ is the number of counties facing regulations below strictness level r.[28] The estimator $DiD^{X,+}_{r,t,l}$ compares the evolution of log establishments from period $t-l-1$ to t in counties leaving treatment r for the first time in $t-l$ with counties where Offshore-FRI$^{D}_{c,t} = r$ from period 1 to t and counties with a higher level of stringency of AML regulations. The estimator $DiD^{X,-}_{r,t,l}$ compares that evolution with counties with a lower level of stringency. After averaging the estimators over time, we get

$$DiD^{X,+}_{r,l} = \frac{\sum_{t=l+2}^{AT_r} O^{\neq r,+}_{t,l} \cdot DiD^{X,+}_{r,t,l}}{\sum_{t=l+2}^{AT_r} O^{\neq r,+}_{t,l}} \qquad DiD^{X,-}_{r,l} = \frac{\sum_{t=l+2}^{AT_r} O^{\neq r,-}_{t,l} \cdot DiD^{X,-}_{r,t,l}}{\sum_{t=l+2}^{AT_r} O^{\neq r,-}_{t,l}}. \tag{12}$$

[27] Here we illustrate the basic ideas behind the construction of the estimator with a simpler version than the one that is used in the estimation below.

[28] We use similar notation to that in De Chaisemartin and d'Haultfœuille (2021). $F_{c,\neq r} = \min\{t : D_{c,t} \neq r\}$ is the first date at which county c does not receive treatment r (with $F_{c,\neq r} = T+1$ if county c always receives treatment r); $I_{c,r} = \mathbf{I}\{\sum_{t=1}^{T} D_{c,t} > \sum_{t=1}^{T} r\}$ is an indicator variable that takes value 1 if county c received on average more than r units of treatment from period 1 to T; $O^{\neq r,+}_{t,l} = \sum_{c:F_{c,\neq r}=t-l, I_{c,r}=1} 1$ is the number of counties leaving treatment r for the first time at period $t-l$ with $I_{c,r} = 1$ (and $O^{\neq r,-}_{t,l} = \sum_{c:F_{g,\neq r}=t-l, I_{c,r}=0} 1$); $O^{=r}_{t}$ the number of counties with treatment r up to period t. Let $AT_r = \max_c F_{c,\neq r} - 1$ be the last period with a county whose AML regulations treatment has been r since period 1. Note that $\hat{\gamma}$ is the OLS coefficient from the regression of $\ln \mathrm{N}_{c,t} - \ln \mathrm{N}_{c,t-l-1}$ on $(X_{c,t} - X_{c,t-l-1})$.

Finally, after averaging across treatment levels we obtain

$$DiD_l^X = \sum_r \frac{\left(\sum_{t=l+2}^{AT_r} O_{t,l}^{\neq r,+}\right) DiD_{r,l}^{X,+} + \left(\sum_{t=l+2}^{AT_r} O_{t,l}^{\neq r,-}\right) DiD_{r,l}^{X,-}}{\left(\sum_{t=l+2}^{AT_r} O_{t,l}^{\neq r,+} + \sum_{t=l+2}^{AT_r} O_{t,l}^{\neq r,-}\right)}. \qquad (13)$$

The estimator in Equation (13) evaluates the effect of tighter AML regulations on the logarithm of county-year number of establishments in the first period of treatment ($l = 0$) and in later periods ($l > 0$), conditional on controls.

4.2 Baseline Controls

The choice of baseline controls is guided by the theoretical and institutional framework.

County fixed effects control for all observed and unobserved time-invariant characteristics that affect county business activity, including those that may correlate with Offshore-FRI$_{c,t}$. Our treatment Offshore-FRI$_{c,t}$ is a product of time-invariant county-jurisdiction-specific weights, $w_{c,j}$ and jurisdiction-time-specific indexes, SCI$_{j,t}$. These weights potentially may be correlated with time-invariant *county-specific* characteristics. In particular, the formation of links between U.S. counties and Caribbean jurisdictions, and therefore $w_{c,j}$, could depend on unobservable county characteristics, such as the history of criminal activities, regional variations in demand for illicit goods, and the tradition of compliance with laws and regulations. These county features in turn likely affect current BBML. However, such dependence is eliminated by controlling for county fixed effects.

State-year fixed effects control for all observed and unobserved factors that vary across states over time and affect county business activity, including those that may correlate with Offshore-FRI$_{c,t}$. Although the efforts of Caribbean nations to fight FBML are exogenous to U.S. county business activity, the institutional changes that drive them may share commonalities. That is, U.S. efforts to combat ML, both on state and federal levels, are likely to be correlated with those of the Financial Action Task Force, of which the United

States is a member. This possibility suggests the inclusion of state-year fixed effects, which control for both state and federal yearly policy changes.[29]

Finally, our model suggests that business activity depends on per-capita income. We incorporate this effect by including in our regressions county-year lagged log-income and its interaction with the dummy variable for positively exposed counties. This approach permits the influence of income on the number of establishments to differ between exposed and non-exposed locations, in accordance with our analysis in Appendix A.2.

4.3 Threats to Identification

There are several potential threats to the identification of the coefficients β_1 in the linear constant-effects causal relationship model (Equation (8)) and β_2 in the interaction model (Equation (9)).

Identification requires that conditional on the baseline controls, business activity in counties that were exposed to tighter AML regulations would have been on the same trajectory as those not exposed. This assumption may be violated in two cases. First, pre-treatment trends in business activity could differ between exposed and non-exposed counties. We address this issue in an event-study framework in Section 4.4, where we also rule out anticipation effects. Second, local business activity could be affected by the tightening in AML regulations through other county factors that are correlated with the offshore financial regulations index. We deal with this concern in Section 5 by showing that our results are robust to the addition of an array of county-year controls relating to wealth, income, and demographics.

A second identification threat is that our estimates may pick up the effects of tighter AML regulations happening contemporaneously in countries outside the Caribbean sample. These external policy changes could differentially affect activity in our exposed counties. Note that this possibility is highly unlikely, for it would require variations in, say, Eastern European regulations to correlate strongly with those in our sample nations, in terms of both the particular

[29] In the context of the intertemporal estimator we include state-specific trends, as discussed in the Appendix to De Chaisemartin and d'Haultfœuille (2021).

AML standards and the specific implementation years. It would also require a substantial overlap between any county-level financial linkages with, and exposure to, these external nations and those involving our Caribbean-exposed counties, regarding both jurisdictions and annual timing. The intersection of these events is surely small. Nevertheless, we address this concern by estimating regressions in which we replace the offshore financial regulations index with the compliance indexes of each Caribbean country separately, finding consistently positive and significant coefficients. The results are reported in Appendix G.1.

Similarly, De Chaisemartin and d'Haultfœuille (2021) lists the assumptions under which the intertemporal difference-in-differences estimators are identified. Our research design satisfies both the sharp design and non-pathological design assumptions in CH (Assumption 1 and 15, respectively). In Section 4.4.2 we test the validity of the common-trend assumption and rule out statistically significant anticipation effects.

4.4 Event Study

We structure our event study analysis in two steps. We start by testing the parallel-trend and no-anticipation assumptions in the linear model and continue with CH tests in a setup with dynamic effects.

4.4.1 Linear Model

To compare the trends of exposed counties (those that had links to the offshore jurisdictions) to non-exposed counties we use the following specification:

$$\ln N_{t,c} = \alpha_0 + \sum_{i=\{2006,\ldots,2012,2013^+\}} \beta_i \mathbf{1}_{(\sum_{j\in\mathbf{J}} L_{c,j}>0)} \mathbf{1}_{t=i} + X'_{t,c}\gamma + \epsilon_{t,c} \tag{14}$$

Thus, we regress county-year log-establishments on the interaction of the exposure dummy ($\sum_{j\in\mathbf{J}} L_{c,j} > 0$) and year dummies before and after the year 2009, when the CFATF regulations were primarily implemented, conditional

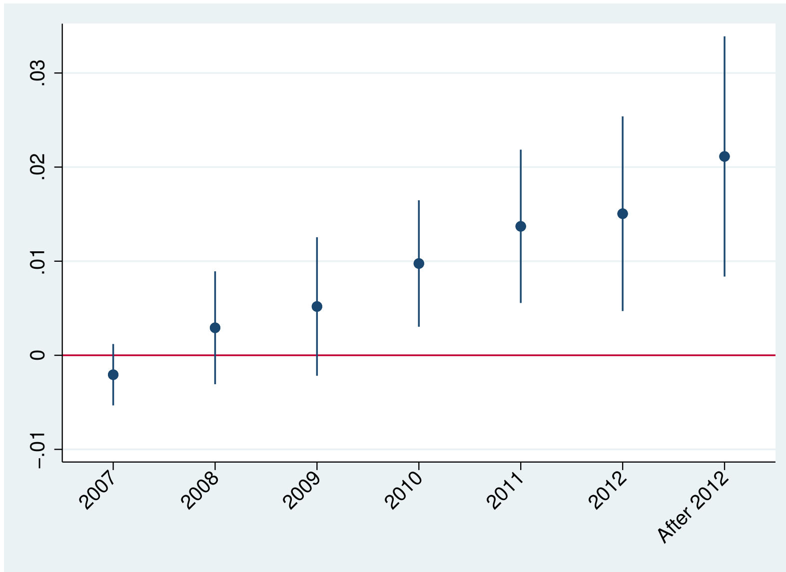

Figure 4: **Parallel-Trend Analysis.** Estimated coefficients (β_i) on the interaction terms between the exposure dummy ($\sum_{j \in \mathbf{J}} L_{c,j} > 0$) and indicator variables for years 2006-2012 and an indicator variable for years 2013 forward, from an OLS regression of county-year log-establishments over these interaction terms and the baseline controls (see Equation (14)). All results are expressed relative to the interaction between the exposure dummy and year 2006. Error bars show 95% confidence intervals. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

on the baseline controls. The years 2013-2015 share the same dummy (and are denoted by 2013^{+}).[30] Figure 4 reports the estimated coefficients on the interaction terms, expressed relative to the interaction between the exposure dummy and year 2006. Coefficients are insignificant before 2009, suggesting that there were no differences in pre-treatment trends between exposed and non-exposed counties and showing little evidence of any anticipatory response in U.S. counties. While positive, the coefficient in 2009 was also insignificant at the five-percent level, suggesting it may have taken time for the policy to build up its effect, which is consistent with our treatment variable increasing over time. Subsequent coefficients indeed become significant and increasingly

[30]Our selection of a three-year-prior window matches the maximum common-trends that could be estimated using the long-difference placebo tests developed by CH, and discussed in Section 4.4.2. For a similar specification of the parallel-trend analysis, although in a different context, see Autor (2003).

positive, a finding that motivates our intertemporal treatment-effect analysis in Section 7.

