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Abstract

Proceeds from illicit activities percolate into the legal economy through several channels. We exploit international regulations targeting money laundering via the financial sector to identify the flows of "dirty money" into legitimate establishments: business-based money laundering (BBML). Our variant of the monopolistic competition model embeds a drug cartel that channels illicit proceeds into an offshore financial investment and into BBML. Tighter regulations in one channel increase the flow in the other. We use a research design that links U.S. county business activity to the evolution of anti-money-laundering regulations in Caribbean jurisdictions to provide the first empirical evidence of the phenomenon.

JEL-Codes: F300, K400, G280, H000, D580.

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

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

Keith E. Maskus[♯] Alessandro Peri[♮] Anna Rubinchik[§]

Countries share considerable policy concerns about the mechanisms by which those engaged in illicit activities—such as distribution of illegal drugs, counterfeit goods, or contraband weapons—move the resulting profits into seemingly legitimate commerce. Such practices, generally termed money-laundering

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[§]

(ML), may involve investing ill-gotten profits into either financial assets or business establishments. Making such investments requires access to a money-laundering network among shell companies, hidden bank accounts, anonymous trusts, and intermediaries located in different countries.[1] With them come the potential for criminality and corruption, the targets of financial regulations and law enforcement.

Evidence exists of money laundering on a vast scale. For example, 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, filed by banks required to report them to U.S. authorities.[2] According to investigative reporters, "Terrorist networks, drug cartels, organized crime rings, and rapacious kleptocrats have all benefited, using the U.S. financial system to wash clean their illicit profits." Experts cited in that report suggest this is a small fraction of total suspicious or illicit financial flows over that period. Moreover, there are broad measures of illegal transactions in domestic markets and international trade that generate illicit profits requiring cleansing. For example, the U.S. illegal drug market alone in 2010, estimated at around $109 billion, was comparable to the entire output of American agriculture.[3] In international trade, shipments of counterfeit goods and pirated copyrighted products are estimated to be about two percent of global merchandise trade in 2005.[4]

Money-laundering activities exist primarily in the shadow of weak regulatory policy and are difficult for authorities to detect. Our main contribution is to provide a theoretical and econometric framework for identifying one of the

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

[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]See Beau Kilmer and others, What America's Users Spend on Illegal Drugs: 2000-2010, Research Report Series, document No. RR-534-ONDCP (Santa Monica, California, Rand Corporation, 2014).

[4]See OECD Annual Report 2008, `https://www.oecd.org/newsroom/40556222.pdf` and Fink et al. (2016). Also common is the simple misclassification or under- or over- invoicing of traded products, plus other illegally traded goods, such as banned weapons.

key money-laundering channels: business-based money laundering (BBML)—the flow of “dirty money” into legitimate businesses. To do so, we proceed as follows.

First, we introduce a firm, which we label a drug cartel, into a general-equilibrium, monopolistic competition model.[5] This firm has profits from selling an illicit good (say, banned drugs) that must be laundered. In the model, consumers enjoy a variety of differentiated goods produced by legitimate firms (legal products) and the illegal good.[6] The drug cartel is also a regular consumer of legal goods. However, to purchase such goods, it first must launder its ill-gotten profits. To do so, it has access to a money-laundering technology, which consists of two interrelated channels: financial-based (FBML) and business-based (BBML) money laundering. First, it can deposit dirty money in the financial sector and withdraw a fraction as clean income (FBML). Alternatively, it can buy a legitimate business (BBML), earn regular profits, and spend the proceeds like other consumers.[7] Engaging in BBML can be costly, however, for too many such purchases may be noticed by the enforcement authorities. To pick up this effect, we assume that the higher is the relative investment of dirty to clean money in the legal sector, the more of it gets apprehended. In this way we capture the tradeoff between the benefits and costs of BBML.

Our model predicts a negative relation between the money-laundering yield in the financial sector and the equilibrium number of varieties sold in the legitimate sector. As stricter financial regulations reduce the unobserved yield of FBML, more dirty money is channeled to BBML, boosting the overall number

[5]The model is based on Parenti et al. (2017), who generalizes the monopolistic competition framework of Krugman (1979). This class of models is often used to assess market structure and policy effects in a sector with differentiated products (Anderson et al. (1995)).

[6]Consistent with the empirical evidence, we assume that the demand for the illicit good is inelastic and is unaffected by money laundering regulations. For instance, a recent UNODC report estimated that global opium production in 2017 was the highest on record since monitoring began in 2000 and that production continues to rise sharply despite recent tightening of financial regulations to combat money laundering.

[7]The acquired firm, such as a casino, could be used for subsequent money laundering. For clarity, however, we think of the acquisition of the establishment itself as the endpoint of BBML, which is consistent with our static model.

of firms. According to our model, this observable growth in business activity is a *lower-bound* on the unobservable growth in the number of BBML-financed firms, which partially replace legitimate firms.[8]

Second, we test empirically this substitution prediction of our model between FBML and BBML. To do so, we adopt an exposure-based research design strategy (e.g., Autor et al., 2013) that measures the effect of changes in compliance of Caribbean countries on the number of establishments in U.S. counties linked to these countries via offshore accounts. A primary insight is that specific locations, which we take to be U.S. counties, may be differentially exposed to regulatory changes in foreign jurisdictions through illicit financial linkages. To implement this idea, we construct a county-year index that measures the exposure to offshore anti-money-laundering (AML) regulations. The index has two components. The first component is obtained by constructing an index of status of compliance of selected Caribbean jurisdictions to AML recommendations issued by the Caribbean Financial Action Task Force (CFATF) over the period 2008-2015. The second component is the degree of exposure of each U.S. county to offshore accounts in these jurisdictions. We measure this component using the financial ties between individual investors via offshore accounts, disclosed in the Offshore Leaks database by the International Consortium of Investigative Journalists (ICIJ).[9] Combining the two, we construct our key explanatory variable, a county-year index of exposure to financial regulations, as the weighted average of changes in the compliance of Caribbean countries with AML recommendations—where the weights are based on the share of links of each county to the financial sectors of those jurisdictions. Our identification strategy is based on the assumption that the

[8]This prediction rests on standard assumptions imposed on the underlying demand elasticities as justified in Parenti et al. (2017).

[9]The ICIJ is an international network of more than 200 investigative journalists and 100 media organizations in over 70 countries. It collects data from multiple investigations by journalists on the links between over 785,000 offshore entities and people or companies in more than 200 countries and territories, up through 2016. The publicly available data are arranged in four databases: The Panama Papers, the Paradise Papers, the Bahamas Leaks, and the Offshore Leaks. *Source*: International Consortium of Investigative Journalists (2017).

degree of compliance by any Caribbean nation with the AML regulations is exogenous to the business activity in a given U.S. county.[10]

An appealing feature of our identification strategy is that it relies on *publicly available* micro-data to identify a phenomenon (BBML) that—as discussed in Section 2—has proven difficult for authorities to detect in the absence of detailed transactions data.

Using this approach, we find that the tightening in AML regulations in the Caribbean islands over the period 2008-2015 caused on average at *least* a 2.29% increase in the number of establishments due to BBML in exposed counties, conditional on state-year and county fixed effects, plus other controls. In doing so, we provide the first evidence of an increase in BBML in the wake of regulatory reforms targeting FBML.

Further, we show that the impact varies by production sector, as predicted in our extended model. Specifically, the effect is strongest in retail trade and other services, but absent in manufacturing. In addition, there are differences between U.S. geographical regions: roughly, the response of business activity to the change in offshore AML regulations is more pronounced in areas prone to higher illicit drug consumption according to the recent reports of the U.S. Drug Enforcement Administration. Finally, we find evidence that this business activity is tied to the presence of illicit global financial networks.

1 Related literature

Our research agenda belongs to a developing literature on unobserved economic activity.[11] Here we summarize some of the key prior contributions using similar data sources, while other related papers are mentioned in the balance of the text.

Alstadsæter et al. (2018) used leaks from the Swiss subsidiary of HSBC in 2007, involving over 30,000 bank clients, and, with the help of tax authorities,

[10]There is no reason to believe that county-level enterprise operations should cause legislative changes in the Caribbean. It is also helpful that AML activities focus considerably more on financial channels than on BBML itself, as described in Delston and Walls (2011).

[11]For a survey, see, for example, Medina and Schneider (2018).

matched relevant records to tax returns in Denmark, Norway, and Sweden. They also matched the names of owners of shell companies revealed by the Panama Papers leak in 2015 to individual wealth data in Norway and Sweden. Finally, they had information on the voluntary disclosure by households in those two countries of previously hidden assets during tax amnesties after 2006. After constructing a Scandinavian wealth distribution with such data, they related the extent of tax evasion computed from the leaks to wealth levels. They found that tax evasion is highly concentrated among the richest taxpayers, with the richest 0.01 percent of wealth holders evading about 25 percent of their taxes.

The Panama Papers also revealed that firms use secret offshore vehicles (SOVs) to evade taxes, shift tax liabilities across jurisdictions, and facilitate bribery, as analyzed by O'Donovan et al. (2019). Combining corporate databases, the authors identified those publicly listed firms that use SOVs, along with their subsidiaries around the world. An events study found that those firms mentioned in the Panama Papers suffered a total decline in market capitalization of $174 billion after the disclosures.

A third relevant paper is Bayer et al. (2020), which used information from the Panama Papers to study whether economic agents in countries with a reported increase in public expropriations of assets and property seizures (presumably tied to greater law enforcement) were more likely to incorporate offshore vehicles. They found significant evidence of local links to offshore activities, even within the same month, but primarily in economies with transparent governance. They interpreted this result to show that when well-functioning governments choose to crack down on organized crime there is an endogenous response by agents to move ill-gotten assets offshore.

Tax evasion and asset hiding are important outcomes of the access criminal organizations have to tax havens and SOVs, but no papers to date explicitly address the impacts of money laundering. To our knowledge, our analysis is the first to pose this question and to isolate how organizations seeking to wash illicit profits shift into establishing or acquiring legitimate businesses in the wake of greater enforcement. This is a difficult effect to identify because the databases leaked by the ICIJ do not directly link such investments to offshore vehicles or shell companies.

2 Institutional Background

A brief review of the basics of laundering money provides useful context.[12] Much of what is described by official sources relates to the use of professional money laundering services (PMLs) in the financial sector. Owners of illicit funds transfer them to PMLs, such as shell companies and trusts, passive private holding companies that do not offer any substantive products. They are managed by legal agents while the identity of the ultimate owner of the deposits is obscure. Such companies may exist for legitimate investment purposes. Many, however, also facilitate a key stage in the money laundering process, called money layering, wherein they receive wire transfers from a multitude of accounts, some of which may contain proceeds from illicit activities.[13] Large sums may be structured into small accounts and deposits may flow through multiple institutions. When complete the original depositors own offshore accounts, reduced by the fees taken by PMLs. Trusts may also purchase legitimate assets, such as real estate or yachts, and transfer them to selected individuals or business entities. These processes are the essence of what we term the financial-based money laundering (FBML) channel.

The series of “leaks” made by the ICIJ in recent years provides a rare opportunity to identify the owners of thousands of such shell companies, trusts, and other offshore vehicles from across the world.[14] We use this data in our investigation. To illustrate, we present in Figure 1 the result of a query of the ICIJ database called Offshore Leaks. At the center is an address in New York state used by nine financial entities in the Bahamas. In turn, these are

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

[13] The process of breaking up large sums into small deposits is called structuring.

[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.

owned by investors listed in the large circles and registered, in this example, in Mexico and Argentina. At least in this example such a network could serve as a channel for transferring funds from New York to Mexico and Argentina. Although the complete network might be worth studying, we focus on the links between U.S. agents (represented implicitly as an address or explicitly as a firm or an individual) and financial entities in the Caribbean.

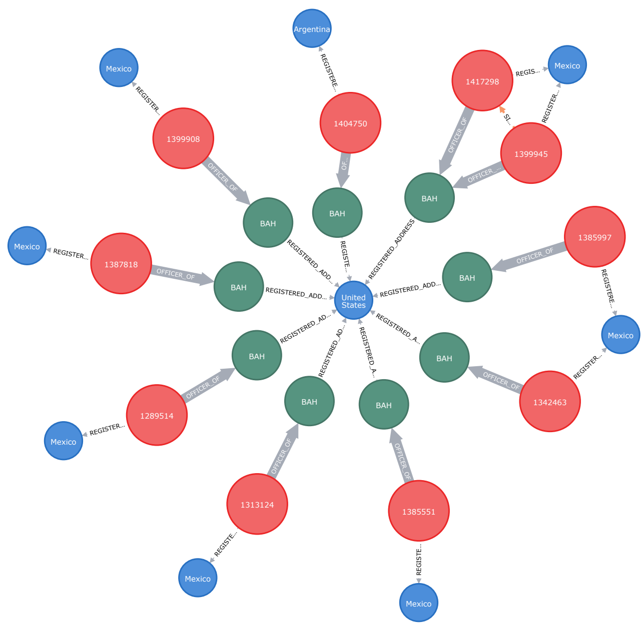


Figure 1: **The NY-Mexico connection through Bahamas financial entities.** Large red circles represent owners of financial institutions in the Bahamas (green circles). The corresponding registered addresses of the institutions and the owners are in the small blue circles. Generated by the *Neo4j Desktop for ICIJ* interface.

In part as a reaction to the 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 1989 the G-7, 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 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.[15] These regulations are designed to raise barriers to money laundering, primarily in the financial sector. Somewhat later, a related organization, the Caribbean Financial Action Task Force (CFATF) was created to perform these tasks in Caribbean economies. We use the CFATF evaluations, which began for some countries in 2008 and continues today, to quantify the evolution of such regulatory impediments to financial ML in Caribbean nations that seem to serve as centers for financial irregularities.

