Tracking Illicit Money: The Move from Financial Money Laundering to Business-Based Money Laundering

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Abstract

This paper attempts to show an increase in business-based money laundering when it becomes harder to launder money through the financial sector. To do this, it measures the effect of Anti-Money Laundering (AML) policies in Aruba on the amount of new business establishments in counties with links to offshore accounts in Aruba. Exposed counties and non-exposed counties are compared to show that the number of business establishments in exposed counties are similar to the number in non-exposed counties before changes in AML policies begin. The regression model used is a log-linear model that measures the effect of AML policies on the number of business establishments in exposed counties compared to non-exposed counties. We find that there is a positive correlation between stricter AML policies in Aruba and new business establishments in exposed counties, suggesting that there is an increase in business-based money laundering when policies against offshore accounts become more strict.

1 Introduction

The majority of crimes committed in the United States every year revolve around one thing: money. Almost every single crime committed, minus a few exceptions, can be linked back to the motivation for money and wealth. This is especially true when it comes to organized crime. The main goal of organized crime is to create a business of obtaining money through illegal activities such as selling drugs, weapons, or committing other criminal acts. However, when profiting large amounts of illegally obtained money, it cannot be spent the same way as legal money. In order to use this money for large spending, it must appear to be obtained legally. This process is known as money laundering, where profits obtained through illegal practices are put into the legal sector to hide its origin.

Money laundering is a major issue in both the United States and in other countries. According to the United Nations Office of Drugs and Crime, roughly 2-5% of global GDP, or 800 million-2 trillion U.S. dollars, is laundered each year. This illegally obtained money is not only used to further finance criminal activity and organized crime, it is also used to finance terrorism. Money that is used to finance terrorism goes through the money laundering process in order to hide the use of both illicit money and legally obtained money in financing terrorist organizations. It is important for law enforcement agencies and governments to be able to track money that is being laundered and seize it to prevent it from being used to further establish organized crime and finance terrorism.

There are two ways that money is laundered, through the financial sector and through business establishments. The first utilizes offshore accounts and shell companies in order to move money around so it cannot be traced. This is done in two stages, placement and layering. Placement is when a person puts funds that have been obtained illegally into the financial sector.

Criminals take advantage of countries' less strict Anti-Money Laundering (AML) policies and offshore their money there. They then layer the money, in which the person makes movements in order to hide where the source of the money came from. This makes the money appear though it was obtained using legal practices. Business-based money laundering uses legal establishments to turn illegal money into legal profit. A business is purchased with illegal money. Then transactions are inflated to mix in the illegal money with the clean profits. In countries like the United States, where there are strict policies against money laundering and law enforcement actively enforce them, financial based money laundering is commonly used and illegal money is placed into offshore accounts in countries with less strict AML policies.

The goal of this paper is to study where the money goes when countries finally crack down on offshoring and improve upon their AML policies. To do this, I will measure the effect of AML financial regulations in Aruba on the number of business establishments in exposed counties in the United States. In the past, Caribbean countries were a common spot of financial based money laundering due to their low amounts of regulations and ineffectiveness on enforcement. However, the Caribbean made this a point of issue and created a task force, the Caribbean Financial Action Task Force (CFATF), in order to improve upon the AML policies and crack down on money laundering through offshore accounts. The CFATF evaluated each of the Caribbean countries and made a series of recommendations they had to follow in order to improve upon their policies. These recommendations are used to measure Aruba's changes in AML policies. The Panama Papers, which are a series of leaks that connect agents to offshore accounts in the Caribbean, are used to find counties that are affected by changes in the main X variable. Lastly, data on the annual average number of business establishments in United States counties was taken from the U.S. Bureau of Labor Statistics.

This paper uses a log-linear regression model to estimate the effect of AML regulations in Aruba on the number of business establishments in exposed United States counties. Taking the log of the number of business establishments allows the model to estimate the change in business establishments due to the key X variable. To ensure that changes in AML regulations only affect counties that are exposed, I added a dummy variable that is equal to 1 if the county is exposed and 0 if it is not and multiplied it by the key X variable. There are also a number of controls in the regression, including county-fixed effects, state-year-fixed effects, and county income level.