4.4.2 Intertemporal Treatment-Effects Model

We test the common-trends and no-anticipation effects assumptions using the placebo estimators developed in De Chaisemartin and d'Haultfœuille (2020, 2021). Table 2 reports the results.

Table 2: Event Study: Long-difference and First-Difference Placebos

	Long-Diff Estimator			**First-Diff Estimator**		
l	$DiD_l^{X,pl}$	LB CI	UB CI	$DiD_l^{X,fpl}$	LB CI	UB CI
0	.0022	-.0038	.0081	-.0002	-.0006	.0002
1	.0065	-.0145	.0275	-.0001	-.0006	.0004
2	.0036	-.0152	.0224	-.0002	-.0007	.0003

Note. Long-difference $DiD_l^{X,pl}$ and first-difference $DiD_l^{X,fpl}$ placebo estimators and their respective lower bound (LB CI) and upper bound (UB CI) of the 95% confidence intervals. The outcome variable is county-year log-establishments and the treatment variable is the discretized version Offshore-$\text{FRI}_{c,t}^{D}$ of Offshore-$\text{FRI}_{c,t}$. The estimators are computed as described in De Chaisemartin and d'Haultfœuille (2021) using the Stata `did_multiplegt` command, conditional on the baseline controls: state-specific linear trends, lagged log real personal income and its interaction with exposure dummy. Confidence intervals use standard errors which are estimated using 100 bootstrap replications clustered at the county level. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

First, we construct the long-difference placebo estimators $DID_{+,l}^{pl}$ with $l \in \{0, 1, 2\}$,[31] to test whether the common-trends assumption holds for up to 3 periods. Table 2 shows that the coefficients are small and not statistically different from 0 at the 5% level. In addition, the F-test cannot reject the null hypothesis that all placebo estimates are statistically equal to zero (p-value=0.90). These tests are more powerful than the first-difference placebo

[31] Some of our counties do not have links to offshore jurisdictions (Table 1). Hence, they remain untreated ($r = 0$) from period 1 to period $T = AT_0 = 8$ and can be used as controls. Accordingly, the largest number l of placebo tests that can be performed is the integer part of $(8 - 3)/2$, implying $l = 2$ (De Chaisemartin and d'Haultfœuille (2020)).

tests, which only test for trends over pairs of consecutive periods. Yet, the first-difference estimators provide insights on whether there has been an anticipation effect. Table 2 shows that the coefficients on the first-difference estimators are not significant at the 5% level, indicating that there were no anticipation effects.

5 Linear Model Estimates

We begin by estimating the empirical model in Equation (8), under various specification. Table 3 reports OLS estimates of the key coefficient of interest, β_1, which measures the effect of AML regulations on business activity and, implicitly, on BBML. As a benchmark, Column (1) reports this coefficient in a simple OLS regression. We find a significantly positive effect of the policy index on establishments, but this coefficient is biased in the absence of controls.

Column (2) reports estimates of our main specification, which includes the baseline controls discussed earlier. The coefficient implies that the strengthening of AML regulations by Caribbean jurisdictions over the period 2008-2015 caused, on average, an increase of 1.7%[32] in the number of business establishments in exposed U.S. counties. By Proposition 2 this is a lower bound for the semi-elasticity of the BBML. We conclude that stricter AML regulations in Caribbean jurisdictions caused, on average, an increase in BBML-acquired establishments of at least 1.7% in exposed counties.

Column (3) indicates that the coefficient estimate on Offshore-FRI is immune to introducing other covariates, as its value is very close to that in the baseline model in Column (2), after controlling for county-specific, time-varying economic measures, demographic factors, and the income and wealth indicators. The first group of additional controls includes median household income, median house value, share of county personal income earned as dividends, interests and rents, and share of residents who are homeowners. These

[32] This estimate is obtained by multiplying the estimated coefficient on Offshore-FRI (Column (2)) by the 2008-2015 change in average Offshore-FRI in exposed counties, Δ_{15-08}. That is, $\beta_1 * \Delta_{15-08} = .0003856 * 44.14296 \approx 1.7\%$.

Table 3: Effect of AML regulations on Business Activity.

	OLS	Baseline	All	Discretized
	(1)	(2)	(3)	(4)
Offshore-FRI	0.02301***	0.00039***	0.00036***	0.00036***
	(0.00057)	(0.00009)	(0.00009)	(0.00009)
Log Income		0.20545***	0.19167***	0.20476***
		(0.03085)	(0.02435)	(0.03084)
Log Income x Exposed		0.09898**	0.06883	0.10158**
		(0.04501)	(0.04227)	(0.04531)
Constant	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes
State x Year FE	No	Yes	Yes	Yes
Income/Wealth Controls	No	No	Yes	No
Socio-Demographic Controls	No	No	Yes	No
Observations	24,656	24,648	24,648	24,648
R^2	0.375	0.999	0.999	0.999

Regression coefficients, Standard error clustered at county level in parenthesis.

Note: OLS regression estimates of the logarithm of the number of establishments on: *(i)* Offshore Financial Regulation Index (and its discretized version in Column (5)); *(ii) Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j\in\mathbf{J}} L_{c,j} > 0$); *(iii) County-Year Income and Wealth Controls*: log real median household income, log real median house value, share of real personal income attributed to unemployment insurance, share of real personal income attributed to dividends, interest, and rent, unemployment rate, share of residents in poverty, share of residents who are homeowners. *County-Year Socio-Demographic Controls*: *(a) Ethnicity*: share of residents with Hispanic origin; *(b) Race*: share of Black or African-American; American-Indian or Alaska-Native; and Asian residents. Omitted group: share of White residents, Native-Hawaiian or Other-Pacific-Islander residents, and those of two or more races. *(c) Education*: share of residents with high school diploma. All control variables are lagged. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

variables account for income and wealth variations across counties that may correlate with county business development. The second group includes the share of county personal income from unemployment compensation, the unemployment rate, and the share of households in poverty. These factors control for different facets of poverty. A third group, controlling for socio-demographic characteristics, includes Census-defined categories of ethnicity (Hispanic or non-Hispanic) and race, along with the share of county population with a high-school diploma. The full regression results are in Table 12 in Appendix F. The robustness of the primary coefficient to these controls eases concerns that business activity was affected by other factors that are correlated with the offshore financial regulations index and supports our identification approach.

Finally, Column (4) reports estimates of our baseline model after replacing $\text{Offshore-FRI}_{c,t}$ with its discretized version $\text{Offshore-FRI}^{D}_{c,t}$. This last exercise shows that our discretization does not affect our main findings and can be reliably used in the intertemporal treatment-effect analysis in Section 7.

Robustness. In Appendix G we perform several relevant robustness checks. First, we show that our results are robust to replacing our AML financial regulations index, Offshore-FRI, with the compliance status measure, $\text{SCI}_{j,t}$, for each jurisdiction separately. These alternative instruments shed light on the national sources of identifying variation in addition to providing external validity. A further reason for estimating these regressions, as noted above, is to ease concerns that our estimates may reflect the impacts of AML regulations in countries outside the Caribbean sample. The probability of such coincidence is surely small. Nonetheless, the fact that our baseline coefficients remain positive and significant when using individual compliance measures in our sample raises confidence that Caribbean regulations are indeed what drive our findings through county linkages. We further ease concerns about selection issues by repeating this analysis in the sample of exposed counties.

Second, we show that our baseline model results are robust to using more disaggregated data involving production sectors within counties. In this context, we show that our results hold when we replace county-fixed effects with sector-county fixed effects. Third, we consider an alternative clustering of the regression errors at the state level to capture within-state correlations across counties and the results remain intact. Fourth, we explore the role of the financial crisis, by omitting the year 2008 and adding county-specific trends that could vary with demographic characteristics and poverty at the onset of the crisis in 2008. Results still hold, easing concerns that the response dynamics of business activity to the financial crisis may have depended on such initial characteristics.

In summary, we find robust evidence that when Caribbean nations that host offshore financial accounts strengthen their AML regulations, there is a positive and significant impact on business establishments in exposed U.S. counties, indicative of a shift from FBML to BBML.

6 Heterogenous Effects

The effect of AML regulations on BBML could vary across counties. In particular, it may depend on county characteristics that affect the marginal cost of money laundering, such as access to FBML services and industry mix. In the following sections, we examine the role of key characteristics that are likely important in this regard, including exposure to international networks of money-laundering services, detailed sectoral output composition, and geographical location.

6.1 Differential Exposure to Illicit Networks

A key county characteristic that may affect the marginal cost of FBML is the differential access to international networks linking criminal activity to money-laundering services.