The second common channel for disguising illicit profits is to transform them into enterprises selling real goods and services, and owning business assets, a process we call BBML. This process, and its cousin trade-based money laundering (TBML), in which illegal profits are converted into "legitimate" income through, say mis-invoicing trade prices, are considered to be the "weakest link in the fight against dirty money".[16] The reason is that money laundering takes a variety of forms and can almost perfectly mimic a legitimate trade activity. For example, TBML often involves using dirty money attained in one location to purchase local products and, through exports, convert them into the desired currency, now cleansed, in the target country.[17] It is evident

[15] There might be some reservations about the accuracy of these reports. For example Allred et al. (2017) conducted an anonymous survey eliciting offers for opening a shell company in 176 countries, subsequently evaluating compliance with FATF regulations of the newly created firms. They claim that "the grades issued to countries by the FATF in their periodic reviews do not correlate particularly well with the findings on cross-national compliance from our audit study". However, one reason for that could be severe selection bias. Indeed, according to the findings, informing the potential provider about FATF regulations and about formal penalties for violating the regulations decreased the rate of response by potential providers to the solicitation as compared to the group of contacted providers who did not receive any additional information about the regulations. In addition, providing the information did not increase the compliance (reducing it in some cases) conditional on agreeing to provide the service. This can be driven by the adverse selection of those who agreed to offer the service.

[16] The Economist, "Trade and Money Laundering. Uncontained." 3 May 2014.

[17] As an example, consider the case referred to in the same article (Economist, 2014): "A few years ago American customs investigators uncovered a scheme in which a Colombian cartel used proceeds from drug sales to buy stuffed animals in Los Angeles. By exporting

that shipping mis-invoiced goods or establishing or acquiring commercial enterprises is often accompanied by a corresponding transfer of seemingly legitimate funds. Moreover, if the reported values of exports, construction projects, or acquisitions deviates from their true market values, such transactions can be an effective means of moving dirty money across borders by requiring fewer physical goods to be moved. The difficulty for authorities lies in detection, for illegal valuations stand out only if they are really stretched beyond normal price variations. Thus, single TBML or BBML transactions are difficult to identify. In a database with a large volume of transactions, however, they can leave identifiable traces across locations, an insight we exploit in our empirical work. We propose a strategy that can identify BBML even if the businesses involved in the process price their products in perfect alignment with similar legitimate firms.

3 The model

We extend the monopolistic competition model by Parenti et al. (2017) to include money-laundering activities.

3.1 The commercial sector

In the commercial (legal) sector there is a continuum of firms each producing a separate variety of a consumption good. There are L identical consumers who are endowed with y units of productive labor for work in the official sector, co-own the production firms and enjoy a variety of consumption goods produced there. In addition, consumers buy illicit drugs, or some illicit goods or services.

For simplicity we assume that the total expenditure on illicit goods, $E > 0$, is fixed. One justification for fixing E is that aggregate demand for some illegal activities (like illicit drugs) is inelastic, as we mentioned earlier. This supposition is consistent with the UNODC World Drug Report 2020: "Drug

them to Colombia, it was able to bring its ill-gotten gains home, convert them to pesos and get them into the banking system."

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".[18] For our purposes, it is sufficient to assume that E is affected neither by the way the money is laundered nor by the varieties and their prices in legal markets. Nevertheless, the expenditure on illicit goods may vary by locality, which we account for in our empirical investigation.

There is no disutility from labor, so the supply of official labor is yL provided wages are positive. This is the only input in production of the official goods.

Following Parenti et al. (2017), we denote by $\mathscr{N}$ the mass of potential varieties and by $N \leq \mathscr{N}$ the endogenous mass of available varieties. A consumption profile $x \geq 0$ is a Lebesgue-measurable mapping from the space of potential varieties $[0, \mathscr{N}]$ to $\mathbb{R}_+$ such that for $i \in]N, \mathscr{N}]$, $x_i = 0$, where x_i is the consumption of variety i. Consumers' preferences over the set of official goods are additive, symmetric in varieties, satisfy the love-for-variety property, the Inada conditions and the decreasing marginal revenue property.[19]

In addition to the regular consumers, there is a drug cartel whose preferences over the bundles of official goods also satisfy the assumptions above.

Let $p \geq 0$ be the price profile for the official goods, which is a Lebesgue-measurable map $[0, \mathscr{N}] \to \mathbb{R}_+$, and let p_i denote the price of consumption good of variety i. Entry in production of each variety costs f and has a per-unit cost of c in terms of effective labor. A firm knows its demand and chooses to produce q_i units of this variety by maximizing its operating profit, $\pi_i(q_i) = (p_i - c)q_i$ less the fixed cost f.

[18] *Source*: United Nations Office on Drugs and Crime (2020).

[19] For the formulation and the use of the Inada conditions, see (Parenti et al., 2017, Lemma 1), while Caplin et al. (1991) define the marginal revenue property. The utility representation is assumed to be Fréchet differentiable on the space of square integrable functions on $[0, \mathscr{N}]$. The marginal revenue property requires, strictly speaking, existence of the third derivative of the utility function.

3.2 The Drug Cartel

We take the production of illicit goods as a black box. The revenue from selling the goods to the regular consumers is E, the dirty money, which has to be laundered in order to be used in the official sector.

There are two money-laundering (ML) channels. The first is financial-based money laundering (FBML). The FBML technology is linear: for every dollar of input, $0 < \alpha < 1$ dollars comes out clean, i.e., enters a valid bank account. The rest is used to obscure the origins of the proceeds through layering and structuring, as explained above. Thus, parameter α stands for yield earned in FBML. The second channel is business-based money laundering (BBML). To exercise this option the cartel has to pay the same fixed cost f as a regular investor, only in "dirty money", which then entitles it to be the owner of a firm with operating profits π_i, the clean output of the BBML. The cartel can either buy an existing firm or establish a new one. The business sector is monitored by authorities and a fraction of firms acquired through BBML is discovered. Let M and n be the mass of BBML and clean firms in the official sector, respectively, so that $N = M + n$. We assume that $\frac{M}{N}$ of the BBML firms' assets are confiscated by enforcement authorities and then are given to the consumers.[20]

Let the output of BBML be $V_T(z)$, where z is the amount of dirty money invested in BBML. It costs f to start a new firm in this sector, so the amount of firms M acquired or set up for the purposes of money laundering is $M = \frac{z}{f}$. Then the problem of the drug cartel is to maximize the output of clean money by allocating it across the two channels:

$$R(E) = \max_{0 \le z \le E} \alpha(E - z) + V_T(z) \tag{1}$$

$$V_T(z) = (1 - \frac{M}{N}) \int_n^N \pi_i di, \quad M = \frac{z}{f} \tag{2}$$

[20] The government does not appear as a decision-making agent in this model for simplicity. We assume that the confiscated assets are transferred to the consumers because this is the easiest way to return the assets to the economy, while imposing the cost of their loss on the cartel.

We assume that the money-laundering cartel does not take into account the potential effect of its decision on demand for the official goods and on the total mass of firms in the industry, and hence on the profits of the legitimate firms. Thus, the profits here are determined exactly as in Parenti et al. (2017), by the free entry condition of legitimate firms.

3.3 Equilibrium Characterization and its Implications

Definition. An equilibrium is an allocation of final consumption by individuals across sectors and varieties of goods, 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 variety i 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 drug cartel chooses an optimal allocation of funds to launder across the production and financial sector; and *(v)* all markets clear.

3.3.1 Equilibrium Characterization

As in Parenti et al. (2017), the symmetry of the utility function with respect to different varieties of legitimate consumer goods and an identical production technology leads to a unique symmetric equilibrium where each production firm produces the same amount, $\bar{q}$. Thus, the elasticity of substitution σ between the goods of any two varieties depends only on the amount produced by each firm and the mass of varieties, N.

We show in Lemma 1, that N is not altered by the introduction of the drug cartel if $1 - 2\frac{E}{Nf} > \alpha$, i.e., if the yield of FBML is small.[21] In this case all the dirty money is laundered through the BBML channel and so all the proceeds from the drug trade flow back into the commercial sector and the equilibrium

[21] Notice that the characterization is indirect, since the condition imposed on α that separates the two cases ($1 - 2\frac{E}{Nf} \lesseqgtr \alpha$) involves the mass of firms N which is determined by the equilibrium equations in the two cases. However, the conditions 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.

mass of firms (varieties) is as in Parenti et al. (2017). This implies that dirty money crowds out clean investment: mass $M < N$ of the goods' varieties is produced by the firms bought by the drug cartel. The same condition can be satisfied if E, the revenue to be laundered, is sufficiently small. Therefore, even without assuming that initiating FBML requires a setup cost, the model predicts that some localities will not be exposed to FBML. This can be true either because the yield of FBML is perceived by the cartel as small, or if there is not much dirty money to launder. In either case, such a locality will not experience the effect of decreasing the yield of FBML on N.

If α is sufficiently high, $1 - 2\frac{E}{Nf} \leq \alpha$, it is worthwhile for the drug cartel to initiate use of the FBML channel. In this case, part of the revenues gets lost in the financial sector, implying that the stringency of AML regulations has a real effect on economic activity in the official economy, as can be seen from Equation (3). All proofs of the following formal results are in Appendix A.1.

Lemma 1. *An equilibrium is characterized by the following conditions:*
If $1 - 2\frac{E}{Nf} \leq \alpha$ *then* $\bar{q} = \frac{Ly-E}{cN} - \frac{f}{c}\frac{1+\alpha}{2}, \quad M = \frac{N}{2}(1-\alpha)$ *and*

$$N(\sigma(\bar{q}, N) - \frac{1-\alpha}{2}) = \frac{Ly - E}{f}, \tag{3}$$

Otherwise, if $1 - 2\frac{E}{Nf} > \alpha$*, then* $\bar{q} = \frac{Ly}{cN} - \frac{f}{c}, \quad M = \frac{E}{f}$ *and*

$$N\sigma(\bar{q}, N) = \frac{Ly}{f} \tag{4}$$

3.3.2 The main theoretical result

Our main result rests on additional assumptions that are supported by previous empirical research.[22]

[22] The assumption that the demand elasticity is increasing in the mass of varieties is consistent with many other models of product differentiation (Anderson et al., 1995; Tirole, 1988). Further, one could interpret recent empirical findings as being consistent with the second assumption, $\frac{\partial\sigma(\bar{q},N)}{\partial q} \leq 0$, (Parenti et al., 2017).

Proposition 1. *Assume that* $\alpha < 1$ *and that 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 amount produced by the individual firm* $\frac{\partial \sigma(\bar{q}, N)}{\partial q} \leq 0$.

Then both the total equilibrium mass of firms N *and BBML firms* M *decrease in* α*:* $\frac{dN}{d\alpha} \leq 0$, $\frac{dM}{d\alpha} \leq 0$.

Corollary 1 (Crowding-out effect)**.** *Under the assumptions of Proposition 1, and if the semi-elasticity of* N *with respect to* α *is not too big,* $|\frac{dln(N)}{d\alpha}| < \frac{1}{2}$, *then the effect of* α *on BBML is stronger than the overall observed effect on business activity:* $|\frac{dN}{d\alpha}| \leq |\frac{dM}{d\alpha}|$. *Hence,*

$$\left|\frac{dN}{d\alpha}\right| \frac{1}{N} \leq \left|\frac{dM}{d\alpha}\right| \frac{1}{M}. \tag{5}$$

We call $1 - \alpha$ the marginal cost of FBML, which is not directly observed. We assume that tighter AML regulations targeting the financial sector increases this cost. Hence, the strictness of such regulations can be viewed as a proxy for the marginal cost of FBML.

Testable Implications. *Tighter AML regulations targeting the financial sector should result in an increase in the* ***observed*** *total mass of firms (*N*). This increase is stronger for the* ***unobserved*** *mass of BBML firms (*M*). The semi-elasticity of* N *with respect to the strictness of the AML regulations is a lower bound for the semi-elasticity of* M.

4 Empirical Analysis

In this section we test and quantify the main implications of our theory using the U.S. data. Our research question can be presented as follows: What is the causal effect of more rigorous AML regulations imposed on money-laundering activities in the financial channel on business activity in U.S. counties? To answer the question, an ideal experiment would randomly assign anti-FBML regulations of different strictness to the relevant U.S. counties. In the absence of such an experiment, we rely on an *exposure research design* strategy[23] to construct a proxy for the regulatory strictness. The proxy combines the information about changes in the status of AML recommendations compliance of selected Caribbean countries and the exposure of each U.S. county to these countries via offshore accounts. We use this variable to assess the impact of regulatory reforms on the *observed* level of establishments across U.S. counties, hence providing a lower bound estimate of the impact on the *unobserved* level of BBML. Henceforth, we will refer to our proxy, which varies by county (c) and year (t), as the index of exposure to offshore financial regulations (Offshore-$\text{FRI}_{c,t}$).

4.1 Data

Our sample consists of three data sources. First, we use documents released by the Caribbean Financial Action Task Force (CFATF) to assess the status of regulatory compliance of selected countries in the Caribbean region with its recommended standards. We consult periodic reports issued by CFATF documenting 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 (ICIJ) 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 24,681 county-year observations from 2008 to 2015.

4.1.1 Constructing the Exposure Index

The standard concern is that changes in AML regulations in U.S. counties or states may arise endogenously as a policy response to local money-laundering activities. Such regulations are national or state responsibilities, obviating

[23]See, for example, Autor et al. (2013).

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 our policy-exposure variable using changes in relevant international AML regulations. In addition, we include state-year control variables to neutralize the influence of state and federal 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) cross-sectional exposure of U.S. counties to these offshore regulations.

As a first step, we select a subset $\mathbf{J}$ of seven Caribbean jurisdictions: Anguilla (ANG), The Bahamas (BAH), Barbados (BRB), Bermuda (BER), British Virgin Islands (BVI), Cayman Islands (CAY), and Saint Kitts and Nevis (KNA). 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 (more than 5000).[24] Moreover, each country satisfies the following criteria. First, it has links to legal agents (individuals, trusts, corporations) in the United States. Second, it is a member of the CFATF, and it goes through the same evaluation process designed by that organization.

To quantify the two sources of variation, we construct two variables. First we develop an index, $\mathrm{SCI}_{j,t}$, which measures the evolution in the status of compliance of a Caribbean jurisdiction $j \in \mathbf{J}$ in year t with the CFATF AML recommendations. Second, we compute the exposure-share variable $w_{c,j}$, which 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 (c) and entities in a specific Caribbean

[24] Following is the list of the countries in our sample with the approximate number of world-wide links in the database, 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 follow-up reports on the degree of compliance with CFATF regulations were inconsistently dated and were considerably less informative than reports about the included countries.

jurisdiction (j), 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. The exposure shares are zero if a county has no offshore links at all.

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

We combine these variables in computing Offshore-FRI$_{c,t}$, our exposure index, as a weighted average of the status-of-compliance index for each 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). Indeed, its first component, $w_{c,j}$ is time-independent and the second component, SCI$_{j,t}$, is location-independent as regards U.S. counties. Thus, our index, Offshore-FRI$_{c,t}$, provides an empirical proxy for the time-varying county exposure to stringency in foreign AML financial regulations, which is our key explanatory variable.