The main contribution that this thesis will make is to a research paper called *Hiding Filthy Lucre in Plain Sight: Theory and Identification of Business-Based Money Laundering,* written by Keith E. Maskus, Alessandro Peri, and Anna Rubinchik. In this research paper, they developed the model that I used to evaluate the CFATF reports on AML regulations and applied it to seven of the Caribbean countries. They then linked counties exposed to offshore accounts in these countries through the Panama Papers and studied the effect of the regulations on new business establishments in United States counties that are exposed. They found that changes in AML regulations in these seven Caribbean countries led to, on average, a 1.7% increase in business establishment due to business-based money laundering. This paper's addition to (Maskus, Peri & Rubinchik, 2021) is focusing its attention on Aruba. Aruba is one of the Caribbean countries that had the greatest issues with their AML policies, and essentially had to restructure all of their policies in order to improve their effectiveness on regulating money laundering in the country. This could lead to capturing an even bigger effect of AML regulations on new business establishments than the one captured in the previous report.

2 Literature Review

This paper relates to literature that has been done on linking offshore accounts to criminal activity. The research done in this paper relies on the assumption that offshore accounts in Aruba are being used to launder money, and increasing anti-money laundering policies will lead to that money to be laundered in a different way. In (Bayer, 2020) the Panama Papers are used to show that agents are more likely to shift their wealth offshore when fear of expropriation is increased. They collected information on offshore entities and the countries that they are linked to. The paper found that increased news and media coverage on expropriation in a country leads to a higher probability of entities in that country offshoring their wealth. This relates to this paper because it looks at offshore accounts linked to the United States, where sanctions on money laundering are strict and law enforcement utilizes expropriation.

More literature has been done to show what these offshore accounts are used for. Papers have been written linking offshore accounts to criminal activity, such as tax evasion and money laundering. In (Alstadsæter, 2019), *Tax Evasion and Inequality,* it discovered that the offshore accounts that were being used for tax evasion belonged to the richest individuals. It stated that "...0.01 percent richest households evaded around 25 percent of their taxes" (Alstadsæter, 2019). (Pacini and Forbes, 2020) uses the Panama Papers to show that offshore accounts were being used for evading taxes, laundering money, and other illegal activities. These two papers link offshore accounts to large amounts of criminal activity. However, this paper will show the mobility of this money when countries begin to crack down on these accounts, causing criminals to move their money elsewhere. If organized criminals move their money into the business sector, we should see an increase in new business establishments in counties that are exposed.

The use of businesses to launder money is shown in (Riccardi & Levi, 2018). In the paper they explain that cash businesses are an ideal vessel to launder money through, because criminals are able to mix in the illicit funds into the legally obtained revenue, making those illicit funds appear like it was revenue from the business. My findings will contribute to this by showing that business-based money laundering increases as it becomes more difficult to launder money in the financial sector, proving laundering money through businesses is a viable option.

Although there is literature that shows what offshore accounts are being used for, there has not been much research done on the effects of cracking down on offshore accounts. The paper most closely related to this paper (Maskus, Peri & Rubinchik, 2021) makes the model for measuring the effect of AML regulations on business establishments in exposed counties. In their paper they look at 7 different Caribbean countries; Anguilla, The Bahamas, Barbados, Bermuda, British Virgin Islands, Cayman Islands, and Saint Kitts and Nevis. They used the Panama Papers to link entities in these countries to United States mailing addresses, and then measured the effect of an increase in the Status of Compliance (SCI) in each country on the number of business establishments in counties with links to these entities. They found that there is, on average a 1.7%, increase in new business establishments caused by changes in SCI. My contribution to this paper is taking the model they used and applying it to a country that they did not look at. Aruba had a lot of changes in their SCI, which makes it a good country to study those effects on business establishments. This paper also uses more indirect links to entities, as opposed to direct links.

3 Data

The data used in this paper contains all of the counties in the United States over the course of 2008 through 2014. The major variables that will be used are the number of business establishments in a given year and the shock caused from new AML regulations in Aruba. There is also a dummy variable to indicate which counties are exposed to agents connected to offshore accounts in Aruba and which ones are not.