The 2019 National Drug Threat Assessment[33] identifies four most prominent Transnational Criminal Organizations (TCO): the Mexican, Colombian, Dominican and East-Asian TCOs (the last consisting mostly of groups from China and Hong Kong). The DEA underscores the key role played by Asian TCOs in assisting the other TCOs in the money laundering process. 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

[33] *Source:* https://www.dea.gov/sites/default/files/2020-01/2019-NDTA-final-01-14-2020_Low_Web-DIR-007-20_2019.pdf, retrieved on November 1, 2020.

provide." (p. 122). According to the report, TCOs operations rely on local criminal groups of *related origin*.[34]

This evidence points to *observable* county demographic composition as an important source of variation in the marginal cost of laundering money and revenues from illicit activities. Table 17 in Appendix H.1 shows that counties with relatively larger population shares of Asian and Hispanic origin have significantly greater responsiveness of establishments to international AML regulations.[35]

Importantly, the NDTA assessment points at international money laundering networks as a key connection between the East Asian TCOs and the U.S.-Caribbean links analyzed above: "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." (p. 108).

To identify this potential East Asian TCO channel, we extract the subnetwork of direct and indirect links between U.S. and the Caribbean jurisdictions with connections via China and Hong Kong. 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. We refer to this sub-network as the East Asian network. Table 18 in the Appendix confirms the presence of a substantial number of

[34]The emphasis is added by the authors. According to the document, the Mexican TCOs "work with smaller local groups and street gangs of Hispanic origin [...] to handle retail-level distribution," (p. 102). Similarly, the "Asian TCOs collaborate with and recruit Asian-Americans, blending into existing immigrant communities, to exploit U.S. drug markets" (p. 108).

[35]These results could be consistent with the possibility that counties with larger Asian or Hispanic shares have higher average incomes or invest more in new legitimate businesses. However, inclusion of lagged county incomes controls for the former case, while county fixed effects neutralize the latter tendency. Moreover, neither hypothesis squares with the significantly positive interaction terms, suggesting additional factors may be at work.

indirect links there. Using this subnetwork, we construct our explanatory variable Offshore-FRI$_{c,t}$ following the same steps as described above for the original database.

Table 4: Effect of AML recommendations on Business Activity via Exposure to Asian Intermediaries

	(1) Full Network	(2) Asian Network	(3) Full Network	(4) Asian Network
Offshore-FRI	0.00039***	0.00167***	0.00008	0.00074***
	(0.00009)	(0.00020)	(0.00009)	(0.00024)
Offshore-FRI × Share of Asian			0.00013***	0.00012***
			(0.00002)	(0.00004)
Share of Asian			0.00907	0.01630***
			(0.00633)	(0.00595)
Constant	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes
Observations	24,648	24,648	24,648	24,648
R^2	0.999	0.999	0.999	0.999

Regression coefficients, Standard error clustered at county level in parenthesis.

Note: OLS regression estimates of county-year logarithm of the number of establishments on: *(i)* Offshore Financial Regulation Index; *(ii) Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j \in \mathbf{J}} L_{c,j} > 0$); *(iii) Socio-Demographic Controls*: lagged share of Asian residents. *(iv) Interaction Terms*: interaction of Offshore Financial Regulation Index with lagged share of Asian residents. *Data Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

In Table 4, we juxtapose our baseline estimates (Full Network) with those obtained using the East Asian network links. Column (1) repeats the estimate of β_1 from Column (3) of Table 3. Column (2) shows that the direct effect is approximately four times larger in the East Asian Network than in this baseline case. Columns (3) and (4) show that this effect is also an order of magnitude larger in the interaction model. Crucially, the effect increases with the share of Asian residents, as measured by the coefficient β_2 in Equation (9). Thus, although we have no direct evidence suggesting involvement of any entity in the network in money-laundering activities, we can draw some indirect conclusions. Those U.S. counties with connections to East Asian intermediaries had a stronger increase in business activity in response to the tightening of AML regulations in Caribbean countries. Such counties, potentially, had access to cheaper FBML services provided by the intermediaries in the network and, hence, invested more in offshore entities. As a result, they were more exposed to financial regulations against FBML in CFATF jurisdictions, inducing a stronger rerouting of illicit proceeds into BBML.

6.2 Differences across Economic Sectors

A further source of heterogeneity in estimated effects lies in the industry mix of establishments across counties. One would expect BBML activity to be concentrated in sectors where starting up a business is easy and where revenues can be generated quickly. To explore this insight we estimate the interaction model in Equation (9) on a more granular database with sector-county-year observations. Hence, we interact Offshore-FRI$_{c,t}$ with time-invariant indicator dummies for the two-digit NAICS industries to which establishments are assigned by the BEA. In Figure 5 we display the estimated interaction coefficients by industry, along with the 95% confidence intervals around them. The coefficient estimates for primary industries and manufacturing are essentially zero, indicating that they are not acquired for purposes of BBML. In contrast, the highest and most significant estimates are found in retail trade, real estate, professional services, and accommodation and food services, suggesting these are the most vulnerable areas. Most of these are industries with relatively low fixed setup costs and somewhat higher marginal or operational costs, compared with manufacturing.

6.3 The Geography of BBML

A final source of heterogeneity in BBML we explore is the location of counties within the United States. We estimate our main regression Equation (8) in each of the nine U.S. Census divisions separately. In Table 19 in Appendix H.2, we observe notable regional variations of our estimates for the sensitivity of business activity to changes in Caribbean AML regulations. Unsurprisingly,

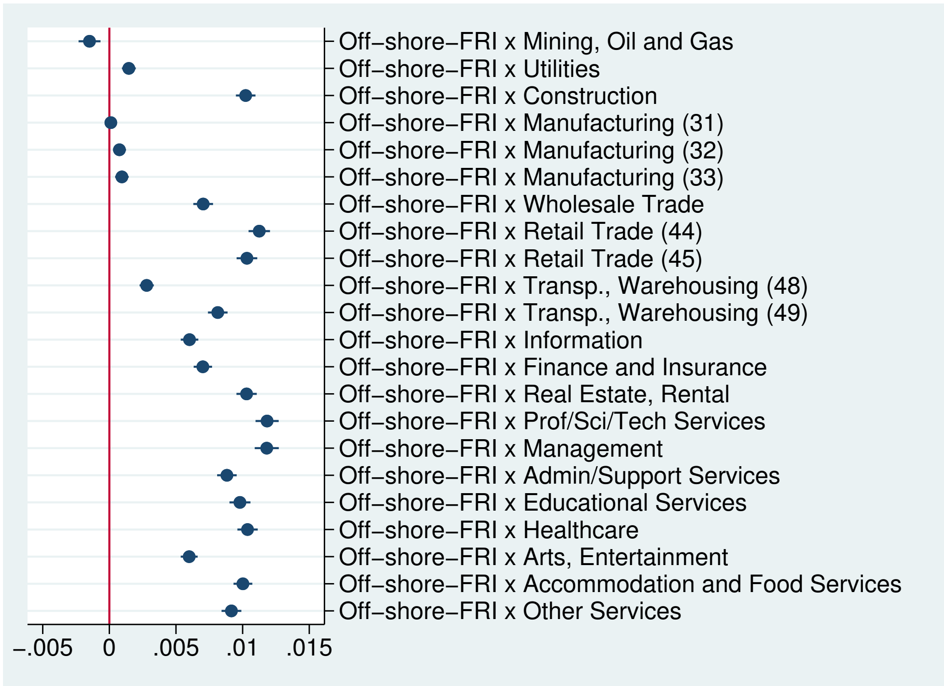

Figure 5: **Sectors at Risk of Money Laundering.** Estimated coefficients of the interaction terms between the index of exposure to offshore financial regulations (Offshore-FRI$_{c,t}$) and two-digit NAICS dummies, from the OLS regression of sector-county-year logarithm of the number of establishments on: *(i)* Offshore Financial Regulation Index; *(ii) Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j\in\mathbf{J}} L_{c,j} > 0$); *(iii)* two-digits NAICS dummies; *(iv)* interaction of Offshore Financial Regulation Index with two-digit NAICS dummies. *Data Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

we find the strongest effects in the Census divisions with larger metropolitan areas, as well as those in coastal and border areas. Accordingly, as laundering money via offshore FBML becomes more costly, we expect the rerouting of dirty money from FBML to BBML to be more prevalent in counties located within such regions.

7 Intertemporal treatment-effects

The effect of AML financial regulations on BBML may build gradually over time for several reasons. It may take time for the enforcement of new AML regulation to be implemented. In addition, it may take time for criminal enterprises to reorganize their money-laundering network and redirect resources from FBML to BBML. To explore this idea, we estimate the intertemportal treatment effects of stricter AML regulations on business activity, using the procedure developed in De Chaisemartin and d'Haultfœuille (2021).

We start by describing the evolution of our treatment, Offshore-FRI$^{D}_{c,t}$. The index equals 0 in every county in 2008, consistent with the beginning of the mutual-evaluation process. A total of 2120 counties in our sample remain untreated (Offshore-FRI$^{D}_{c,t} = 0$) and are always part of the control group. Next, 960 of the remaining 962 counties experience the first switch before 2012, 836 of which happened in 2009.[36] Table 20 in Appendix I displays the transition of counties across the different treatment groups.

The maximum number of dynamic effects we can compute using the CH procedure is 6 (the periods in our sample $T = 8$ minus 2). Accordingly, Figure 6 reports $DiD^{X,D}_{l}$ with $l \in \{0, 1, \ldots, 6\}$, which measures the average increase in AML regulations when a county first gets treated ($l = 0$) and successive periods ($l > 0$), conditional on the baseline controls.[37] On average, the AML regulations index increases by $DiD^{X,D}_{0} = 29.37$ points when a county first deregulates ($l = 0$), while 6 years after the first treatment the index peaks to an average of $DiD^{X,D}_{6} = 49.15$. The latter is associated with the 836 counties that experience the first increase in 2009.

Finally, Figure 7 reports on the right of period 0 the intertemporal treatment-effects estimators, DiD^{X}_{l} with $l \in \{0, 1, \ldots, 6\}$ and on the left of period 0 the mimicking long-difference placebo estimators $DiD^{X,pl}_{l}$ discussed in Section

[36] Because of the discretization procedure of the AML regulation index, the number of treated counties ($r > 0$) is reduced from 1046 to 962 (Table 1).