4.1.2 The Status-of-Compliance Index

Our variable 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 the 49 recommendations, [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.[25]

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. The

[25] Cf. Appendix D.1 for the list of core and key recommendations.

field-based *Mutual Evaluation Reports* (MER)[26] 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), non-compliant (NC) in accordance with FATF methodology.[27] We translate these ratings into numerical values by associating **scores**, from 3 (C) to 0 (NC) for each rating.

If the majority of the core recommendations scored less than partially compliant, the country was subject to subsequent frequent follow-up evaluations conducted twice a year.[28] Otherwise, the follow-up evaluations were done on a biannual basis. The *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.

The earliest publicly available data for all the jurisdictions in our sample is from the third round of the MER. While encoding the ratings from the 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.[29] For example, the 5th follow-up report of the Bahamas (Oct, 12, 2012) states: "The Bahamas has also achieved full compliance with Recommendations 19 and 30." In this case, we code recommendations 19 and 30 as compliant (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 up the 49 scores $S_{j,t}(r)$ for each

[26] *Source:* Caribbean Action Finance Task Force (2020).

[27] `http://www.fatf-gafi.org/publications/mutualevaluations/documents/fatf-methodology.html`.

[28] For consistency with other data, we use only end-of-year reports.

[29] 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.

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:

$$\mathrm{SCI}_{j,t} = \frac{100}{147} \sum_{r=1}^{49} S_{j,t}(r) \tag{8}$$

Figure 2 illustrates the evolution of the status-of-compliance index over time for the jurisdictions in our sample. As is evident from Figure 2, the countries

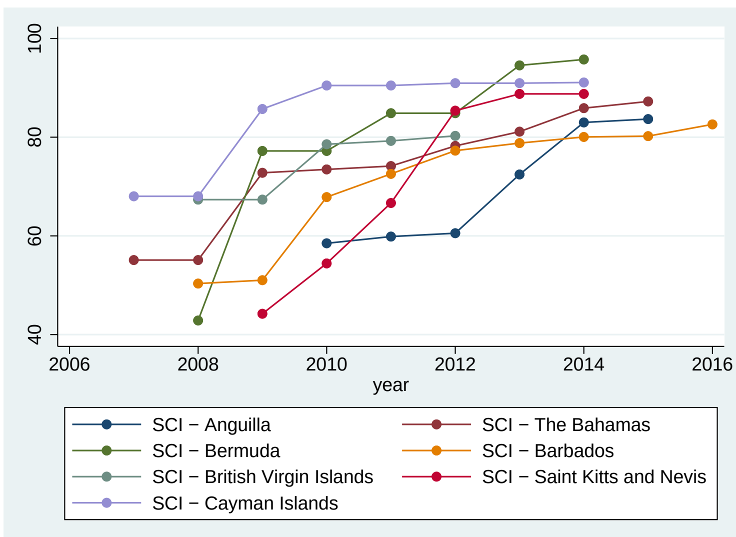


Figure 2: The status-of-compliance index by jurisdiction. *Source*: Caribbean Financial Action Task Force (CFATF).

entered and completed the mutual evaluation and follow-up process in different years. To add missing values for all the years from 2008 to 2015, we use a constant extrapolation back and forward in time.

In order to verify the robustness of the results, we work with alternative formulations of the index. In Appendix G.2, we analyse the impact of $\mathrm{SCI}_{j,t}$ for each jurisdiction separately, thus using the original data only, as presented in Figure 2.

4.1.3 The County-Jurisdiction Exposure

To construct the exposure shares in (6), we use the Bahamas Leaks, Offshore Leaks, Panama Papers, and Paradise Papers from the Offshore Leaks database compiled by the ICIJ.[30] The database distinguishes and provides links between three types of agents: (i) *entities*, which are firms, corporations, and trusts with an associated jurisdiction, which determines the laws and regulations to which they are subject; (ii) *officers*, who are owners, beneficiaries, and shareholders of the entities; and (iii) *intermediaries*, who assist in setting up the entities. Most of the agents are linked to their registered mailing addresses.

For the purpose of this paper, we focus on entities under Caribbean regulations. As suggested in the CFATF reports, these entities may include financial enterprises that provide FBML services. Hence we focus on officers who connect these offshore entities with registered addresses in U.S. counties. Consistent with DEA reports discussed in Section 4.4.2, intermediaries may provide international money-laundering networks that reduce the cost of FBML.

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[31] are also assigned the role of intermediaries. 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 (grey arrows, Figure 3). We classify such multiple links as a single connection.

Next, we identify direct (1,724) and indirect (57,855) links as follows. *Direct links* comprise all entities in a Caribbean jurisdiction that have a U.S. mailing address with a listed zip code. If an entity is connected to more than one U.S. zip code,[32] each zip-jurisdiction connection counts as a separate link. See, for example, Figure 1, which depicts several Bahamas entities with a New York address. *Indirect links* consist of all unique connections between officers with a U.S. address, including zip code, and entities in the Caribbean jurisdictions,

[30] *Source*: International Consortium of Investigative Journalists (2017).
[31] Only in the Offshore Leaks database and only 0.16% there.
[32] In the database no entity is connected to more than two addresses.

where these entities are not already counted as direct links. See Figure 3 illustrating both types of links for a Florida county.

Thus, we create a list of all U.S. addresses linked to the Caribbean jurisdictions. As a first step, we assign the compiled list of registered addresses to counties based on the zip code, using the 2010-1Q USPS county-zip crosswalk.[33] 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, c, we count the number of direct and indirect links from that county to all entities in each of the offshore jurisdictions, j. We denote this number by $L_{c,j}$. Hence, we use (6) to compute the associated exposure shares $w_{c,j}$. Figure 3 exemplifies how we calculate $L_{c,j}$ and $w_{c,j}$.

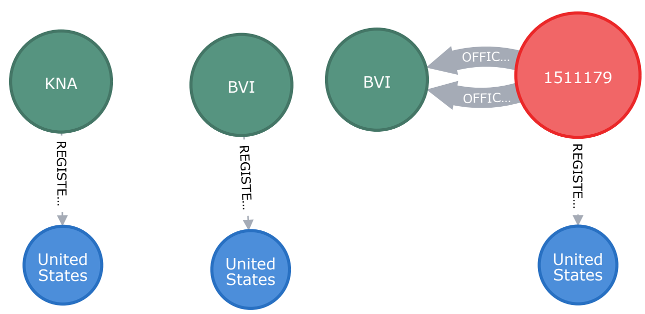


Figure 3: Officers are depicted as the largest (red) circles (their names are replaced by the internal id numbers), the entities are smaller green circles, the links are the grey arrows. The smallest blue circles are the registered addresses. This Florida county has three links. Two of them are direct: 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 $w_{c,KNA} = 1/3$.

Panel A of Table 1 reports descriptive statistics for county-level linkages, both their number and an indicator of the overall exposure. More than a third of U.S. counties (1,096) are exposed to changes in AML regulations via connections to offshore Caribbean entities, providing substantial cross-sectional

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

variation.[34] Panel B shows the degree of exposure of those counties to particular jurisdictions. The average county has 53 links, about 71 percent of which on average are with Bermuda, suggesting considerable concentration in the shares. The British Virgin Islands and the Cayman Islands also are prominent.

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

Panel A: Unconditional Descriptive Statistics						
	Counties	Mean	Median	Std	Min	Max
Total Links	3087	18.84	0.00	224.88	0.00	8383
Exposure Dummy	3087	0.36	0.00	0.48	0.00	1
Panel B: Descriptive Statistics for Exposed Counties ($\sum_{j \in \mathbf{J}} L_{c,j} > 0$)						
	Counties	Mean	Median	Std	Min	Max
Total Links	1096	53.06	2.97	375.12	0.00	8383
Share of Links to ANG	1096	0.22	0.00	4.30	0.00	100
Share of Links to BAH	1096	1.04	0.00	8.74	0.00	100
Share of Links to BER	1096	70.63	89.97	37.53	0.00	100
Share of Links to BRB	1096	0.82	0.00	7.08	0.00	100
Share of Links to BVI	1096	13.07	0.00	27.93	0.00	100
Share of Links to KNA	1096	0.08	0.00	1.30	0.00	33
Share of Links to CAY	1096	14.13	0.00	28.21	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 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 value of 1. The reported share of links, $w_{c,j}$, is multiplied by 100, i.e., expressed in percentage terms. *Source*: ICIJ.

Figure 4 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, which we account for with county fixed effects.

The corresponding heatmaps in Figure 9 in Appendix E point to cross-sectional variation that could help identify the impacts of AML regulations. For example, the British Virgin Islands (BVI) and the Cayman Islands (KNA)

[34] The maximum number of links (8383) is recorded in New York county (Manhattan).

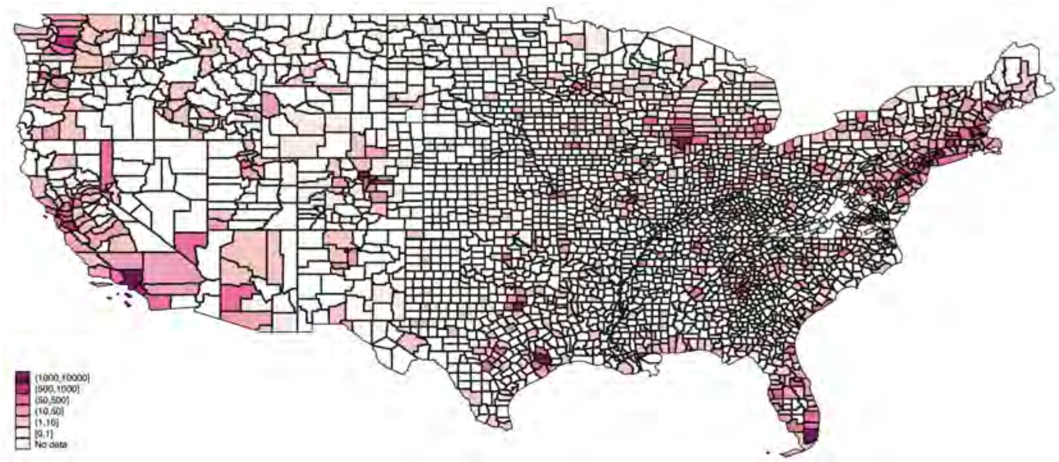


Figure 4: Intensity of the counties' exposure to all jurisdictions, $\sum_{j \in \mathbf{J}} L_{c,j}$.

both account for around 13 to 14 percent of initial-year linkages. Counties in the Pacific Northwest of the United States appear more exposed to BVI than to KNA, 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 either: some county features might affect the intensity of exposure. This is the reason for introducing county fixed effects, as explained in Section 4.2.

4.1.4 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, $\ln \mathrm{N}_{c,t}$. We collect U.S. county demographic and economic information at yearly frequency from several sources, including BLS, U.S. Census Bureau, Population Division, Bureau of Economic Analysis (BEA) database and Small Area Income and Poverty Estimates Program (SAIPE). See Table 8 in Appendix B for the details. As recommended by the Census Bureau,[35] we adjust nominal variables for inflation by using

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

the All Items CPI-U-R (CPI Research series). Real variables are expressed in 2010 U.S. dollars. All controls in the regressions are lagged one year, unless stated otherwise.

4.2 Identification Strategy

Using our explanatory variable Offshore-FRI$_{c,t}$ (see Equation (7)) the testable prediction of the basic model can be summarized as follows: an increase in Offshore-FRI$_{c,t}$ implies an increase in the number of business establishments ($N_{c,t}$) in county c in year t.

To estimate this relationship one could run the following OLS regression

$$\ln \mathrm{N}_{c,t} = \beta_0 + \beta_1 \cdot \text{Offshore-FRI}_{c,t} + \mu_{c,t} \tag{9}$$

between *realized* outcomes and *realized* treatment, where the dependent variable is the natural logarithm of the number of establishments by county c, year t. However, that specification would be prone to a selection problem: the realized Offshore-FRI$_{c,t}$ may correlate with observable and unobservable components of the error term $\mu_{c,t}$. To deal with this identification threat, we decompose the error term into these basic controls: county fixed effects ($\underline{d}_c$), state-year fixed effects ($\underline{d}_{s,t}$), lagged county income ($X_{c,t}$), and the remaining error term, $\varepsilon_{c,t}$.[36]

County fixed effects control for all unobserved time-invariant characteristics that affect county business activity, including those that may correlate with Offshore-FRI$_{c,t}$. Recall that the explanatory variable Offshore-FRI$_{c,t}$ is a product of a county-jurisdiction specific weight, $w_{c,j}$ and a jurisdiction-time-specific index, SCI$_{j,t}$. Hence $w_{c,j}$ is the only component in Offshore-FRI$_{c,t}$ that can potentially be correlated with time-invariant *county-specific* characteristics in the error term of regression (9). Indeed, the formation of links, and therefore the respective weights, might be a function of unobservable county characteristics, such as the history of criminal activities, regional variations in

[36] See, for example, the discussion of the Rubin causal model as in Holland (1986), see also Angrist and Pischke (2009).

supply and demand for illicit goods, and the tradition of compliance with laws and regulations. These county features in turn affect BBML. However, such dependence can be eliminated by controlling for county fixed effects.

State-year fixed effects control for all 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 orthogonal to U.S. county business activity, the institutional changes that drive them may be common. U.S. efforts in combatting ML, both on state and federal levels, are likely to be correlated with those of FATF, of which the U.S. is a member. It implies that state-year controls are called for, while federal efforts apply uniformly to all counties.

Finally, our model suggests that the scope for BBML is positively related to the time-varying county-specific revenue from illicit activities (E), other things being equal, as is shown in Appendix A.2. We address this concern by including county-year lagged log-income. Therefore, we make the following assumption.

Assumption 1 (**Conditional Independence Assumption**). Conditional on county fixed effects, state-year fixed effects and lagged value of log county personal income (henceforth, baseline controls), Offshore-FRI$_{c,t}$ is independent of the remaining error, $\varepsilon_{c,t}$.