[37] $DiD^{X,D}_{l}$ is computed as in Equation (13), after replacing (recursively) the outcome $\ln \mathrm{N}_{c,t}$ with the treatment Offshore-FRI$^{D}_{c,t}$ in Equations (10), (11), and (12).

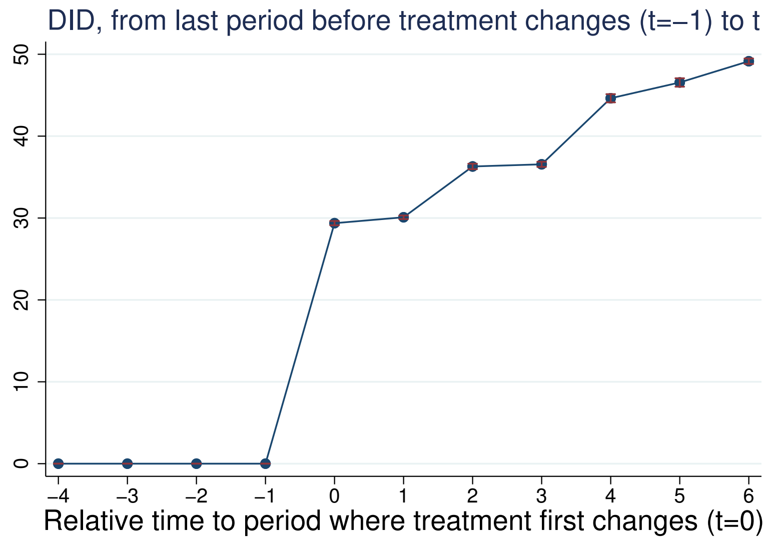

Figure 6: **Strictness of AML regulations, before and after first treatment.** The figure reports, to the right of zero, the average increase in AML regulations when a county first gets treated ($l = 0$) and successive periods ($l > 0$), $DiD_l^{X,D}$. The long-difference placebo estimators equal zero by construction to the left of 0. The outcome variable and treatment variable are both Offshore-FRI$_{c,t}^{D}$. The estimators are computed using the Stata `did_multiplegt` command, conditional on the baseline controls: state-specific linear trends, lagged log real personal income and its interaction with the exposure dummy. Standard errors are estimated using 100 bootstrap replications clustered at county level. 95% confidence intervals are reported in red. *Data Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

4.4.2.[38] The coefficients in Figure 7 show the effect of tighter AML regulations on the logarithm of county-year number of establishments in the first period of treatment ($l = 0$) and in later periods ($l > 0$), conditional on the baseline controls. The estimators suggest that the effect of stricter AML regulations on BBML progressively increases over the years after the first switch, and becomes statistically significant after one year. The effect peaks after 6 years at $DiD_6^X = 2.6\%$.

[38]The mimicking long-difference placebo estimators $DiD_l^{X,pl}$, $l \in \{0, 1, 2\}$ in Table 2 are associated respectively with $z = \{-2, -3, -4\}$ on the horizontal axis. The Stata `did_multiplegt` normalizes the placebo effect at $z = -1$ to zero.

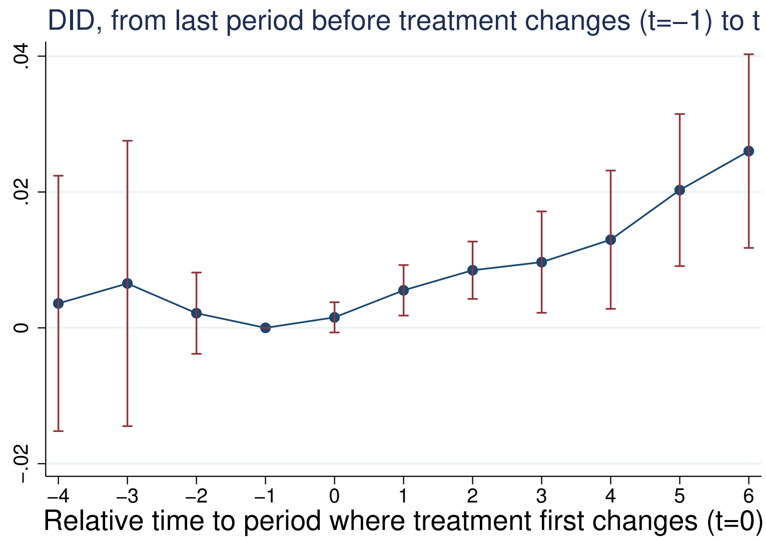

Figure 7: **Intertemporal effects of stricter AML regulations on business activity.** The figure reports, to the right of zero, the DiD_l^X estimates of the effect of tighter AML regulations on the logarithm of county-year number of establishments in the first period of treatment ($l = 0$) and in later periods ($l > 0$), according to Equation (13). The placebo estimator is normalized to zero at $x = -1$. The long-difference placebo estimators $DiD_l^{X,pl}$, $l \in \{0, 1, 2\}$ in Table 2 are associated respectively with $z = \{-2, -3, -4\}$ on the horizontal axis. The outcome variable is county-year log-establishments and the treatment variable is Offshore-FRI$^D_{c,t}$. The estimators are computed using the Stata `did_multiplegt` command, conditional on the baseline controls: state-specific linear trends, lagged log real personal income and its interaction with exposure dummy. Standard errors are estimated using 100 bootstrap replications clustered at county level. 95% confidence intervals are reported in red. *Data Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

Importantly, the instantaneous and dynamic effects estimated by DiD_l^X are not normalized by the stringency of AML regulations, which gradually increases over time. By dividing the average of the intertemporal effects DiD_l^X by the average of the increase in treatment $DiD_l^{X,D}$, De Chaisemartin and d'Haultfœuille (2020) show how to construct a measure of the average effect per unit of treatment. We find that on average a one-unit increase in the index of AML regulations produces a 0.03% increase in business activity, across all instantaneous and dynamic effects (statistically significant at 1%). This estimate can be directly compared with our baseline estimates. Our dynamic estimator accounts for 76% of the estimated effect in Column 2 of Table 3. Accordingly, the CH estimators find that stricter AML regulations in Caribbean jurisdictions caused, on average, an increase in BBML-acquired establishments of at least 1.34% in exposed counties.

Column (5) in Table 3 shows that a third of the difference between the linear causal model estimate (0.039%) and the CH period-average estimate (0.03%) is accounted for by the discretization Offshore-$\mathrm{FRI}^{D}_{c,t}$ of our treatment variable, Offshore-$\mathrm{FRI}_{c,t}$. We attribute the rest to the difference in control groups, which change dynamically in the CH procedure, and state-specific trends.

8 External Validation of our Mechanism

Despite the fact that our results are robust, doubts may remain about the mechanism we propose, in which foreign regulatory tightening aimed at raising the cost of FBML induces substitution into BBML at the county level. We provide external validation in two ways. First, we show that CFATF regulatory changes reduce the creation of offshore financial vehicles, supporting the first part of the mechanism. Second, we demonstrate that asset decisions involving publicly listed firms, a strong proxy for legitimate businesses, are not affected by stronger AML regulations, supporting the idea that our method identifies shady activity.

8.1 The Effect of AML Regulations on FBML

In the model, anti-money laundering regulations squeeze the financial-channel yield, diverting dirty money from FBML to BBML. For this substitution to work, it must be that the CFATF regulations in fact reduce FBML, indirectly corroborating Assumption 1. In the absence of a direct measure of offshore account transfers, we operationalize this idea by using the jurisdiction-year number of offshore entities in the ICIJ Offshore Leaks database as an extensivemargin proxy for the stock of funds invested in potentially money-laundering vehicles. Hence, we regress the jurisdiction-year log number of offshore entities on the yearly Status-of-Compliance Index, which is defined in Equation (5).

$$\ln \text{Offshore-Entities}_{j,t} = \gamma \text{SCI}_{j,t} + \delta \text{GDP growth}_{j,t} + \underline{d}_j + \underline{d}_t + \varepsilon_{j,t}$$

We include GDP growth to account for the natural impact of economic size on entities, along with country and year fixed effects. The coefficient γ estimates the average percentage change in offshore vehicles due to a tightening in AML regulations in the Caribbean jurisdiction, conditional on these controls.

Table 5 presents the results. In Column (1) we find a negative but insignificant coefficient. However, the coefficient becomes statistically significant when we exclude Anguilla and thereby restrict the sample to countries that started the mutual-evaluation process before 2009, when the bulk of the regulatory shock in the Caribbean Islands happened. Due to the absence of a control group, these results do not have a causal interpretation. Yet, they provide suggestive indirect evidence that such policy changes are associated with a reduction in FBML.

Table 5: Effect of AML regulations on FBML.

	All Jurisdictions	No Anguilla	No Anguilla - Controls
	(1)	(2)	(3)
Status of Compliance Index	-0.00038	-0.00350*	-0.00287**
	(0.00383)	(0.00156)	(0.00092)
Constant	Yes	Yes	Yes
Jurisdiction FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Real GDP growth	No	No	Yes
Observations	47	41	41
R^2	0.993	0.999	0.999

Note: OLS regression estimates of log Offshore-Entities on: *(i)* Status-of-Compliance Index ($\text{SCI}_{j,t}$); *(ii)* jurisdiction and year fixed effects; *(iii)* jurisdiction-year real gdp growth. *Data Source*: CFATF, ICIJ, United Nations. *Sample period*: 2008-2015.

8.2 AML Regulations and Publicly Listed Firms

We use the geographical information in the Compustat Database (Historical Segment) to restrict the sample of publicly listed firms to those with reported assets in the United States. These assets are defined as property, plant and equipment (PPE), 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 PPE on the index of exposure to offshore financial regulations (Offshore-FRI$_{c,t}$), conditional on the baseline controls (after replacing county fixed effects with firm-specific fixed effects).

Column (1) in Table 6 shows that the coefficient on Offshore-FRI$_{c,t}$ is insignificant, indicating that the real investment decisions of Compustat firms are not affected by stronger AML regulations targeting the financial sector in Caribbean countries. A clear concern here is that larger firms in the data may have their establishments spread across the United States, so that attribution of PPE to the headquarters county is a mismeasurement. Thus, we also estimate the equations after splitting the Compustat sample into quartiles of the PPE size distribution in the year 2008. Columns (2)-(5) in Table 6 confirm that the estimated effect is insignificant across all size groups, including small firms.

The fact that the volume of physical assets owned by listed firms is insensitive to AML regulations, whereas the number of county establishments in exposed locations is sensitive, supports the idea that our approach identifies substitution of illicit funds into BBML.

Table 6: Effect of AML regulations on Publicly Listed Firms Assets.

	All	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
	(1)	(2)	(3)	(4)	(5)
Offshore-FRI	0.00071	0.00208	0.01725	0.00080	-0.00143
	(0.00362)	(0.02633)	(0.01335)	(0.00348)	(0.00372)
Constant	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Observations	7,389	995	1,359	1,470	1,618
R^2	0.977	0.851	0.848	0.868	0.951

Regression coefficients, Standard error clustered at county level in parenthesis.

Note: OLS regression estimates of firm-year logarithm of property plant and equipment on: *(i)* Offshore Financial Regulation Index; *(ii) Baseline controls*: firm ($\underline{d}_i$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j \in \mathbf{J}} L_{c,j} > 0$). Column (1) reports estimates on the entire sample. Column (2)-(5) reports estimates when the sample is restricted to the firms with values of PPE belonging to the respective quartile of the distribution in 2008. *Data Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division, Compustat. *Sample period*: 2008-2015.

9 Conclusions

Profits from illicit activities percolate into the legal economy through several channels for laundering money. These activities are virtually impossible to detect directly, as they are not reported to the authorities and tend to adapt to changing AML regulations and enforcement strategies. We develop and implement a theoretically-grounded identification strategy that uses publicly available micro-data to indirectly quantify an important trace: the increase in business-based money laundering induced by stricter regulations of financial-based money laundering. In doing so, we provide the first evidence of this process in the United States.

We introduce a money-laundering technology into a monopolistic-competition model and prove that AML regulations that increase the cost of FBML boost the number of overall and BBML-established firms. Because the latter relative impact is greater due to a crowding-out effect, an estimate of the semi-elasticity of overall business activity provides a lower bound for that of BBML. To test this prediction, we construct a measure of the exposure of each U.S. county to changes in anti-money-laundering regulations in Caribbean jurisdictions using CFATF evaluations and ICIJ leaks data. We use this index in econometric models designed to quantify the response of business activity in specific locales, which, according to our model, can be attributed to BBML.

In a linear causal regression model, we find that the average exposed county saw an increase of at least 1.7% in BBML-established establishments as a consequence of stronger regulations in the financial sector. We also document considerable heterogeneity in the substitution elasticity between FBML and BBML, depending on county characteristics. These differences are evidently related to international money-laundering networks and industry features that facilitate BBML. Finally, because these effects may take time to build up, we supplement this analysis by estimating intertemporal treatment effects. We find the effect to gradually cumulate over time, peaking after 6 years from the first treatment to 2.6%. Our results are robust to an array of additional specifications and consistent with additional evidence providing external validation.

This line of research could be extended in fruitful directions in the future. For example, the empirical analysis could incorporate regional spillover effects by allowing the illicit enterprise to choose neighboring counties for BBML if doing so is profitable. We conjecture that there should be an increase in BBML in counties near those exposed to stricter external financial regulations, especially if the local AML enforcement is weak. Such research would provide initial evidence on the geographic breadth of money-laundering networks. More broadly, our analysis could be extended beyond analyzing the impacts on U.S. counties of regulatory reforms in Caribbean economies. The Financial Action Task Force has produced recommendations for regulatory changes in many additional countries reputed to be havens for money laundering, such as Panama and Luxembourg. Localities in several countries beyond the United States, including Canada and members of the European Union, likely are exposed to such changes. Accordingly, they would be candidates for this analysis and would offer additional heterogeneity to refine estimates of the substitution between money-laundering channels.

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Appendix

Table 7: **List of Acronyms**

AML	Anti-money-laundering
BLS	Bureau of Labor Statistics database
BBML	Business-based money laundering
CFATF	Caribbean Financial Action Task Force
FATF	Financial Action Task Force
FBML	Financial-based money laundering
ICIJ	International Consortium of Investigative Journalists
SCI	Caribbean Jurisdictions Status-of-Compliance Index

A Theory

A.1 Equilibrium Description and Proofs of the Main Results

Lemma 1. *Let $\gamma = \frac{M}{N}$ be the fraction of CE-financed firms. If $V'(E) \geq \alpha$, then the CE invests in BBML only and so $\gamma^* = \frac{E}{(f+c\bar{q})N}$, which is independent of φ for any fixed N. Otherwise, CE uses both ML channels and*

$$\gamma^* = \frac{1}{2}(1 - \alpha(\varphi)\frac{f + c\bar{q}}{\bar{p}\bar{q}}) \tag{15}$$

Proof. Recall that the optimization problem of the CE is

$$\max_{0 \leq z \leq E} \alpha(\varphi)[E - z] + V(z) \tag{16}$$

$$V(z) = \left(1 - \frac{M}{N}\right) M\bar{p}\bar{q}, \quad M = \frac{z}{f + \bar{q}c} \tag{17}$$

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 $\bar{\pi} = f$, so optimal investment in BBML, z, is strictly positive. If $V'(E) \geq \alpha$, the CE invests only in BBML, $z = E$. Otherwise, there is an interior optimum, where $V'(z) = \alpha$, since V is increasing and concave. The optimality condition requires

$$(1 - 2\gamma(z))\gamma'(z)N\bar{p}\bar{q} = \alpha(\varphi) \implies \tag{18}$$

$$(1 - 2\gamma^*)\frac{\bar{p}\bar{q}}{f + c\bar{q}} = \alpha(\varphi) \implies \frac{1}{2}(1 - \alpha(\varphi)\frac{f + c\bar{q}}{\bar{p}\bar{q}}) = \gamma^* \tag{19}$$

□

Equilibrium Description. In the main text we have provided a partial description of a symmetric equilibrium where all the production firms are choosing the same quantity of output. This part of the characterization follows the same line of argument as in Parenti et al. (2017). This was done in order to present the problem of the criminal enterprise. 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 $z = M(f + c\bar{q})$ to local workers. This payment, effectively, reduces the amount that the local consumers owe to CE for illicit goods, as by working in CE-owned firms they produce not only additional varieties, but also the "clean revenues" for the CE. To sum up, 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 BBML firms owned by CE, expending $cM\bar{q} + fM$ units of labor there. Third, they dedicate some of the resources to repay the rest of the illicit goods, $E - z$.[39]

$$nf + nc\bar{q} + cM\bar{q} + fM = Ly - (E - z) \tag{20}$$

Therefore we can solve for a quantity produced by each firm:

$$\bar{q} = \frac{Ly - E}{c(N - M)} - \frac{f}{c} \tag{21}$$

[39]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.

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.[40]

Combining the definition of $\bar{\pi}$ and firms' pricing decisions from Equation (1), we get the free-entry condition,

$$c\bar{q} = f(\sigma(\bar{q}, N) - 1) \tag{22}$$

Substituting the equilibrium quantity $\bar{q}$ produced by each firm from Equation 21, we get

$$\sigma(\bar{q}, N)(N - M) = \frac{Ly - E}{f} \tag{23}$$

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 CE will choose to purchase $M^* = N\gamma^*(\varphi)$ firms for BBML, where $\gamma^*(\varphi) = \frac{1}{2}(1 - \alpha(\varphi))$. It is easy to see that in this case an increase in φ decreases α by Assumption 1, which increases γ^*.[41]

To sum up, the equilibrium is satisfies the following conditions.

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

$$N\sigma(\bar{q}, N)(1 - \gamma^*(\varphi)) = \frac{Ly - E}{f}, \text{ where} \tag{24}$$

$$\bar{q} = \frac{Ly - E}{cN(1 - \gamma^*(\varphi))} - \frac{f}{c} \tag{25}$$

[40] 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, under the free entry, $\bar{\pi} = f$.

[41] In our specification $V(z) = Nv(\gamma(z))$, where $v(\gamma) = (1 - \gamma)\gamma\bar{p}\bar{q}$. The particular form of v is immaterial. For the proof to go through it is sufficient for v to be differentiable, concave in γ and satisfy $Nv'(0) > \alpha$.

Otherwise, none of the equilibrium variables depend on φ:

$$\sigma(\bar{q}, N)(N - \frac{E}{f + c\bar{q}}) = \frac{Ly - E}{f}, \text{ where} \tag{26}$$

$$\bar{q} = \frac{Ly - E}{c(N - \frac{E}{f + c\bar{q}})} - \frac{f}{c} \tag{27}$$

Note that the inequality distinguishing the two cases can be formulated using a well-defined threshold α_0, because the equilibrium value of N and parameter α are negatively related, as we show in Proposition 1. As a result, the left-hand side of the inequality decreases in α.