To be consistent with our static model we make additional assumptions, which are common in the exposure-design literature (Goldsmith-Pinkham et al., 2020). First, we abstract away from any sources of spatial correlation.[37] Second, we focus on comparisons across equilibria of the static model. Stationarity, in particular, implies that the time trends (in business activity) can be safely ignored. We verify this assumption empirically by identifying the same "parallel trends" in exposed and non-exposed counties, see Appendix G.1. With these assumptions, our econometric findings should have a causal interpretation.

[37]For completeness, we analyze the spatial correlation effects in Appendix I.

4.3 Main Specification and First Empirical Results

Following our identification strategy, we decompose the error term in regression (9) to arrive at our main specification to be estimated:

$$\ln \mathrm{N}_{c,t} = \beta_0 + \beta_1 \cdot \text{Offshore-FRI}_{c,t} + \underline{d}_c + \underline{d}_{s,t} + X'_{c,t}\gamma + \varepsilon_{c,t} \tag{10}$$

The coefficient β_1 is the key target of the estimation, as we intend to assess the effect of AML regulations targeting FBML on business activity and, subsequently, on BBML.

Table 2 reports estimates of the average treatment effect (ATE) of the AML regulations on business activity. Column (1) reports estimates of the simpler, yet apparently biased OLS regression in Equation (9). Column (2) adds the log of county personal income to proxy for county-specific expenditure on illicit goods. Counties with higher illicit profits are more likely to be exposed to AML regulations targeting FBML in the offshore jurisdictions, explaining the positive bias in the column (1) estimate. Finally, column (3) reports estimates of our main specification, Equation (10), which includes the baseline controls discussed in Section 4.2.

The estimate in column (3) implies that the tightening of AML regulations by Caribbean nations over the period 2008-2015 caused the average increase of 2.29%[38] in the number of business establishments in exposed U.S. counties. By Corollary 1 the increase in the total business activity in response to the tightening of the financial regulations is a lower bound on the related increase in BBML activity due to the crowding-out effect. The same is true for the corresponding semi-elasticities. We conclude that stricter AML regulations in the Caribbean jurisdictions caused an average increase in the number of establishments for the purpose of hiding filthy lucre in exposed counties by *at least* 2.29%.

The results reported in column (4) indicate that the coefficient estimate

[38]This estimate is obtained by multiplying the estimated coefficient on Offshore-FRI (column (3)) by the 2015-2008 change in average Offshore-FRI in exposed counties, Δ_{15-08}. That is, $\beta_1 * \Delta_{15-08} = 0.00053 * 42.9792 = 2.29\%$.

Table 2: Effect of AML regulations on Business Activity.

	Conditional Independence Analysis				No Fin Crises	
	(1)	(2)	(3)	(4)	(5)	(6)
Offshore-FRI	0.02272***	0.00040**	0.00053***	0.00046***	0.00113***	0.00085***
	(0.00056)	(0.00016)	(0.00007)	(0.00007)	(0.00015)	(0.00016)
Log Real Personal Income		0.94899***	0.22605***	0.20676***	0.20465***	0.19437***
		(0.00472)	(0.02657)	(0.02091)	(0.02608)	(0.02177)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Counties FE	No	No	Yes	Yes	Yes	Yes
States FE x Years FE	No	No	Yes	Yes	Yes	Yes
Income/Wealth Controls	No	No	No	Yes	No	Yes
Socio-Demographic Controls	No	No	No	Yes	No	Yes
Observations	24,681	24,681	24,673	24,673	21,592	21,592
R^2	0.373	0.963	0.999	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) Fixed Effects*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects; *(iii) County-Year Income and Wealth Controls*: log real personal income, 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 explanatory variables are lagged. *Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

on Offshore-FRI is immune to introducing other variables, which supports our choice of baseline controls. Estimates of β_1 are robust to the inclusion of county-specific, time-varying economic measures, demographic factors, and income and wealth indicators listed in the note to Table 2. In particular, the median household income, house value, share of county personal income in dividends, interests and rents, and share of residents who are homeowners account for income and wealth variations across counties that may correlate with county business development. The share of county personal income from unemployment insurance compensations, unemployment rate and poverty share complements this picture, by controlling for different aspects of poverty. We also control for socio-demographic characteristics related to ethnicity (Hispanic or non-Hispanic) and race.

In the last two columns we demonstrate that the effect becomes stronger if we drop 2008, the year plagued by the financial crisis. While our sample begins in 2008, some might argue that the financial crisis itself moved resources from FBML to BBML, generating a spuriously positive coefficient on Offshore-FRI. Contrary to this claim, the magnitude of the basic coefficient is increased, which is consistent with the drop in demand for illegal goods during the crisis, which, in turn, affected the revenue (E) to be laundered through either channel.

Appendix G contains a battery of robustness checks. First, we replace our exposure variable, Offshore-FRI, with the $\mathrm{SCI}_{j,t}$ for each jurisdiction separately to investigate the particular national sources of identifying variation and provide external validity to our estimates. Second, we control for county-specific trends that may be driven by differential impact of the financial crisis on counties with different initial poverty shares or demographic characteristics in 2008. Third, we consider alternative clustering of the errors at the state-level to capture within-state correlations across counties. Fourth, we replicate our analysis using sector-county-year observations and provide further support of our conditional independence assumption. Among others, we show that our results continue to hold when the sector-county fixed effects are included.

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 establishment in exposed U.S. counties, indicative of a shift from FBML to BBML.

4.4 Heterogenous Effects

So far, we have estimated average effects of AML regulations targeting FBML on BBML. However, we expect this effect to vary across counties. For example, it is the county residents who set up connections with the offshore entities. So, their aptitude can affect the initial (pre-regulation) yield, α, of the FBML, and hence the allocation of dirty money across the two channels. As a result, we expect the same change in regulations to have a stronger effect in counties that had higher initial investment in FBML. Similarly, the amount of money to be laundered may depend on county characteristics that affect the total demand for drugs, and there may be other factors involved. Thus, to explore the heterogenous effect of the stringency of AML regulations targeting FBML, we consider the following interaction model

$$\begin{aligned}\ln \mathrm{N}_{c,t} =& \beta_0 + \beta_1 \cdot \text{Offshore-FRI}_{c,t} + \beta_2 \cdot \text{Offshore-FRI}_{c,t} \cdot \text{Characteristic}_{c,t} \\ &+ \beta_3 \cdot \text{Characteristic}_{c,t} + \underline{d}_c + \underline{d}_{s,t} + \varepsilon_{c,t} \end{aligned} \tag{11}$$

The additional element in this regression involves a county-specific time-varying characteristic. In the following sections, we examine the role of key characteristics that are likely important in this regard. In Section 4.4.1 we explore the county demographics as the source for heterogenous effects, while in Section 4.4.3 we study the sectoral decomposition in a more granular database. The key coefficient is β_2, which measures the impact of a change in the interaction term on business activity.

It is worth mentioning that the interest in decomposing the "county effect" is not purely academic. Identifying a statistical connection between certain features of a county and the magnitude of the measured effect can point to the value of illicit activities in the locality. If the sensitivity of BBML to changes in the stringency of the linked offshore jurisdictions is stronger in some county, then there might be more dirty money to launder there.

4.4.1 Demographics and BBML

To guide our search for the determinants of heterogenous effects, we read the 2019 National Drug Threat Assessment (NDTA),[39] which identifies the four most prominent Transnational Criminal Organizations [TCO]: the Mexican,

[39] `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.

Table 3: Heterogenous Effect of AML regulations targeting FBML on BBML.

	(1) Hispanic	(2) Asian
Offshore-FRI	0.00033***	0.00018**
	(0.00007)	(0.00007)
Offshore-FRI × Share of Hispanic	0.00002***	
	(0.00000)	
Offshore-FRI × Share of Asian		0.00014***
		(0.00002)
Share of Hispanic	0.00630***	
	(0.00200)	
Share of Asian		0.00897
		(0.00653)
Constant	Yes	Yes
Baseline Controls	Yes	Yes
Observations	24,673	24,673
R^2	0.999	0.999
Linear Combination at Average (Exposed)	0.040	0.041
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. *(iii) Demographic Controls*: share of Asian residents, share of residents with Hispanic origin. All 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. *Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

Colombian, Dominican and Asian organizations, all of which rely on local criminal groups of related origin.[40] The DEA underscores the key role played

[40] According to the document, the Mexican TCOs: *(i)* "coordinate the transportation and distribution of bulk wholesale quantities of illicit drugs to U.S. markets," (p.102), *(ii)* "generate billions of dollars annually through the sale of illegal drugs in the United States. (p. 103)"; *(iii)* "remain the greatest criminal drug threat to the United States; no other groups are currently positioned to challenge them," (p. 6); *(iv)* "work with smaller

by the Asian TCOs in laundering illicit drug proceeds of the other TCOs, citing their effectiveness.[41] These findings point to county demographic composition as a source for heterogenous effects: both the revenue from illicit activities and the yield of FBML depend on the effectiveness of the TCOs, which rely on its connections with the corresponding local communities.

To explore this channel, we estimate the interaction between our index of exposure to Caribbean regulations and the share of Hispanic and Asian county residents (each share plays the role of "Characteristic$_{c,t}$" in Equation (11)). When these demographic components are considered separately, both direct and interaction terms are significant, as shown in columns (1) and (2) in Table 3. Although the average effect in exposed counties is quantitatively stable, the impact of the interaction term involving the Asian share is almost seven times larger than that involving the Hispanic share. This observation is consistent with the dominant role played by the Asian TCOs in money laundering cited above. This interpretation hinges on the alleged involvement of these TCOs in establishing financial entities in the Caribbean that were later affected by changes in AML regulations, and thus caused the estimated increase in BBML. We find a way to empirically validate this assumption in the next section.

4.4.2 The Asian-Intermediaries Network

The key to detecting a possible connection between the Asian TCOs and the U.S.-Caribbean links analysed above is, again, in the NDTA assessment, stressing the international nature of their operations.[42]

local groups and street gangs of Hispanic origin [...] to handle retail-level distribution," (p. 102).

[41] "Asian Money Laundering Organizations have emerged within the last few years as leaders within the money laundering networks, due to a combination of charging lower fees and the efficiency of the services they provide." (p. 122). "Asian TCOs collaborate with and recruit Asian-Americans, blending into existing immigrant communities, to exploit U.S. drug markets" (p. 108).

[42] "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), confer footnote 39.

In order to allow for the possibility of identifying the Asian TCO channel, we extract the subnetwork of U.S. entities or officers with direct and indirect links using a similar taxonomy to the one introduced above. 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 from China or Hong Kong. Direct links are all the entities in CFATF jurisdictions with a U.S. address that includes zip code, which are either associated with China or Hong Kong country code or connected to intermediaries from China or Hong Kong. We refer to this subnetwork as the Asian Network. Table 4 confirms the presence of a substantial number of indirect links there. Using this subnetwork, we construct our explanatory

Table 4: Number of U.S.-Caribbean Jurisdictions Links by Type

Direct	Indirect	Direct-Asian	Indirect-Asian
1724	57855	7	3483

Source: ICIJ.

variable Offshore-FRI$_{c,t}$ following the same steps as described above for the original database. In Table 5, we report the estimates of our basic model using this variable on the Asian Network. These results are juxtaposed with our baseline estimates of the original model (Full Network). The coefficients of Offshore-FRI$_{c,t}$ are approximately 4 times larger in the Asian Network than in the baseline (5 times that of the interaction model). Although we have no direct evidence suggesting involvement of any entity in the network in money-laundering activities, we can draw some indirect conclusions. The U.S. counties that had connections to Asian intermediaries had a stronger increase in business activity in response to tightening of AML regulations in the Caribbeans. Such counties, potentially, had access to cheaper FBML services provided by the intermediaries and hence, invested more in the offshore entities. As a result, they were more exposed to financial regulations targeting FBML in CFATF jurisdictions, inducing entities in those counties to reroute larger amounts of illicit proceeds, resulting in a stronger local increase in BBML.

Table 5: 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	0.00053***	0.00193***	0.00018**	0.00092***
	(0.00007)	(0.00021)	(0.00007)	(0.00025)
Offshore-FRI × Share of Asian			0.00014***	0.00012***
			(0.00002)	(0.00004)
Share of Asian			0.00897	0.01772***
			(0.00653)	(0.00616)
Constant	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes
Observations	24,673	24,673	24,673	24,673
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; *(iii) Socio-Demographic Controls*: lagged share of Asian residents. *(iv) Interaction Terms*: interaction of Offshore Financial Regulation Index with lagged share of Asian residents. *Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

One may still wonder what economic factors facilitate involvement of Chinese and Hong Kong nationals in setting up financial entities for U.S. agents in the Caribbean countries. It might be a side effect of the accumulated foreign currency reserves in China coupled with limitations imposed on foreign cash withdrawals by Chinese nationals. The country's foreign exchange reserves grew rapidly between 2005 and 2014.[43] In the face of massive foreign currency inflows China *promoted outbound FDI and portfolio investment by enterprises and individuals* (People's Bank of China, 2008). Over roughly the same period, 2007-2013, there was an unprecedented growth in *shadow banking* in China (Chen et al., 2016),[44] which is a tacitly government-endorsed system

[43] *Source*: https://tradingeconomics.com/china/foreign-exchange-reserves.

[44] It is partially attributed to the tight monetary policy that followed immediately the post-financial-crisis stimulus.

of bank operations that circumvent regulations.[45] Recent analysis shows that the role of these financial institutions has been expanded: "The main area of growth has shifted from shadow credit provision to private firms with less privileged access to formal bank credit, towards offering alternative savings instruments," (Ehlers et al., 2018). In part, such networks grew in response to official restrictions imposed on individuals' daily and yearly withdrawals of U.S. dollars from accounts in China that have been formally in place since the beginning of the century and are aimed at curbing short-term speculative currency trading.

4.4.3 BBML by Sector

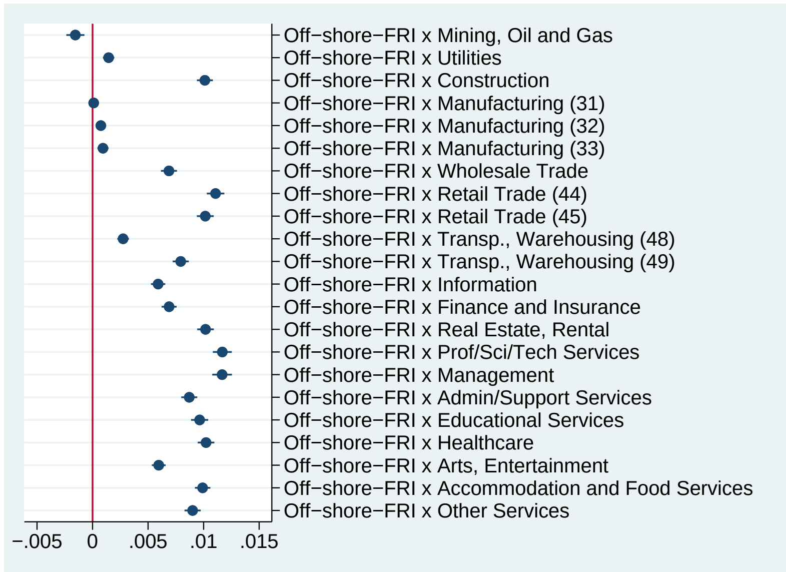
A further avenue for heterogeneity lies in the industry mix of establishments across counties. Our theoretical findings predict greater BBML activity in sectors where fixed entry costs are low relative to operating costs, as shown in Proposition 2 in Appendix A.3. To explore this theoretical insight we estimate the interaction between our explanatory variable Offshore-FRI$_{c,t}$ and the sectoral identifiers, two-digit NAICS dummies (which play the role of Characteristic$_{c,t}$ in Equation (11)).

Figure 5 reports the estimated interaction coefficients by industry along with the 95% confidence interval 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. These are the industries with relatively low fixed setup costs and somewhat higher marginal or operational costs, compared with manufacturing.

4.4.4 The Geography of BBML

We conclude our study of BBML with a geographic decomposition of the average treatment effect. We estimate our main regression (10) in each of the

[45] "...[banks] issue off-balance-sheet wealth management products (WMPs) to depositors and make trust loans to borrowers" (Wang et al., 2019).



Note: 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; *(iii)* two-digits NAICS dummies; *(iv)* interaction of Offshore Financial Regulation Index with two-digit NAICS dummies. *Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

Figure 5: Sectors at Risk of Money Laundering.

nine U.S. Census divisions separately. In Table 6 we observe notable regional variations of our estimates for the sensitivity of business activity to changes in AML regulations targeting FBML. As expected, we find the strongest effect in the Census divisions with larger metropolitan areas as well as coastal and border areas.

To illuminate the findings, we provide the "heatmap" of the estimated coefficients in Figure 6a. We offer broader perspective by placing alongside, in Figure 6b, a map from an independent source, the U.S. Drug Enforcement Administration, which presents the 10 states with highest indication of heavy drug use. There is a noticeable correlation between these maps, which is consistent with our story. The 2019 National Drug Threat Assessment indeed confirms a strong presence of the Mexican TCOs on the coasts and Southwest

Table 6: BBML by Census Division

	New England	Middle Atlantic	East North Central
Offshore-FRI	0.00044*	0.00014	0.00052***
	(0.00026)	(0.00017)	(0.00016)
Observations	536	1,200	3,496
Share Treated	0.791	0.767	0.428
	West North Central	**South Atlantic**	**East South Central**
Offshore-FRI	0.00031*	0.00091***	0.00046**
	(0.00018)	(0.00014)	(0.00018)
Observations	4,936	4,288	2,912
Share Treated	0.220	0.430	0.220
	West South Central	**Mountain**	**Pacific**
Offshore-FRI	0.00052***	0.00008	0.00136***
	(0.00019)	(0.00026)	(0.00038)
Observations	3,760	2,248	1,297
Share Treated	0.262	0.306	0.524

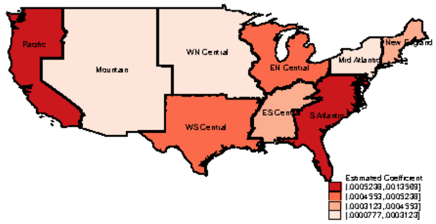
Note: The table reports by Census Division, the OLS estimates of the effect of the Offshore Financial Regulation Index on county-year logarithm of the number of establishments, in a regression that controls for *Baseline controls*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed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

Border,[46] the Asian TCOs on both U.S. coasts,[47] and the Dominican Cartel throughout the Northeast.[48] Accordingly, as laundering money via offshore FBML becomes more costly, we expect the rerouting of dirty money from FBML to BBML to be more visible in regions with more illicit activities.

[46] "Most of the methamphetamine available in the United States is produced in Mexico and smuggled across the Southwest Border," p. 5.

[47] "Asian TCOs actively conduct drug trafficking activities on both U.S. coasts and have distribution networks stretching across the country," p. 108.

[48] "Dominican TCOs dominate the mid-level distribution of cocaine and white powder heroin in major drug markets throughout the Northeast," p. 6.



(a) The estimated effect of the Offshore Financial Regulation Index on county-year ln N, by division, from Table 6.

(b) Top 10 States with the Most Heroin, Fentanyl, and Cocaine Reports in National Forensic Laboratory Information System, 2017, *Source: U.S. DEA.*

Figure 6: Our estimates of regional sensitivity of BBML to changes in financial regulations and indirect indications of drug use by the U.S. DEA.

5 Conclusions

Profits from illicit activities percolate into the legal economy through several money-laundering channels. Existing regulations target individual transactions and, once known to the criminals, become easy to circumvent. This clouds identification on the case-by-case level by the enforcement authorities. We develop and implement an identification strategy that uses publicly available micro-data.

Our basic premise is that impediments in one money-laundering channel will flush more dirty money into another. We use the differences in the status of compliance with international AML regulations in Caribbean havens to identify the flows of dirty money into legitimate establishments: business-based money laundering (BBML). We provide the first evidence of BBML in U.S. counties, as resulting from a tightening of financial regulations in Caribbean jurisdictions.

We prove analytically that more stringent AML regulations in the financial sector boost the number of firms in the legitimate sector, as they reduce the relative attractiveness of the financial channel for laundering money. Moreover, we construct the measure of exposure of each U.S. county to the changes in anti-money-laundering regulations in Caribbean jurisdictions using CFATF evaluations and ICIJ leaks data. Next, we use this measure to identify unusual spikes in business activity in specific locales, which, according to our model, can be attributed to BBML. Finally, we identify in the data additional factors that amplify this effect. These include demographic, geographic and industry characteristics. We document considerable heterogeneity in the substitution elasticity between FBML and BBML, depending on county characteristics, and relate it to international money-laundering networks, and industry features that facilitate BBML.

The suggested methodology can be used to identify money laundering in other countries. Further, more detailed data on business establishments and variations in commodity prices in illicit markets, can provide additional tools for pinpointing suspicious economic activity. These tools can bolster the ability of law-enforcement authorities to combat international criminal networks.

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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
ML	Money laundering
PMLs	Professional money laundering services
PP	Panama Papers
SCI	Caribbean Jurisdictions Status of Compliance Index
SOVs	Secret Offshore Vehicles
TBML	Trade-based money laundering

A Theory

A.1 Baseline Model

Proof of Lemma 1. Production firms' problems are symmetric and have a unique solution given the assumptions imposed, so each firm produces the same amount, $q_i = \bar{q}$ and charge the same price, $p_i = \bar{p}$. This implies that the profit $\pi_i = \bar{\pi}$ is the same for all.

Consumers maximize their utility subject to the budget constraint taking all prices and profits as given. Note that consumers co-own the clean firms that produce n varieties and get the distribution of the confiscated assets, $M/N \int_n^N \pi_i di$

$$\int_0^N p_i x_i di = Y \stackrel{\text{def}}{=} y + \frac{1}{L}(\int_0^n (\pi_i - f)di + \frac{M}{N}\int_n^N \pi_i di) - \frac{E}{L} \tag{12}$$

The budget constraint of the drug cartel that consumes $\tilde{x}_i$ of variety i reads:

$$\int_0^N p_i \tilde{x}_i di = (1 - \frac{M}{N}) \int_n^N \pi_i di \tag{13}$$

The sum of all the budget constraints yields

$$\int_0^N p_i(\tilde{x}_i + Lx_i) di = Ly + \int_0^N \pi_i di - fn - E \tag{14}$$

The market clearing condition for each variety i reads:

$$q_i = \tilde{x}_i + Lx_i \tag{15}$$

Recall that firms producing any variety choose the same quantity, $\bar{q}$, so combining market clearing (15), the sum of the budget constraints, (14) and the definition of profits, π_i, we can solve for $\bar{q}$, as in Parenti et al. (2017)

$$N\bar{p}\bar{q} = Ly + N(\bar{p}\bar{q} - c\bar{q}) - E - fn \implies \bar{q} = \frac{Ly - E - fn}{cN} > 0 \tag{16}$$

Thus the equilibrium mass of clean firms has an upper bound, $n < \frac{Ly-E}{f}$. The optimal price charged by the monopoly satisfies the usual markup rule:

$$\bar{p} = c\frac{\sigma(\bar{x}, N)}{\sigma(\bar{x}, N) - 1} \tag{17}$$

where $\sigma(\bar{x}, N)$ is the demand elasticity for any variety (see Parenti et al. (2017)).

To solve the drug cartel problem, (1), first notice that the revenue from the BBML is quadratic and concave in the amount invested:

$$V_T(z) = (1 - \frac{M}{N})M\bar{\pi} = \frac{z}{f}\bar{\pi} - \frac{z^2}{Nf^2}\bar{\pi} \tag{18}$$

The marginal revenue, $V_T'(z) = \bar{\pi}(\frac{1}{f} - 2\frac{z}{Nf^2})$, is decreasing. If $V_T'(0) = \frac{\bar{\pi}}{f} \leq \alpha$ all the money is laundered through the financial system. If the financial system is very strict, $V_T'(E) \geq \alpha$, then all the money is laundered through trade, $z^* = E$. If

$$\bar{\pi}(\frac{1}{f} - 2\frac{E}{Nf^2}) \leq \alpha < \frac{\bar{\pi}}{f} \tag{19}$$

then there is a unique z^* that solves

$$V_T'(z^*) = \alpha \tag{20}$$

which is the optimal level of BBML for the cartel. Hence

$$z^* = \max\{0, \min\{\frac{Nf}{2}(1 - \alpha\frac{f}{\bar{\pi}}), E\}\} \tag{21}$$

A clean firm will be producing as long as the profits are positive:

$$\bar{\pi} \geq f \implies \bar{p} - c \geq \frac{f}{\bar{q}} \tag{22}$$

Using Equation (16), and $n = N - M$ and the condition the above yields

$$\frac{1}{\sigma(\bar{q}, N) - 1} \geq \frac{fN}{Ly - E - f(N - M)} \implies \frac{Ly - E}{f} \geq N\sigma(\bar{q}, N) - M \tag{23}$$

Since free entry implies $\frac{\bar{\pi}}{f} = 1 \geq \alpha$, the amount of money in BBML, z^*, is strictly positive. There are $M = \frac{z^*}{f}$ BBML firms in equilibrium. If $\frac{Nf}{2}(1-\alpha) > E$ and so, by Equation (21), $z^* = E$, then the zero profit condition for the clean firms implies

$$\frac{Ly}{f} = N\sigma(\bar{q}, N) \tag{24}$$

Otherwise, if $1 - 2\frac{E}{Nf} \leq \alpha < 1$ then using optimality condition (21), we get $M = \frac{N}{2}(1 - \alpha)$ and so the zero profit condition for the clean firms implies

$$\frac{Ly - E}{f} = N(\sigma(\bar{q}, N) - \frac{1 - \alpha}{2}) \tag{25}$$

$\square$

Proof of Proposition 1. Let $F(N,\alpha) \stackrel{\text{def}}{=} N(\sigma(q(N,\alpha),N)-\frac{1-\alpha}{2})-\frac{Ly-E}{f}$. Then, by lemma 1, in case

$$1-2\frac{E}{Nf} \leq \alpha \tag{26}$$

the equilibrium is characterized by the two equations:

$$F(N,\alpha)=0, \quad q(N,\alpha)=\frac{Ly-E}{cN}-\frac{f}{c}\frac{1+\alpha}{2} \tag{27}$$

Applying the implicit function theorem, we can evaluate for a given α at the equilibrium (N)

$$\frac{dN}{d\alpha}|_{N,\alpha} = -\frac{\frac{\partial F(N,\alpha)}{\partial \alpha}}{\frac{\partial F(N,\alpha)}{\partial N}} \tag{28}$$

The derivatives evaluated at the equilibrium are as follows.

$$\frac{\partial F}{\partial \alpha} = \frac{N}{2}(1-\frac{f}{c}\frac{\partial \sigma(\bar{q},N)}{\partial q}) \tag{29}$$

$$\frac{\partial F}{\partial N} = \sigma(\bar{q},N)-\frac{1-\alpha}{2}+N\frac{\partial \sigma(\bar{q},N)}{\partial N}-\frac{\partial \sigma(\bar{q},N)}{\partial q}\frac{Ly-E}{cN} \tag{30}$$

Note that combining the equilibrium equations (3), we can establish the following inequality

$$\sigma(\bar{q},N)-\frac{1-\alpha}{2}=\frac{Ly-E}{fN}=\bar{q}\frac{c}{f}+\frac{1+\alpha}{2}>0 \tag{31}$$

Similarly,

$$\frac{Ly-E}{cN}=\bar{q}+\frac{f}{c}\frac{1+\alpha}{2}>0 \tag{32}$$

Hence, by (29), if $\frac{\partial \sigma(\bar{q},N)}{\partial q} \leq 0$ then $\frac{\partial F}{\partial \alpha}>0$ and by (30) if, in addition, $\frac{\partial \sigma(\bar{q},N)}{\partial N} \geq 0$ then $\frac{\partial F}{\partial N}>0$. In this case, by (28), $\frac{dN}{d\alpha}|_{N,\alpha}<0$. Then also the left hand side of inequality (26) is decreasing in α, so it holds for sufficiently high α.