Proof of Proposition 1. If $V'(E) < \alpha$, that is, if

$$1 - 2\frac{E}{N(f + c\bar{q})} < \alpha \tag{28}$$

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 φ at a given equilibrium point,[42] using the implicit function theorem,

$$\frac{dN}{d\varphi}|_{N,\varphi} = -\frac{\frac{\partial F(N,\varphi)}{\partial \varphi}}{\frac{\partial F(N,\varphi)}{\partial N}} \tag{29}$$

The derivatives evaluated at the equilibrium are as follows.

$$\frac{\partial F}{\partial \varphi} = \frac{N}{2}\sigma(\cdot)\alpha'(\varphi) + \frac{\partial \sigma(\cdot)}{\partial q}\frac{\partial q(\cdot)}{\partial \alpha}\alpha'(\varphi)\frac{N}{2}(1 + \alpha(\varphi)) \tag{30}$$

$$\frac{\partial F}{\partial N} = \frac{1}{2}(1 + \alpha(\varphi))\sigma(\cdot) + \big(\frac{\partial \sigma(\cdot)}{\partial N} + \frac{\partial \sigma(\cdot)}{\partial q}\frac{\partial q(\cdot)}{\partial N}\big)\frac{N}{2}(1 + \alpha(\varphi)) \tag{31}$$

By Assumption 2, $\frac{\partial \sigma(\cdot)}{\partial q} \leq 0$. Direct computation shows that $\frac{\partial q(\cdot)}{\partial \alpha} < 0$. By

[42] The reference to the equilibrium point will be dropped thereafter.

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 α is too low, so that inequality (28) is violated, then α and hence, φ have no effect on the equilibrium N. □

Proof of proposition 2. 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

$$\frac{M'(\varphi)}{M} = \gamma^*(\varphi)\frac{N'(\varphi)}{M} + (\gamma^*)'(\varphi)\frac{N}{M} > (\gamma^*)(\varphi)\frac{N'(\varphi)}{M} = \frac{N'(\varphi)}{N} \tag{32}$$

If $V'(E) \geq \alpha$ neither N nor M are affected by φ. □

A.2 The effect of an increase in income

We use IFT to show that $\frac{dN}{dy} > 0$, meaning the localities with higher income produce more varieties, or have a higher level of business activity overall.

We distinguish between the following two cases: with and without FBML, as our equilibrium characterization requires. Note that for the purposes of empirical analysis this corresponds to two types of localities, those exposed and those not exposed to stricter financial regulations aimed at reducing FBML.

Recall that if $1 - 2\frac{E}{N(f+c\bar{q})} < \alpha$ then the CE in the locality invests in FBML and BBML, in which case the equilibrium equation is

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

where $q(N, y) = \frac{2(Ly-E)}{cN(1+\alpha(\varphi))} - \frac{f}{c}$. Note that $\frac{\partial F(\cdot)}{\partial N} > 0$ as we saw in the proof of Proposition 1 and $\frac{\partial F(\cdot)}{\partial y} = \frac{N}{2}(1 + \alpha(\varphi))\frac{\partial \sigma(\cdot)}{\partial q}\frac{\partial q}{\partial y} - \frac{L}{f} < 0$, as $\frac{\partial q(\cdot)}{\partial y} > 0$ and $\frac{\partial \sigma(\cdot)}{\partial q} \leq 0$ by Assumption 2. This implies $\frac{dN}{dy} > 0$.

If, to the contrary, $1 - 2\frac{E}{N(f+c\bar{q})} \geq \alpha$, in which case the CE is not routing its money into FBML, then

$$F(N,y) = \sigma(\bar{q}(N,y),N)(N - \frac{E}{f+c\bar{q}}) - \frac{Ly-E}{f} = 0, \text{ where} \tag{33}$$

$$\bar{q}(N,y) = \frac{Ly-E}{c(N - \frac{E}{f+c\bar{q}})} - \frac{f}{c} \tag{34}$$

Then, as $N - \frac{E}{f+c\bar{q}} = N - M = n$,

$$\frac{\partial F}{\partial N} = \sigma(\cdot) + n\big(\frac{\partial \sigma(\cdot)}{\partial N} + \frac{\partial \sigma(\cdot)}{\partial q}\frac{\partial q(\cdot)}{\partial N}\big) > 0 \tag{35}$$

as in the proof of the Proposition 1, while $\frac{\partial F}{\partial y} < 0$, as $\frac{\partial q(\cdot)}{\partial y} > 0$ and $\frac{\partial \sigma(\cdot)}{\partial q} \leq 0$ by Assumption 2. This implies $\frac{dN}{dy} > 0$.

To sum up, *an increase in personal income boosts the total mass of firms in the official sector, though quantitatively there is a difference depending on whether the criminal enterprise channels some of its proceeds into FBML.*

B Variables Description

Table 8: Main Variables

Variable	Description
SCI	Status-of-compliance index for a given year and Caribbean jurisdiction (Equation (5)). See Section 3.1.1 for details. *Units:* Jurisdiction-year Index in $[0, 100]$. *Source:* CFATF.
County-Jurisdiction Exposure Shares, $w_{c,j}$	County c exposure to AML regulatory changes in jurisdiction j, via links to financial entities in any Caribbean jurisdiction, see Section 3.1.2 *Units:* County-jurisdiction shares in $[0, 1]$. *Source:* CFATF.
Offshore-FRI	The index of exposure to offshore financial regulations, see Section 3.1. *Units:* County-year Index in $[0, 100]$. *Source:* CFATF, International Consortium of Investigative Journalists (2017).
Establishments	Annual average number of quarterly establishments for a given year by county. *Units:* County-year counts. *Source:* United States Bureau of Labor Statistics (2015).
Population	Total number of residents for a given year by county. *Units:* County-year residents in thousands. *Source:* United States Census Bureau, Population Division (2010) and United States Census Bureau, Population Division (2019).
Race and Ethnicity	Shares of county-year residents by demographic group[43] *(a) Ethnicity*: Hispanic origin; *(b) Race*: Asian, Black or African American, American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, White. Shares do not impute combinations of two or more races. *Units:* County-year in percent. *Source:* United States Census Bureau, Population Division (2010) and United States Census Bureau, Population Division (2019).

[43] https://www.census.gov/programs-surveys/cps/data/data-tools/cps-table-creator-help/race-definitions.html

Table 8 – *Continued from the previous page*

Variable	Description
CPI	All Items CPI-U-R (CPI Research series). We reset the base year from December 1977 to December 2010, to express nominal variables in 2010 U.S. dollars. *Units:* Yearly Index, December 2010 = 100. *Source:* United States Bureau of Labor Statistics (2020).
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.[44] The variable is computed by multiplying population by personal income per capita. Nominal figures are expressed in 2010 dollars using CPI. *Units:* County-year personal income in thousands of 2010 U.S. dollars per thousands of county residents. *Source:* United States Census Bureau, Population Division (2010), United States Census Bureau, Population Division (2019), United States Bureau of Economic Analysis (2020).
Share of Personal Income from Dividends, Interest Rates, Rents	*Units:* County-year in percent. *Source:* United States Bureau of Economic Analysis (2020).
Share of Personal Income from Unemployment Insurance Compensation	*Units:* County-year in percent. *Source:* 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. *Units:* County-year, in thousands of 2010 U.S. dollars. *Source:* United States Census Bureau (2016).[45]
Unemployment Rate	Unemployment rate for a given year by county.

[44]https://www.bea.gov/resources/methodologies/local-area-personal-income-employment.

[45]https://www.census.gov/programs-surveys/saipe.html

Table 8 – *Continued from the previous page*

Variable	Description
	Units: County-year in percent. *Source:* United States Bureau of Labor Statistics (2016).
Share of Residents in Poverty	*Units:* County-year in percent. *Source:* United States Census Bureau (2016).
Share of Home Owners	Share of residents who are home owners for a given year by county. *Units:* County-year in percent. *Source:* Wu et al. (2020)
Median House Value	Median house value in 2010 dollars using CPI for a given year by county. *Units:* County-year, in thousands of 2010 U.S. dollars. *Source: ibid.*
Education	Share of residents with high school diploma for a given year by county. *Units:* County-year in percent. *Source: ibid.*

C Outcome Variables and Controls

Table 9: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Establishments	24656	2690.275	10922.61	5	446065
Offshore-FRI	24656	27.692	39.539	0	95.748
Off-shore-FRI^D	24656	10.319	17.83	0	52.5
Real Personal Income	24656	4204.897	15249.8	2.214	513740.2
Real Median Household Income	24656	43.36	10.902	19.171	119.075
Real Median House Value	24656	127.181	86.004	26.094	994.658
Share of Income: Dividends, Interest Rates, Rents	24656	17.296	5.193	5.241	76.192
Share of Home Owners	24656	75.924	8.134	20.756	96.954
Share of Income: Unemp. Insurance Comp.	24656	.641	.5	.002	7.106
Unemployment Rate	24656	7.5	3.032	1.1	28.9
Share of Residents in Poverty	24656	15.968	5.978	3.08	57.801
Share of Residents with High School Diploma	24656	25.838	12.078	0	100
Share of Black Residents	24656	8.983	14.455	0	86.149
Share of White Residents	24656	85.787	16.14	8.875	99.683
Share of Natives Residents	24656	2.149	7.402	0	89.213
Share of Asian Residents	24656	1.252	2.568	0	44.853
Share of Hispanic Residents	24656	8.629	13.418	0	96.134

Data Source: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division.
Sample period: 2008-2015.

D The status-of-compliance index

D.1 The CFATF recommendations

Table 10 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.[46]

[46] Link to the definitions of the 40 FATF recommendations; link to the 9 special recommendations.

Table 10: The 40+9 CFATF recommendations

AML/CFT 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 offence	Key
R.4	Confiscation and provisional measures	Key
Terrorist Financing and Financing of Proliferation.		
R.5	Terrorist financing offence	Core
R.6	Targeted financial sanctions related to terrorism & terrorist financing	
R.7	Targeted financial sanctions related to proliferation	
R.8	Non-profit organisations	
Terrorist Financing and Financing of Proliferation.		
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

Table 10 – *Continued from the previous page*

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	
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
International Cooperation.		
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	

Table 10 – *Continued from the previous page*

VIII.	Non-profit organisations
IX.	Cash couriers

D.2 Descriptive Statistics

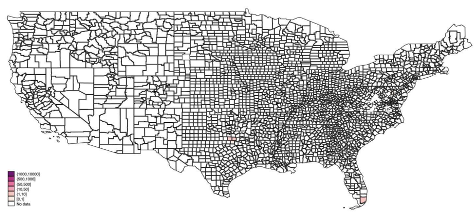
Table 11: Descriptive Statistics of status-of-compliance index by Jurisdiction.