In case α is too low, so inequality (26) is violated, then α has no effect on the equilibrium N. $\square$

Proof of corollary 1. By lemma 1, if $1 - 2\frac{E}{Nf} \leq \alpha$ then $M = \frac{N}{2}(1-\alpha)$ in equilibrium. Therefore, by the implicit function theorem, in a neighbourhood of the equilibrium,

$$\frac{dM}{d\alpha} = \frac{1-\alpha}{2}\frac{dN}{d\alpha} - \frac{N}{2} = -\left(-\frac{1-\alpha}{2}\frac{dN}{d\alpha} + \frac{N}{2}\right) \tag{33}$$

By proposition 1, $\frac{dN}{d\alpha} \leq 0$,

$$|\frac{dM}{d\alpha}| = -\frac{1-\alpha}{2}\frac{dN}{d\alpha} + \frac{N}{2} = \frac{1-\alpha}{2}|\frac{dN}{d\alpha}| + \frac{N}{2} \tag{34}$$

By the additional assumption, $|\frac{dN}{d\alpha}| < \frac{N}{2}$, so

$$\frac{1-\alpha}{2}|\frac{dN}{d\alpha}| + \frac{N}{2} > (\frac{1-\alpha}{2}+1)|\frac{dN}{d\alpha}| > |\frac{dN}{d\alpha}| \tag{35}$$

Combining this with Equation (34), we get the strict inequality, $|\frac{dM}{d\alpha}| > |\frac{dN}{d\alpha}|$.

By lemma 1, if $1 - 2\frac{E}{Nf} > \alpha$ neither N nor M are affected by α. $\square$

A.2 The effect of revenue change from illicit activities

Let us compare the effect of a change in α in two economies that differ only in their level of spending on illicit activities: $E_1 > E_2$. First notice that by the IFT (given $\frac{\partial F}{\partial N} > 0$ and $\frac{\partial F}{\partial E} > 0$) implies $N_1 < N_2$.

Considering the effect of α on the number of firms, we have to evaluate and compare

$$\frac{\partial F}{\partial \alpha} = \frac{N_i}{2}(1 - \frac{f}{c}\frac{\partial \sigma(\bar{q}, N_i)}{\partial q}) \tag{36}$$

$$\frac{\partial F_i}{\partial N} = \sigma(\bar{q}, N_i) - \frac{1-\alpha}{2} + N_i\frac{\partial \sigma(\bar{q}, N_i)}{\partial N} - \frac{\partial \sigma(\bar{q}, N_i)}{\partial q}\frac{Ly - E_i}{cN_i}, \quad i = 1, 2 \tag{37}$$

Overall the effect is ambiguous and depends on cross derivatives of elasticity of demand σ. However, if the effect of E on overall number of firms is neutralized, so that $N_1 = N_2$, then $\frac{\partial F_i}{\partial N}$ falls with E, because $\frac{\partial \sigma}{\partial q} \leq 0$. This implies that the magnitude of the effect of α on N goes up with E, by the IFT. Thus, other things being equal, the effect of changes in financial regulations should be more pronounced in localities with higher spending on illicit activities.

A.3 Extensions: Two alternative Sectors for BBLM

The economy is the same as in the basic model, only now there are two sectors $k = 1, 2$ in the official economy. Both sectors can be used by the drug cartel to launder money. They differ by the costs of entry f_k and by costs of production c_k.

To simplify, we will assume that the goods across the two sectors are complimentary for consumers (e.g., food and entertainment) so that their utility, as a functional defined on a pair of square integrable functions x^1, x^2 of the variety index in the two sectors, can be represented as

$$\min\{aU_1(x^1), U_2(x^2)\}, \quad a > 0 \tag{38}$$

where $U_k, k = 1, 2$ are the two functionals satisfying the assumptions imposed on U in the main model. We normalize the two functionals so that when all quantities in x^k are equal (i.e., $x_i^k = \bar{x}^k$ for all varieties i of sector k), then the functional U_k returns the value on the diagonal, $\bar{x}^k$.

Proposition 2. *An equilibrium is fully characterized by the pair* (N_1, N_2) *that solves the system of equations*

$$F(N_1, N_2, \alpha) \stackrel{\text{def}}{=} \frac{f_1}{c_1}(\sigma^1(q^1(N_k, \alpha), N^1) - 1) - q^1(N_k, \alpha) = 0 \tag{39}$$

$$G(N_1, N_2, \alpha) \stackrel{\text{def}}{=} \frac{f_2}{ac_2}(\sigma^2(aq^1(N_k, \alpha), N^2) - 1) - q^1(N_k, \alpha) = 0, \text{ where} \tag{40}$$

$$q^1(N_1, N_2, \alpha) = \frac{Ly - E}{N_1c_1 + aN_2c_2} - \frac{1 + \alpha}{2} \frac{\sum_{k=1}^{2} f_k N_k}{N_1c_1 + aN_2c_2} \geq 0 \tag{41}$$

Let $\sigma^k_N(q,N) \overset{\text{def}}{=} \frac{\partial \sigma^k(q,N)}{\partial N}$ *and* $\sigma^k_q(q,N) \overset{\text{def}}{=} \frac{\partial \sigma^k(q,N)}{\partial q}$.

If $\sigma^k_1(\cdot) \leq 0, \sigma^k_N(\cdot) > 0$, $\lim_{N\to 1} \sigma^k_N(q,N) = \infty$ *and* $|\sigma^k_q(\cdot)| < 1$, *for* $k = 1,2$, *then the equilibrium exists and is unique.*

Proof. The proof follows the same steps as in case with a single sector. The main difference here is that the problem of the drug cartel has two stages. First, it allocates the investment z across the two sectors, z_1, z_2:

$$V_T(z) = \max_{z_1,z_2:\, z_1+z_2=z} \sum_{k=1}^{2} (1 - \frac{M_k}{N_k}) M_k \pi_k = \max_{z_1+z_2=z} \sum_{k=1}^{2} (1 - \frac{z_k}{f_k N_k}) \frac{z_k}{f_k} \pi_k \tag{42}$$

The marginal revenue $\pi_i(\frac{1}{f_i} - 2\frac{z_i}{N_i f_i^2})$ from investing in either sector ($i = 1,2$) is decreasing in the amount invested, z_i. Both sectors get a positive amount of the ML investment if they are not too dissimilar, i.e., if

$$\pi_1(\frac{1}{f_1} - 2\frac{z}{N_1 f_1^2}) < \frac{\pi_2}{f_2} \tag{43}$$

This condition always holds in the presence of the free entry condition, he zero-profit condition for the clean firms ($\pi^k_i = f_k$).

The optimal allocation requires the two marginal revenues across the two sectors to be equal if investment is positive in both:

$$\pi_1(\frac{1}{f_1} - 2\frac{z_1}{N_1 f_1^2}) = \pi_2(\frac{1}{f_2} - 2\frac{z_2}{N_2 f_2^2}) \tag{44}$$

This, along with the zero-profit condition for the clean firms ($\pi^k_i = f_k$) implies

$$\frac{z_1}{z_2} = \frac{N_1 f_1}{N_2 f_2}, \quad \frac{M_1}{M_2} = \frac{N_1}{N_2} \tag{45}$$

Thus the proportion of the BBML firms should be equal across the two sectors. Loosely speaking, this implies that one should observe more BBML firms in a more crowded sector. Further,

$$z_1 = \frac{N_1 f_1}{N_2 f_2}(z - z_1) \implies z_1 = \frac{N_1 f_1}{N_1 f_1 + N_2 f_2} z \tag{46}$$

As a result, the value of investing z dollars into BBML is

$$V_T(z) = (1 - \frac{z}{N_1 f_1 + N_2 f_2})z \tag{47}$$

The marginal value, V_T', is decreasing, $V_T'(z) = 1 - \frac{2z}{N_1 f_1 + N_2 f_2}$. As before, if

$$V_T'(E) = 1 - \frac{2E}{N_1 f_1 + N_2 f_2} > \alpha, \tag{48}$$

then the ML firm should invest everything in the trade sector, $z^* = E$.

Otherwise, there is a unique optimal z^* that solves

$$V_t'(z^*) = \alpha \implies z^* = \frac{1-\alpha}{2}(N_1 f_1 + N_2 f_2) \tag{49}$$

Therefore, by Equation (46),

$$z_k = \frac{1-\alpha}{2} N_k f_k, \quad M_k = \frac{1-\alpha}{2} N_k \tag{50}$$

We consider equilibria in which firms in each sector produce the same quantity $q_i^k = q^k, k = 1, 2, \forall i$, as in the one-sector model above. The preference specification implies that the consumers' demand (for all strictly positive prices) will dictate these quantities to be produced in fixed proportions:

$$aq^1 = q^2 \tag{51}$$

Using market clearing and consumer optimization in the official sector, we get, as in the single sector model,

$$\sum_{k=1}^{2} N_k c_k q^k = Ly - \sum_{k=1}^{2} f_k N_k + \sum_{k=1}^{2} M_k f_k - E \tag{52}$$

Substituting into the above equation the cartel's optimal decision condition

$M_k = \frac{1-\alpha}{2} N_k$, we get

$$\sum_{k=1}^{2} N_k c_k q^k = Ly - E - \frac{1+\alpha}{2} \sum_{k=1}^{2} f_k N_k \tag{53}$$

The zero profit condition for the clean firms in each sector, $\pi^k = f_k$ implies

$$\frac{c_k q^k}{\sigma^k(q^k, N_k) - 1} = f_k, \quad k = 1, 2 \tag{54}$$

The consumer optimization condition (51), resource constraint condition (53) and the profit maximization conditions (54) fully characterize an equilibrium. We can reduce it to the system of two equations by substituting (51) into (53), we can solve for $q^1 \geq 0$, which can now be presented as a function of the equilibrium variables N_k and parameter α:

$$q^1(N_k, \alpha) = \frac{Ly - E}{N_1 c_1 + a N_2 c_2} - \frac{1+\alpha}{2} \frac{\sum_{k=1}^{2} f_k N_k}{N_1 c_1 + a N_2 c_2} \tag{55}$$

The two equations in the statement of the proposition defining curves F and G are the profit maximizing conditions (54).

Next we show equilibrium uniqueness. For that it is sufficient to prove that the two curves, G, F cross only once in the N_1, N_2 space. The slope of the curve $F(\cdot) = 0$ is steeper than the slope of $G(\cdot) = 0$ in the N_1, N_2 space iff

$$\frac{\partial F(\cdot)}{\partial N_1} / \frac{\partial F(\cdot)}{\partial N_2} > \frac{\partial G(\cdot)}{\partial N_1} / \frac{\partial G() \cdot}{\partial N_2} \iff \frac{\partial F(\cdot)}{\partial N_1} \frac{\partial G() \cdot}{\partial N_2} > \frac{\partial F(\cdot)}{\partial N_2} \frac{\partial G(\cdot)}{\partial N_1} \tag{56}$$

The latter is equivalent to the claim of the following lemma.

Lemma 2. *Let* $A(\cdot) \stackrel{\text{def}}{=} \begin{pmatrix} \frac{\partial F(\cdot)}{\partial N_1} & \frac{\partial F(\cdot)}{\partial N_2} \\ \frac{\partial G(\cdot)}{\partial N_1} & \frac{\partial G(\cdot)}{\partial N_2} \end{pmatrix}$. *Then* $\det(A) > 0$ *under the assumptions of proposition 2.*

Proof. Let $\mathbf{N_c} \stackrel{\text{def}}{=} N_1 c_1 + a N_2 c_2, \quad C^k \stackrel{\text{def}}{=} c_k q^k(\cdot) + \frac{1+\alpha}{2} f_k$. First, note that quantity produced in the first sector is negatively related to the number of firms in each sector:

$$\frac{\partial q^1(N_1,N_2,\alpha)}{\partial N_1} = -c_1 \frac{Ly - E - \frac{1+\alpha}{2}\sum_{k=1}^2 f_k N_k}{(N_1c_1 + aN_2c_2)^2} - \frac{1+\alpha}{2}\frac{f_1}{N_1c_1 + aN_2c_2} = \frac{-C^1}{\mathbf{N_c}} < 0 \tag{57}$$

$$\frac{\partial q^1(N_1,N_2,\alpha)}{\partial N_2} = \frac{-C^2}{\mathbf{N_c}} < 0 \tag{58}$$

This, along with our assumptions ($\sigma_1^k \leq 0, \sigma_N^k > 0$) implies that both F, G grow with the number of firms in each sector:

$$\frac{\partial F(\cdot)}{\partial N_1} = \frac{-C^1}{\mathbf{N_c}}\frac{f_1}{c_1}\sigma_q^1 + \sigma_N^1\frac{f_1}{c_1} + \frac{C^1}{\mathbf{N_c}} > 0, \quad \frac{\partial F(\cdot)}{\partial N_2} = \frac{-C^2}{\mathbf{N_c}}\frac{f_1}{c_1}\sigma_q^1 + \frac{C^2}{\mathbf{N_c}} > 0, \tag{59}$$

$$\frac{\partial G(\cdot)}{\partial N_1} = \frac{-C^1}{\mathbf{N_c}}\frac{f_2}{ac_2}\sigma_q^2 + \frac{C^1}{\mathbf{N_c}} > 0, \quad \frac{\partial G(\cdot)}{\partial N_2} = \frac{-C^2}{\mathbf{N_c}}\frac{f_2}{ac_2}\sigma_q^2 + \sigma_N^2\frac{f_2}{ac_2} + \frac{C^2}{\mathbf{N_c}} > 0$$

Now we can verify the statement of the lemma using direct computation of the derivatives (59):

$$\frac{\partial F(\cdot)}{\partial N_1}\frac{\partial G()\cdot}{\partial N_2} - \frac{\partial F(\cdot)}{\partial N_2}\frac{\partial G(\cdot)}{\partial N_1} = \sigma_N^1\frac{f_1}{c_1}\frac{-C^2}{\mathbf{N_c}}\frac{f_2}{ac_2}\sigma_q^2 + \frac{-C^1}{\mathbf{N_c}}\frac{f_1}{c_1}\sigma_q^1\sigma_N^2\frac{f_2}{ac_2} \tag{60}$$

$$+\sigma_N^1\frac{f_1}{c_1}\sigma_N^2\frac{f_2}{ac_2} + \frac{C^1}{\mathbf{N_c}}\sigma_N^2\frac{f_2}{ac_2} + \sigma_N^1\frac{f_1}{c_1}\frac{C^2}{\mathbf{N_c}} > 0 \tag{61}$$

□

To assure existence, we will show that the single crossing has to occur in the positive quadrant ($N_1 > 1, N_2 > 1$). Indeed, by (59), and the assumption about the asymptotic behavior of σ_N^1,

$$\lim_{N_1 \to 1} \frac{\partial F(N_1,N_2,\alpha)}{\partial N_1} = +\infty \tag{62}$$

Further, by assumption, $|\sigma_q^k| < M$ and by (58), we can bound $\lim_{N_1\to 1} \frac{\partial F(N_1,N_2,\alpha)}{\partial N_2}$:

$$\lim_{N_1 \to 1} \frac{\partial F(N_1,N_2,\alpha)}{\partial N_2} < \frac{ac_2 q^1(1,N_2,\alpha) + \frac{1+\alpha}{2}f_2}{c_1 + aN_2c_2}\left(\frac{f_1}{c_1} + 1\right) \tag{63}$$

The upper bound decreases in N_2 down to zero, cf. (58). Therefore, the decreasing curve $F(N_1, N_2, \alpha) = 0$ (with the slope $-\frac{\partial F(N_1,N_2,\alpha)}{\partial N_1} / \frac{\partial F(N_1,N_2,\alpha)}{\partial N_2}$) has $N_1 = 1$ as an asymptote. The second curve, $G(\cdot) = 0$, similarly, is decreasing and has $N_2 = 1$ as an asymptote.

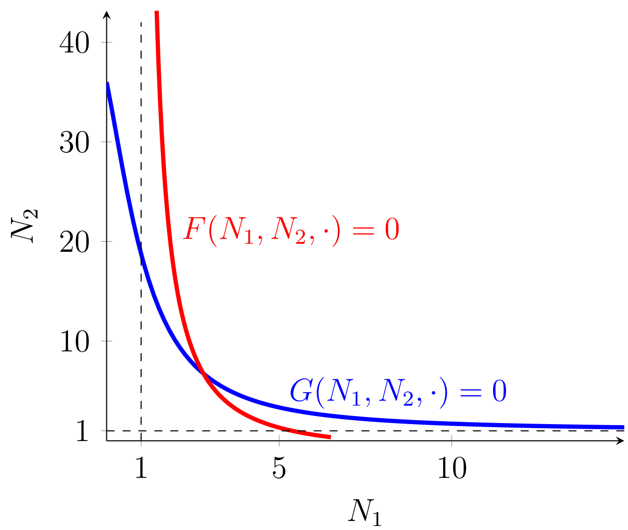


Figure 7: An illustration of an equilibrium combination of the numbers of firms in the two sectors, (N_1, N_2), as an intersection of the two curves, $F(N_1, N_2, \cdot) = 0$ and $G(N_1, N_2, \cdot) = 0$.

Note that for any $N_2 > 1$, the curve $G(N_1, N_2, \alpha) = 0$ has a non-zero, locally integrable slope at $N_1 \geq 1$ thus the curve has to cross $N_1 = 1$ at some finite N_2. It follows that for some $N_1 > 1$ sufficiently close to 1, the curve $G(\cdot) = 0$ is below $F(\cdot) = 0$. Similarly, the curve $F(N_1, N_2, \alpha) = 0$ at some $N_2 > 1$, which is sufficiently close to 1, is below $G(\cdot) = 0$. Therefore the two curves, $F(\cdot) = 0$ and $G(\cdot) = 0$, intersect at some intermediate point $(N_1, N_2) > (1, 1)$, both being continuous functions, cf. figure 7. $\square$

Proposition 3. *Under the assumptions of proposition 2, the number of firms in either sector is decreasing in α. If the ratio of marginal to fixed costs in* *sector 2 is high enough as compared to that of the first sector,*

$$\frac{c_2}{f_2} > \frac{\sigma_N^2}{\sigma_N^1}|\sigma_q^1(\cdot)| - |\sigma_q^2(\cdot)| + \frac{\sigma_N^2}{\sigma_N^1}\frac{ac_1}{f_1} \tag{64}$$

then the reaction of the number of firms in the second sector to changes in α is stronger, $|\frac{dN_2}{d\alpha}| > |\frac{dN_1}{d\alpha}|$.

Proof. Let matrix $A(\cdot)$ be defined as in lemma 2. Then in the vicinity of an equilibrium point

$$A(\cdot)\begin{pmatrix} dN_1 \\ dN_2 \end{pmatrix} + \begin{pmatrix} \frac{\partial F(\cdot)}{\partial \alpha} \\ \frac{\partial G(\cdot)}{\partial \alpha} \end{pmatrix} d\alpha = 0, \text{ where} \tag{65}$$

$$\frac{\partial F(\cdot)}{\partial \alpha} = \frac{\partial q^1(\cdot)}{\partial \alpha}\left(\frac{f_1}{c_1}\sigma_q^1(\cdot) - 1\right), \quad \frac{\partial G(\cdot)}{\partial \alpha} = \frac{\partial q^1(\cdot)}{\partial \alpha}\left(\frac{f_2}{ac_2}\sigma_q^2(\cdot) - 1\right), \tag{66}$$

$$\frac{\partial q^1(\cdot)}{\partial \alpha} = -\frac{1}{2}\frac{\sum_{k=1}^2 f_k N_k}{N_1 c_1 + aN_2 c_2} < 0 \tag{67}$$

By the implicit function theorem, if the determinant of matrix A is not zero, $\det(A) \neq 0$, then

$$\begin{pmatrix} \frac{dN_1}{d\alpha} \\ \frac{dN_2}{d\alpha} \end{pmatrix} = -\frac{1}{\det(A)}A^{-1}\begin{pmatrix} \frac{\partial F}{\partial \alpha} \\ \frac{\partial G}{\partial \alpha} \end{pmatrix}, \quad A^{-1} = \begin{pmatrix} \frac{\partial G(\cdot)}{\partial N_2} & \frac{-\partial F(\cdot)}{\partial N_2} \\ \frac{-\partial G(\cdot)}{\partial N_1} & \frac{\partial F(\cdot)}{\partial N_1} \end{pmatrix} \tag{68}$$

Let $\xi \stackrel{\text{def}}{=} \frac{\sum_{k=1}^2 f_k N_k}{2\det(A)(N_1 c_1 + aN_2 c_2)}$. By lemma 2 $\det(A) > 0$, so $\xi > 0$. Then

$$\begin{pmatrix} \frac{dN_1}{d\alpha} \\ \frac{dN_2}{d\alpha} \end{pmatrix} = \xi A^{-1}\begin{pmatrix} \frac{f_1}{c_1}\sigma_q^1(\cdot) - 1 \\ \frac{f_2}{ac_2}\sigma_q^2(\cdot) - 1 \end{pmatrix} \tag{69}$$

Therefore, using (59), we can compute the derivatives of the implicit functions:

$$\frac{1}{\xi}\frac{dN_1}{d\alpha} = \frac{\partial G(\cdot)}{\partial N_2}\left(\frac{f_1}{c_1}\sigma_q^1(\cdot) - 1\right) - \frac{\partial F(\cdot)}{\partial N_2}\left(\frac{f_2}{ac_2}\sigma_q^2(\cdot) - 1\right) \tag{70}$$

$$= \sigma_N^2 \frac{f_2}{ac_2}\left(\frac{f_1}{c_1}\sigma_q^1(\cdot) - 1\right) < 0 \tag{71}$$

$$\frac{1}{\xi}\frac{dN_2}{d\alpha} = -\frac{\partial G(\cdot)}{\partial N_1}\left(\frac{f_1}{c_1}\sigma_q^1(\cdot) - 1\right) + \frac{\partial F(\cdot)}{\partial N_1}\left(\frac{f_2}{ac_2}\sigma_q^2(\cdot) - 1\right) \tag{72}$$

$$= \sigma_N^1 \frac{f_1}{c_1}\left(\frac{f_2}{ac_2}\sigma_q^2(\cdot) - 1\right) < 0 \tag{73}$$

Now it is possible to compare the two:

$$|\frac{dN_2}{d\alpha}| > |\frac{dN_1}{d\alpha}| \iff \sigma_N^1 \frac{f_1}{c_1}\left(\frac{f_2}{ac_2}|\sigma_q^2(\cdot)| + 1\right) > \sigma_N^2 \frac{f_2}{ac_2}\left(\frac{f_1}{c_1}|\sigma_q^1(\cdot)| + 1\right) \tag{74}$$

Dividing both sides by $\frac{f_1}{c_1}\frac{f_2}{ac_2} > 0$, and letting $w_1 = \frac{c_1}{f_1}$ and $w_2 = \frac{ac_2}{f_2}$ the inequality is equivalent to

$$\sigma_N^1\left(|\sigma_q^2(\cdot)| + w_2\right) > \sigma_N^2\left(|\sigma_q^1(\cdot)| + w_1\right) \tag{75}$$

$$\iff w_2 > \frac{\sigma_N^2}{\sigma_N^1}|\sigma_q^1(\cdot)| - |\sigma_q^2(\cdot)| + \frac{\sigma_N^2}{\sigma_N^1}w_1 \tag{76}$$

□

B Variables Description

Table 8: Main Variables

Variable	Description
SCI	Status-of-compliance index for a given year and Caribbean jurisdiction (Equation (8)). See Section 4.1.2 for details. *Units:* Jurisdiction-year Index in $[0, 100]$. *Source:* Caribbean Action Finance Task Force (2020).
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 4.1.3 *Units:* County-jurisdiction shares in $[0, 1]$. *Source:* Caribbean Action Finance Task Force (2020).
Offshore-FRI	The index of exposure to offshore financial regulations, see Section 4.1.1. *Units:* County-year Index in $[0, 100]$. *Source:* Caribbean Action Finance Task Force (2020), 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[49] *(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.

[49]`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
	Source: United States Census Bureau, Population Division (2010) and United States Census Bureau, Population Division (2019).
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: 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.[50] 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).[51]
Unemployment Rate	Unemployment rate for a given year by county.

[50] https://www.bea.gov/resources/methodologies/local-area-personal-income-employment.
[51] 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	24681	2687.672	10917.38	5	446065
Offshore-FRI	24681	28.988	39.955	0	95.748
Real Personal Income	24681	4200.777	15242.62	2.214	513740.2
Real Median Household Income	24681	43.366	10.901	19.171	119.075
Real Median House Value	24681	127.254	86.007	26.094	994.658
Share of Income: Dividends, Interest Rates, Rents	24681	17.299	5.192	5.241	76.192
Share of Home Owners	24681	75.915	8.137	20.756	96.954
Share of Income: Unemp. Insurance Comp.	24681	.641	.5	.002	7.106
Unemployment Rate	24681	7.504	3.034	1.1	28.9
Share of Residents in Poverty	24681	15.964	5.978	3.08	57.801
Share of Residents with High School Diploma	24681	25.828	12.077	0	100
Share of Black Residents	24681	8.975	14.45	0	86.149
Share of White Residents	24681	85.768	16.152	8.875	99.683
Share of Natives Residents	24681	2.17	7.444	0	89.213
Share of Asian Residents	24681	1.252	2.567	0	44.853
Share of Hispanic Residents	24681	8.624	13.412	0	96.134

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.[52]

[52]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

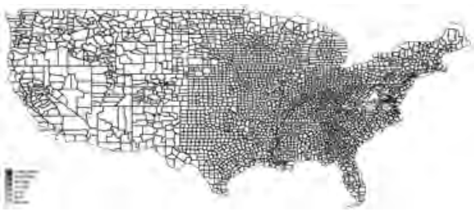
Table 11: Descriptive Statistics of status-of-compliance index by Jurisdiction.

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

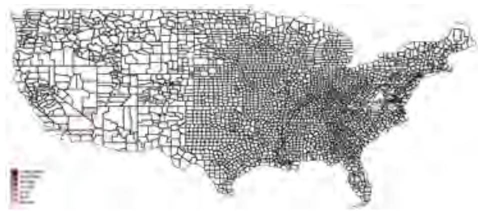
Source: CFATF. *Sample period*: 2008-2015.

E The County-Jurisdiction Exposure

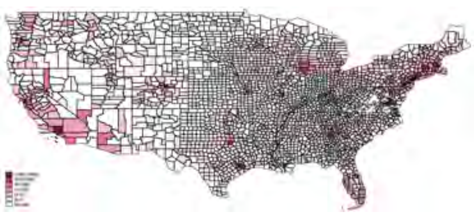
(a) Anguilla



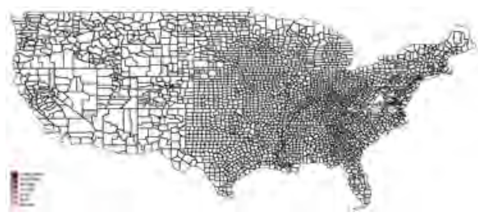
(b) The Bahamas



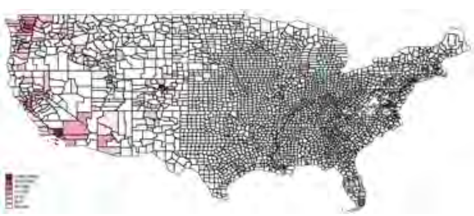
(c) Bermuda



(d) Barbados



(e) British Virgin Islands



(f) Saint Kitts and Nevis

(g) Cayman Islands

(h) All jurisdictions

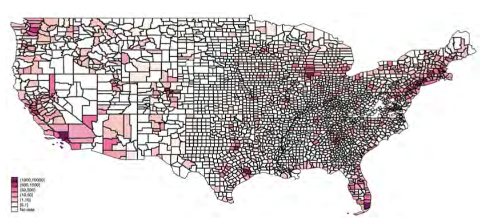
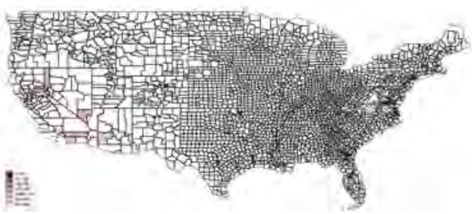


Figure 8: Intensity of the Exposure, $L_{c,j}$, by jurisdiction and county. *Source*: ICIJ.

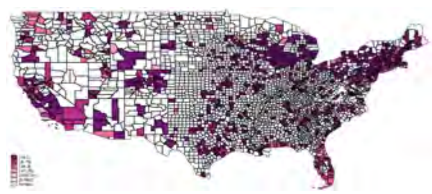
(a) Anguilla

(b) Barbados

(c) The Bahamas



(d) Bermuda



(e) British Virgin Islands

(f) Saint Kitts and Nevis

(g) Cayman Islands

(h) All jurisdictions

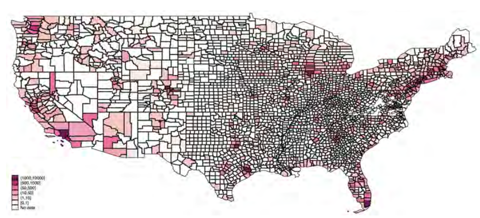


Figure 9: County-jurisdiction exposure shares, $w_{c,j}$. *Source*: ICIJ.