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

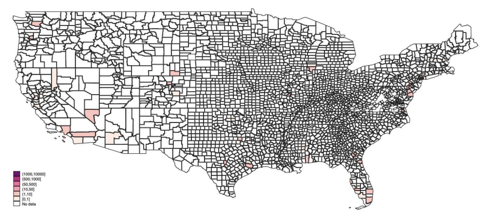
Data Source: CFATF. *Sample period*: 2008-2015.

E The County-Jurisdiction Exposure

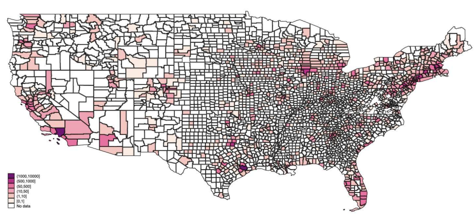
(a) Anguilla



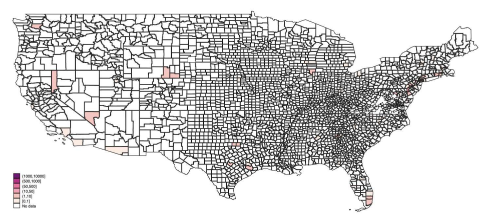
(b) The Bahamas



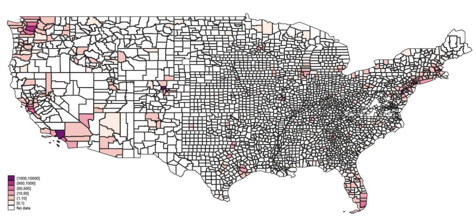
(c) Bermuda



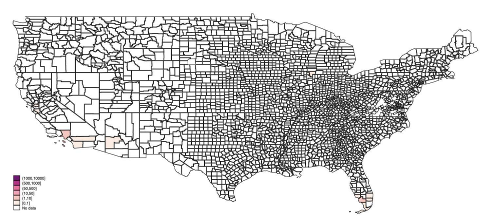
(d) Barbados



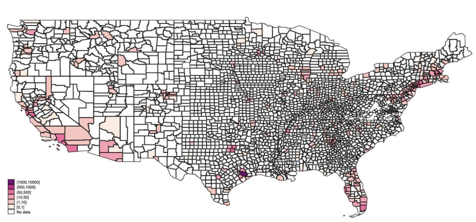
(e) British Virgin Islands



(f) Saint Kitts and Nevis



(g) Cayman Islands



(h) All jurisdictions

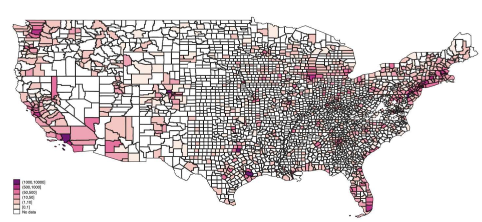
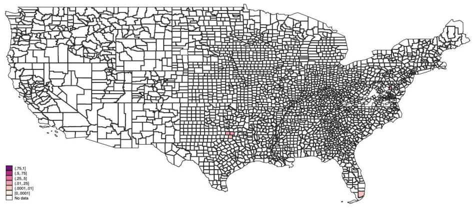
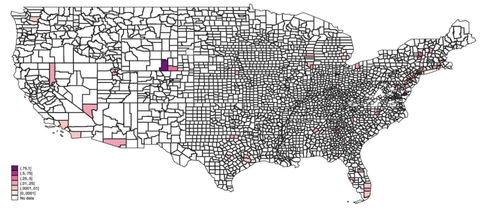


Figure 8: Intensity of the Exposure, $L_{c,j}$, by jurisdiction and county. *Data Source*: ICIJ.

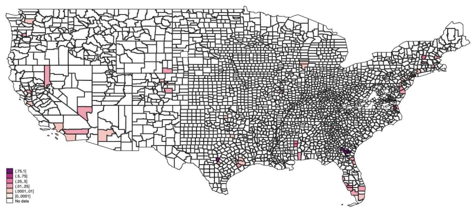
(a) Anguilla



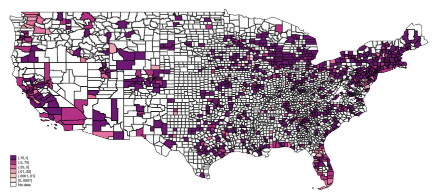
(b) Barbados



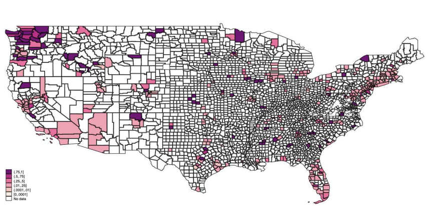
(c) The Bahamas



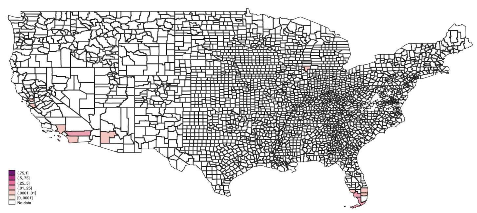
(d) Bermuda



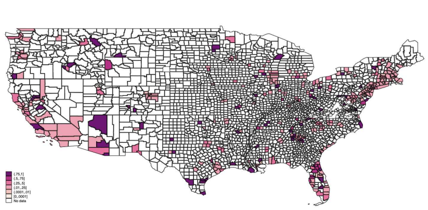
(e) British Virgin Islands



(f) Saint Kitts and Nevis



(g) Cayman Islands



(h) All jurisdictions

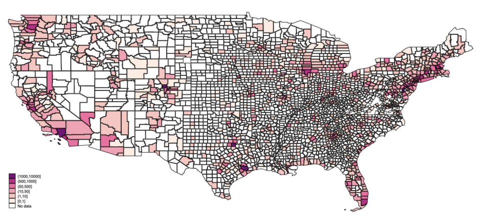


Figure 9: County-jurisdiction exposure shares, $w_{c,j}$. *Data Source*: ICIJ.

F Detailed Table for the Main Specification

Table 12: Effect of AML regulations on Business Activity

	OLS	Baseline	All	Discretized
	(1)	(2)	(3)	(4)
Offshore-FRI	0.02301***	0.00039***	0.00036***	0.00036***
	(0.00057)	(0.00009)	(0.00009)	(0.00009)
Log Income		0.20545***	0.19167***	0.20476***
		(0.03085)	(0.02435)	(0.03084)
Log Income x Exposed		0.09898**	0.06883	0.10158**
		(0.04501)	(0.04227)	(0.04531)
Log Real Median Household Income			0.08607***	
			(0.01470)	
Div., Interest, Rent			0.00353***	
			(0.00090)	
Unemp. Insurance			0.02679***	
			(0.00411)	
Unemployment Rate			-0.00772***	
			(0.00110)	
Poverty Share			-0.00016	
			(0.00034)	
Share of Home Owners			0.00015	
			(0.00035)	
Share with High School Diploma			0.00022	
			(0.00042)	
Log Real Median House Value			0.02249**	
			(0.01045)	
Share of Black			0.00286	
			(0.00224)	
Share of Natives			-0.03141**	
			(0.01242)	
Share of Hispanic			0.00743***	
			(0.00197)	
Share of Asian			0.01743***	
			(0.00653)	
Constant	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes
State x Year FE	No	Yes	Yes	Yes
Observations	24,656	24,648	24,648	24,648
R^2	0.375	0.999	0.999	0.999

Regression coefficients, Standard error clustered at county level in parenthesis.

Note: OLS regression estimates of logarithm of the number of establishments on: *(i)* Offshore Financial Regulation Index; *(ii) Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j\in\mathbf{J}} L_{c,j} > 0$); *(iii) County-Year Income and Wealth Controls*: log real median household income, log real median house value, share of real personal income attributed to unemployment insurance, share of real personal income attributed to dividends, interest, and rent, unemployment rate, share of residents in poverty, share of residents who are homeowners. *County-Year Socio-Demographic Controls*: *(a) Ethnicity*: share of residents with Hispanic origin; *(b) Race*: share of Black or African-American; American-Indian or Alaska-Native; and Asian residents. Omitted group: share of White residents, Native-Hawaiian or Other-Pacific-Islander residents, and those of two or more races. *(c) Education*: share of residents with high school diploma. All control variables are lagged. *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

G Robustness checks

G.1 Status-of-Compliance Indexes and BBML

Columns (1)-(7) in Table 13 report the estimates for the regression where Offshore-FRI$_{c,t}$ is replaced with with jurisdiction-specific compliance indices (SCI) in counties with a positive exposure to that jurisdiction, and zero otherwise. As a result, regressions differ not only by the treatment instrument, but also by the time of treatment (see Figure 1). Moreover, given the county-level variation in exposure to different offshore locations (see Figure 9), the reported estimates correspond to different sample partitions into treatment and control. The results in Table 13 provide evidence of external validity of

Table 13: Effect of Status-of-Compliance Indexes on BBML.

	(1) ANG	(2) BAH	(3) BER	(4) BRB	(5) BVI	(6) KNA	(7) CAY
Offshore-FRI	0.00160**	0.00220***	0.00041***	0.00161***	0.00139***	0.00121***	0.00104***
	(0.00074)	(0.00030)	(0.00008)	(0.00018)	(0.00020)	(0.00019)	(0.00014)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,486	24,648	21,567	24,648	15,405	18,486	21,567
R^2	0.999	0.999	0.999	0.999	1.000	0.999	0.999

Regression coefficients, Standard error clustered at county level in parenthesis.