F Detailed Table for the Main Specification

Table 12: Effect of AML regulations on Business Activity.

	Conditional Independence Analysis				No Fin Crises	
	(1)	(2)	(3)	(4)	(5)	(6)
Offshore-FRI	0.02272***	0.00040**	0.00053***	0.00046***	0.00113***	0.00085***
	(0.00056)	(0.00016)	(0.00007)	(0.00007)	(0.00015)	(0.00016)
Log Real Personal Income		0.94899***	0.22605***	0.20676***	0.20465***	0.19437***
		(0.00472)	(0.02657)	(0.02091)	(0.02608)	(0.02177)
Log Real Median Household Income				0.08595***		0.08112***
				(0.01476)		(0.01389)
Div., Interest, Rent				0.00368***		0.00383***
				(0.00087)		(0.00093)
Unemp. Insurance				0.02757***		0.02957***
				(0.00397)		(0.00422)
Unemployment Rate				-0.00779***		-0.00694***
				(0.00108)		(0.00104)
Poverty Share				-0.00015		0.00009
				(0.00034)		(0.00033)
Share of Home Owners				0.00018		0.00009
				(0.00035)		(0.00034)
Share with High School Diploma				0.00022		0.00022
				(0.00042)		(0.00039)
Log Real Median House Value				0.02259**		0.01757*
				(0.01050)		(0.00986)
Share of Black				0.00276		0.00321
				(0.00225)		(0.00231)
Share of Natives				-0.03146***		-0.03245***
				(0.01205)		(0.01225)
Share of Hispanic				0.00735***		0.00765***
				(0.00197)		(0.00239)
Share of Asian				0.01855***		0.01515**
				(0.00668)		(0.00658)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Counties FE	No	No	Yes	Yes	Yes	Yes
States FE x Years FE	No	No	Yes	Yes	Yes	Yes
Observations	24,681	24,681	24,673	24,673	21,592	21,592
R^2	0.373	0.963	0.999	0.999	0.999	0.999

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

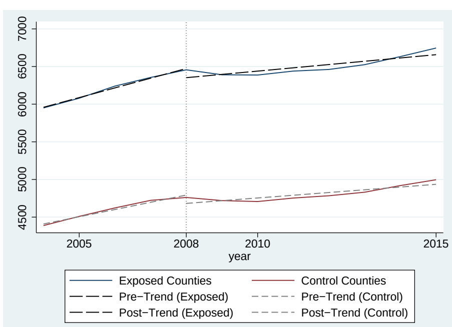
Note: OLS regression estimates of logarithm of the number of establishments on: *(i)* Offshore Financial Regulation Index; *(ii) Fixed Effects*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects; *(iii) County-Year Income and Wealth Controls*: log real personal income, log 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 explanatory variables are lagged. *Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

G Robustness checks

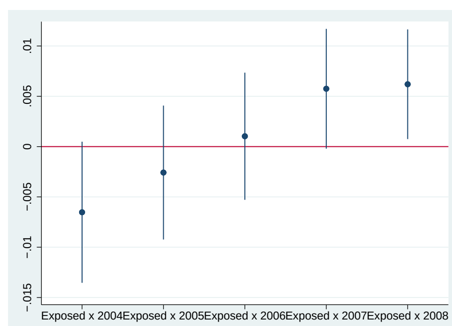
G.1 Parallel Trends

A possible identification threat is that in the years prior to the treatment, business activity in exposed counties may have trended differently from the non-exposed ones. We alleviate these concerns by showing the presence of parallel trends in the level of business activity among control and exposed counties in 2004-2008, the period before the CFATF process pushed Caribbean financial enforcement standards upward in Figure 10a. This is corroborated in Figure 10b displaying insignificant coefficients on the interaction terms between the dummy variable for positively exposed counties and the years prior to the treatment, conditional on county and state-year fixed effects.

At odds with the usual difference-in-difference policy analysis, exposed and non-exposed counties display parallel trends even in the treatment period (2008-2015). This result is consistent with money laundering being a "shadow phenomenon," which is difficult to detect. Identification and detection in this case requires econometric analysis.



(a) Parallel Trends.



(b) Interaction of Exposure Dummy and Years

Figure 10: Panel (a): the annual average number of county establishments for exposed (blue line) and non-exposed counties (red line) with respective trends over the pre-treatment period (2004-2008) and post-treatment period (2008-2015). Panel (b): the estimated coefficients on the interaction term between Exposure Dummy and Years $\{2004, \ldots, 2008\}$ from an OLS regression of county-sector-year log-establishments over the interaction terms, controlling for county and state-year fixed effects. *Source*: ICIJ, BLS. *Sample:* 2004-2015.

G.2 Status-of-Compliance Indexes and BBML

In order to investigate national sources of identifying variation and provide external validity of our estimates, we replace Offshore-FRI with the individual countries' compliance indexes, SCI. In addition, we check validity of our constant extrapolation in constructing the exposure variable, see the discussion following Figure 2.

In Table 13 in columns (1)-(7) we report the estimates for the regression where Offshore-FRI$_{c,t}$ is replaced with with jurisdiction-specific compliance indices (SCI) in observations where counties have positive exposure in that location, but set this variable equal to zero otherwise. As a result, regressions differ not only by main explanatory variables, but also by the time of treatment, see Figure 2. 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 our basic measure, in that the coefficients are significantly positive and of similar magnitude to those in Table 2.

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	0.00137***	0.00223***	0.00047***	0.00174***	0.00139***	0.00113***	0.00101***
	(0.00033)	(0.00029)	(0.00006)	(0.00017)	(0.00019)	(0.00018)	(0.00013)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,511	24,673	21,587	24,673	15,415	18,506	21,587
R^2	0.999	0.999	0.999	0.999	1.000	0.999	0.999

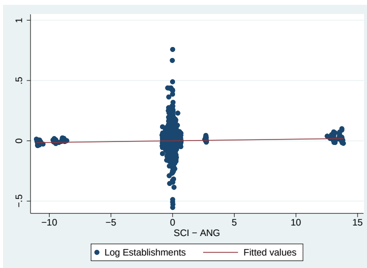
Regression coefficients, Standard error clustered at county level in parenthesis.

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

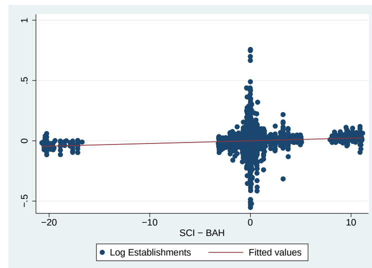
To further investigate the source of identification we use the Frisch-Waugh-Lovell Theorem to examine the residual (fixed-effects-adjusted) variation of log-establishments for the different specifications of OffshoreFRI, see figure

11. Consistent with Figure 9 above, most of the identifying variation comes from Bermuda, followed by the British Virgin Islands and the Cayman Islands.

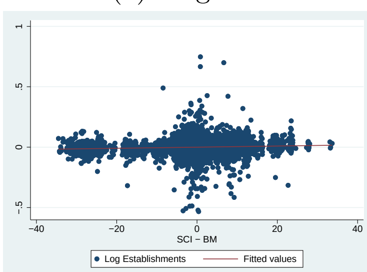
Next, we limit the sample to counties with positive exposure to verify that



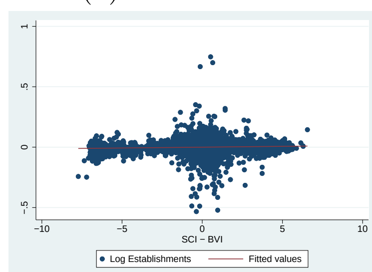
(a) Anguilla



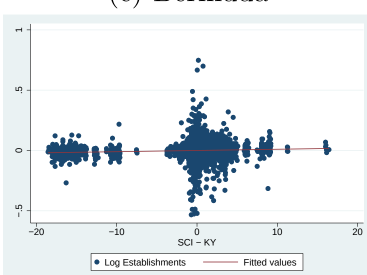
(b) The Bahamas



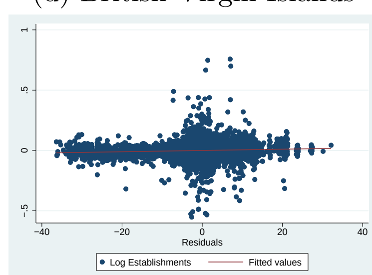
(c) Bermuda



(d) British Virgin Islands



(e) Cayman Islands



(f) Exposure to offshore Financial Regulations Index

Note: logarithm of the number of establishments net of baseline controls is on the vertical axis. On the horizontal axis is the normalized SCI of the corresponding jurisdiction. The original Offshore-FRI$_{c,t}$ is used in the last panel. *Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

Figure 11: Residual (fixed-effects-adjusted) variation of log-establishments.

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	0.00092***	0.00161***	0.00039***	0.00134***	0.00132***	0.00073***	0.00068***
	(0.00030)	(0.00030)	(0.00013)	(0.00017)	(0.00020)	(0.00019)	(0.00014)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,570	8,760	7,665	8,760	5,475	6,570	7,665
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. The sample is restricted to exposed counties. *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.3 County-specific Trends

We perform an additional robustness check of our estimates by controlling for county-specific trends that may have arisen as a result of the differential impact of the financial crisis on counties with different initial poverty shares or demographic characteristics in 2008. The results are presented in Table 15.

G.4 Alternative Clustering

We replicate the analysis, the estimates of which are reported in Table 2, with errors clustered at the state level in place of county level, providing additional support for the statistical significance of our estimates. The results are reported in Table 16.

Table 15: Robustness Check: Differential Impact of the Financial Crises.

	(1) Asian	(2) Hispanic	(3) Poverty	(4) All
Offshore-FRI	0.00038***	0.00052***	0.00047***	0.00031***
	(0.00007)	(0.00007)	(0.00007)	(0.00007)
Constant	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes
Share Asian 2008 x Years FE	Yes	No	No	Yes
Share Hispanic 2008 x Years FE	No	Yes	No	Yes
Poverty Share 2008 x Years FE	No	No	Yes	Yes
Observations	24,673	24,673	24,673	24,673
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. *(iii) Socio-Demographic Controls at year 2008 Interacted with Years FE*: share of Asian residents, share of residents with Hispanic origin, share of residents in poverty interacted with years fixed effects. *Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

Table 16: Effect of AML regulations on Business Activity.

	Conditional Independence Analysis				No Fin Crises	
	(1)	(2)	(3)	(4)	(5)	(6)
Offshore-FRI	0.02272***	0.00040*	0.00053***	0.00046***	0.00113***	0.00085***
	(0.00130)	(0.00024)	(0.00010)	(0.00010)	(0.00020)	(0.00021)
Log Real Personal Income		0.94899***	0.22605***	0.20676***	0.20465***	0.19437***
		(0.01204)	(0.05564)	(0.03890)	(0.05280)	(0.03719)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Counties FE	No	No	Yes	Yes	Yes	Yes
States FE x Years FE	No	No	Yes	Yes	Yes	Yes
Income/Wealth Controls	No	No	No	Yes	No	Yes
Socio-Demographic Controls	No	No	No	Yes	No	Yes
Observations	24,681	24,681	24,673	24,673	21,592	21,592
R^2	0.373	0.963	0.999	0.999	0.999	0.999

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

Note: OLS regression estimates of logarithm of the number of establishments on: *(i)* Offshore Financial Regulation Index; *(ii) Fixed Effects*: county ($\underline{d}_c$) and state-year ($\underline{d}_{s,t}$) fixed effects; *(iii) County-Year Income and Wealth Controls*: log real personal income, 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 explanatory variables are lagged. *Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

H Sector-county-year Observations

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

$$\ln \mathrm{N}_{i,c,t} = \beta_0 + \beta_1 \cdot \text{Offshore-FRI}_{c,t} + \text{Fixed Effects} + \varepsilon_{i,c,t} \tag{77}$$

The results are reported in Table 17. With these additions, the estimates in

Table 17: Robustness: Effect of AML recommendations on BBML.

	Baseline	FE	Zeros
	(1)	(2)	(3)
Offshore-FRI	0.00051***	0.00031***	0.00045***
	(0.00004)	(0.00004)	(0.00004)
Log Real Personal Income	0.09011***	0.15891***	0.08724***
	(0.00990)	(0.01158)	(0.00917)
Constant	Yes	Yes	Yes
Counties FE	Yes	No	Yes
County-Sector FE	No	Yes	No
States FE x Years FE	Yes	Yes	Yes
Observations	6,675,028	6,612,949	6,765,774
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. 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). *Source*: CFATF, ICIJ, BLS, BEA, SAIPE, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.

column (1) remain close to those of the baseline model in Table 2. Replacing county fixed effects by county-sector fixed effects decreases the estimated β_1 by almost a 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 close to the baseline case.

I Spatial Spillovers

In order to investigate the local spatial spillovers effects, we estimate a standard variant of the linear regression as in Vazquez-Bare (2017); Manski (1993):

$$\ln \mathrm{N}_{c,t} = \beta_0 + \beta_1 \text{Offshore-FRI}_{c,t} + \beta_2 \sum_{n \neq c, n \in B_c} P_{c,n} \text{Offshore-FRI}_{n,t} + \underline{d}_c + \underline{d}_{s,t} + \varepsilon_{c,t}$$

We use the Census county adjacency file[53] to discipline the spatial contiguity matrix P and compute the leave-one-out sample average of Offshore-FRI$_{c,t}$ over county c set of neighbors B_c. The estimates indicate the presence of a strong local spillover effect. This, in combination with the direct effect (column (2)) is higher than the estimate provided by our baseline model (column (1)). Therefore, we can view the baseline estimate as a lower bound of the overall effect.

[53] *Source*: United States Census Bureau (2020).

Table 18: Local Spatial Spillover Effects

	(1) Baseline	(2) Spillover
Off-shore-FRI	0.00054***	0.00029***
	(0.00007)	(0.00007)
Leave-one-out Mean Off-shore-FRI		0.00077***
		(0.00016)
Constant	Yes	Yes
Counties FE	Yes	Yes
States FE x Years FE	Yes	Yes
Population	Yes	Yes
Observations	24,635	24,635
R^2	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. *Source*: CFATF, ICIJ, BLS, BEA, U.S. Census Bureau, Population Division. *Sample period*: 2008-2015.