Note: OLS regression estimates of logarithm of the number of establishments on: *(i)* status-of-compliance index by Jurisdiction; *(ii) Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j\in\mathbf{J}} L_{c,j} > 0$). *Data Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

our basic measure, in that the coefficients are significantly positive and of similar magnitude to those in Table 3. By selecting different treatment periods, control and treatment groups, these alternative instruments also ease concerns about the possibility that our estimates may be biased by unobserved tightening of AML regulations in offshore jurisdictions which are not in our sample but are correlated with Offshore-FRI.

Next, we limit the sample to counties with positive exposure to verify that

Table 14: Effect of Status-of-Compliance Indexes on BBML in exposed counties (Exposure Dummy =1).

	(1) ANG	(2) BAH	(3) BER	(4) BRB	(5) BVI	(6) KNA	(7) CAY
Offshore-FRI	0.00146*	0.00183***	0.00041***	0.00134***	0.00128***	0.00085***	0.00075***
	(0.00079)	(0.00031)	(0.00015)	(0.00018)	(0.00021)	(0.00020)	(0.00015)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,270	8,360	7,315	8,360	5,225	6,270	7,315
R^2	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Regression coefficients, Standard error clustered at county level in parenthesis.

Note: OLS regression estimates of logarithm of the number of establishments on: *(i)* status-of-compliance index by Jurisdiction; *(ii) Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j\in\mathbf{J}} L_{c,j} > 0$). The sample is restricted to exposed counties. *Data Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

there are no detectably different trends between exposed and non-exposed counties. The results are reported in Table 14.

G.2 Sector-county-year Observations

In this section we estimate our empirical model using a more granular database with sector-county-year observations.

$$\ln \mathrm{N}_{i,c,t} = \beta_0 + \beta_1 \cdot \text{Offshore-FRI}_{c,t} + \text{Fixed Effects} + \varepsilon_{i,c,t} \tag{36}$$

The results are reported in Table 15. With these additions, the estimates in Column (1) remain close to those of the baseline model in Table 3. Replacing county fixed effects by county-sector fixed effects decreases the estimated β_1 by half, see Column (2). Note that including county-sector data significantly raises the number of observations, including some zeroes, rendering the log transformation infeasible for those cases. Thus, in Column (3) we incorporate these zero observations by using the inverse hyperbolic sine transformation (in place of the log transformation) of the average annual level of county-sector establishments (Burbidge et al., 1988). Doing so produces a primary coefficient

Table 15: Robustness: Effect of AML recommendations on BBML.

	Baseline	FE	Zeros
	(1)	(2)	(3)
Offshore-FRI	0.00036***	0.00016***	0.00030***
	(0.00005)	(0.00004)	(0.00005)
Log Real Personal Income	0.04017***	0.11055***	0.03927***
	(0.01184)	(0.01351)	(0.01077)
Log Income x Exposed	0.10585***	0.10056***	0.10210***
	(0.01676)	(0.02013)	(0.01555)
Constant	Yes	Yes	Yes
County FE	Yes	No	Yes
County-Sector FE	No	Yes	No
State x Year FE	Yes	Yes	Yes
Observations	6,673,286	6,611,248	6,763,997
R^2	0.242	0.964	0.241

Regression coefficients, Standard error clustered at county level in parenthesis.

Note: OLS regression estimates of sector-county-year logarithm of the number of establishments on: *(i)* Offshore Financial Regulation Index; *(ii) Fixed Effects*: county (d_c), county-sector ($d_{c,i}$) and state-year ($\underline{d}_{s,t}$) fixed effects; *(iii)* lagged log real personal income and its interaction with the exposure dummy ($\sum_{j\in\mathbf{J}} L_{c,j} > 0$). The dependent variable logarithm of the number of establishments is replaced by the inverse hyperbolic sine transformation of the average annual level of county-sector establishments in Column (3). *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

close to the baseline case.

G.3 Other Tests

Column (1) in Table 16 reports estimates of our baseline model with standard errors clustered at the state level in place of the county level (as in Column (2) in Table 3). Results are not affected, providing additional support for the statistical significance of our estimates.

Column (2) shows that the primary coefficient estimate is amplified when

Table 16: Effect of AML regulations on Business Activity.

	Cluster	w/o 2008	Trends
	(1)	(2)	(3)
Offshore-FRI	0.00039***	0.00070***	0.00021**
	(0.00012)	(0.00022)	(0.00009)
Log Income	0.20545***	0.18232***	0.19800***
	(0.05919)	(0.02997)	(0.03140)
Log Income x Exposed	0.09898***	0.11618**	0.07431
	(0.02838)	(0.04893)	(0.04721)
Constant	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Share Asian 2008 x Year FE	No	No	Yes
Share Hispanic 2008 x Year FE	No	No	Yes
Poverty Share 2008 x Year FE	No	No	Yes
Observations	24,648	21,567	24,648
R^2	0.999	0.999	0.999

Regression coefficients, Standard error in parenthesis.

Note: OLS regression estimates of logarithm of the number of establishments on: *(i)* Offshore Financial Regulation Index; *(ii) Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j \in \mathbf{J}} L_{c,j} > 0$). Standard errors are clustered at state level in Column (1) and county level in Column (2). *Data Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

we drop the data for the year 2008. By omitting the first year disrupted by the financial crisis, we ease concerns that the financial crisis itself might have moved resources from FBML to BBML, generating a spuriously positive coefficient on Offshore-FRI. Appendix A.2 reconciles the stronger effect obtained by omitting 2008 by showing analytically how the semi-elasticity of the business activity with respect to φ (and hence, its proxy, Offshore-FRI) may have decreased at the outset of the crisis, as a result of a drop in the local demand for illegal goods, E.

Column (3) explores the role of the financial crisis further. In principle, the response dynamics of business activity to the financial crisis may depend on the county characteristics at the onset of the crisis in 2008. Column (2) shows that results are robust to including additional controls accounting for county-specific trends that could vary with initial demographic characteristics and poverty.

H Heterogeneous effects

H.1 The International Money-Laundering Network

Table 17: Heterogenous Effect of AML regulations targeting FBML on BBML.

	(1) Hispanic	(2) Asian
Offshore-FRI	0.00023**	0.00008
	(0.00009)	(0.00009)
Offshore-FRI × Share	0.00001***	0.00013***
	(0.00000)	(0.00002)
Share	0.00668***	0.00907
	(0.00199)	(0.00633)
Constant	Yes	Yes
Baseline Controls	Yes	Yes
Observations	24,648	24,648
R^2	0.999	0.999
Linear Combination at Average (Exposed)	0.029	0.031
p-value	0.00	0.00

Regression coefficients, Standard error clustered at county level in parenthesis.

Note: OLS-regression estimates of county-year logarithm of the number of establishments on: *(i)* Offshore Financial Regulation Index; *(ii) Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j\in\mathbf{J}} L_{c,j} > 0$). *(iii) Demographic Controls*: share of residents with Hispanic origin (Column 1), share of Asian residents (Column 2). All control variables are lagged. *(iv) Interaction Terms*: interaction of Offshore Financial Regulation Index with lagged demographic controls. Row *Linear Combination at Average (Exposed)* reports the sum of the estimated coefficients on Offshore-FRI and interaction (Offshore-FRI×Demographic), weighted by the covariate averages in the exposed counties. The next line contains its p-values. The omitted group is non-Hispanic in the first column and non-Asian in the second column. *Data Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

H.2 Geographical Decomposition

Table 18: Number of U.S.-Caribbean Jurisdictions Links by Type

	Direct	Indirect	Direct-Asian	Indirect-Asian
N. Zip-Jurisdiction Links	1492	51388	6	3227

Data Source: ICIJ.

Table 19: BBML by Census Division

	New England	Middle Atlantic	East North Central
Offshore-FRI	0.00052**	0.00011	0.00055***
	(0.00025)	(0.00016)	(0.00017)
Observations	536	1,200	3,496
Share Treated	0.761	0.747	0.400

	West North Central	South Atlantic	East South Central
Offshore-FRI	0.00003	0.00061***	0.00025
	(0.00030)	(0.00014)	(0.00019)
Observations	4,936	4,288	2,912
Share Treated	0.212	0.400	0.209

	West South Central	Mountain	Pacific
Offshore-FRI	0.00038	-0.00007	0.00113***
	(0.00024)	(0.00025)	(0.00037)
Observations	3,760	2,248	1,272
Share Treated	0.249	0.302	0.528

Note: The table reports by Census Division, the OLS estimates of the effect of the Offshore Financial Regulation Index on county-year logarithm of the number of establishments, in a regression that controls for *Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects, lagged log real personal income and its interaction with the exposure dummy ($\sum_{j \in \mathbf{J}} L_{c,j} > 0$). *Data Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

I Intertemporal treatment effects

Table 20: Staggered Research Design, Offshore-FRI$^{D}_{c,t}$

	2008	2009	2010	2011	2012	2013	2014	2015
0	3,082	2,246	2,143	2,131	2,122	2,121	2,120	2,120
20	0	21	67	70	9	5	5	5
22.5	0	33	40	15	79	71	67	67
25	0	46	45	31	29	14	14	13
27.5	0	74	64	21	24	13	9	10
30	0	95	119	38	35	25	23	23
32.5	0	567	604	40	44	16	19	19
35	0	0	0	63	61	17	15	15
37.5	0	0	0	101	101	33	34	34
40	0	0	0	572	578	43	27	26
42.5	0	0	0	0	0	36	48	49
45	0	0	0	0	0	71	55	55
47.5	0	0	0	0	0	74	72	72
50	0	0	0	0	0	543	67	67
52.5	0	0	0	0	0	0	507	507
Total	3,082	3,082	3,082	3,082	3,082	3,082	3,082	3,082

Note: The table reports the transition of counties across the different treatment groups Offshore-FRI$^{D}_{c,t} = r$ (rows) over the years (columns). *Data Source*: CFATF, ICIJ. *Sample period*: 2008-2015.