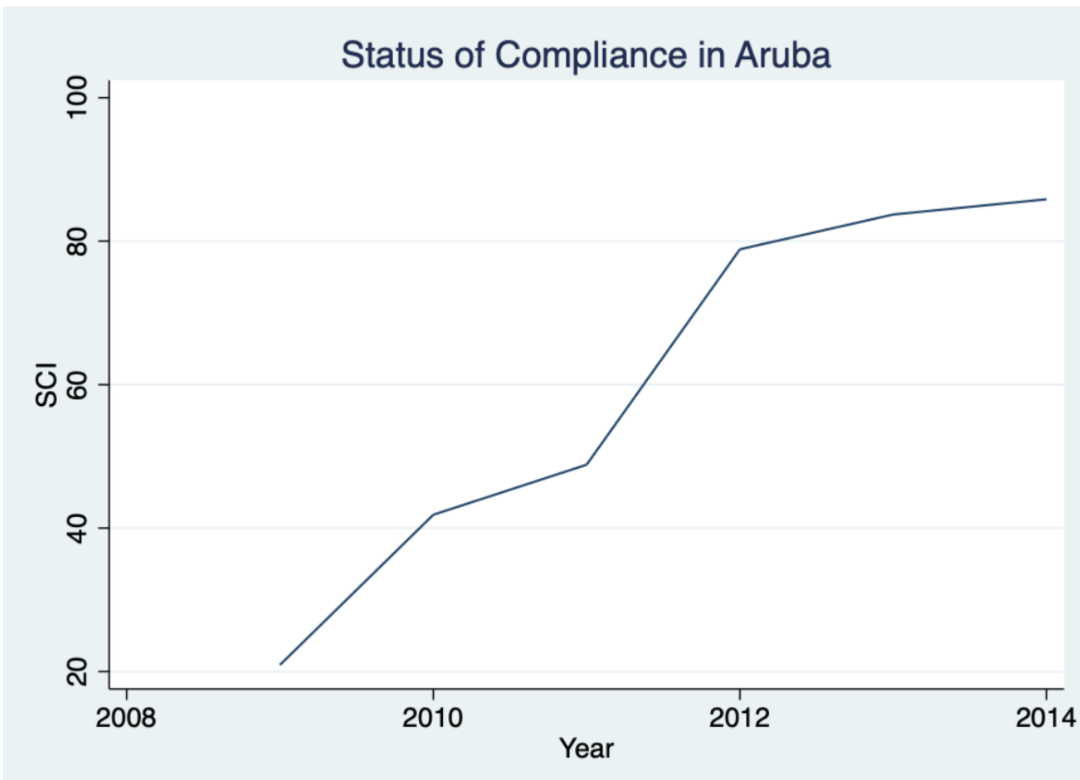
Reports taken from the Caribbean Financial Action Task Force are used in order to measure changes in the AML policies in Aruba from 2009 to 2014. In 2009, Aruba was put onto a series of follow up reports due to its noncompliance on a number of recommendations made by the CFATF to combat money laundering. The CFATF made a list of 49 recommendations to improve policies against money laundering, and then rated each country in the Caribbean on its level of compliance to each of the recommendations. The highest level of compliance is compliant, followed by largely compliant, partially compliant, and finally noncompliant. Aruba scored partially compliant on thirteen of the recommendations and scored noncompliant on twenty-five. The CFATF put Aruba on a list of countries that have to give yearly progress reports to show them how they are improving on each of the recommendations, until Aruba reaches a level of at least largely compliant.

To show the changes in AML regulations in the data sheet, information given in both the initial report and the progress reports are used to assign each recommendation a numerical value. This strategy is taken from (Maskus, Peri & Rubinchik, 2021), where each level of compliance is given a numerical value and compliance changes over time based on yearly progress reports. In the initial report, a level at compliant is given a 3, followed by largely compliant given a 2, partially compliant is given a 1, and noncompliant is given a zero. Progress reports from 2010 through 2014 are then used to update the level of compliance based on the progress that they have made to their AML regulations. There are times when the report will say what level of compliance the recommendation has been updated to, however for the most part the reports provide what progress was made over that year but leaves out the updated level of compliance. In these instances, the level of compliance is changed based on a few factors. First, if there were talks of a policy that would make improvements in a recommendation but no actions have taken place yet, I would increase the level of compliance by 0.25. If the policy was made and submitted into parliament but had not gone into place yet, I would increase the compliance by 0.5. Even though a policy is not put into place and thus not being enforced, we should still see movement on offshore accounts based on the anticipation of the policy. This is why the rating of compliance is given a half point. I would then increase the level of compliance by 1 if a policy is put into place and covers requirements made by the recommendation or any other actions made by Aruba that improves on the requirements. Using this system of rating, I went through each recommendation across the four years of follow up reports and scored each on their improvements. An in depth description of each policy change along with the names of each of the 49 recommendations can be found in Appendix C. In 2014, Aruba reached a level of at least largely compliant on each of the 49 recommendations and was removed from the yearly progress reports.

There will be a few recommendations left out of the data sheet based on no changes being made throughout the five-year span. Two of the recommendations were given the highest level of compliance in 2009, so these will be taken out of the final data sheet. There were also four recommendations that either did not apply to Aruba or were not mentioned in the progress reports, so those were taken out as well. The final value for the overall compliance of Aruba is represented by the Status of Compliance (SCI) variable, which is represented by all of the ratings in a given year add up, and divided by the highest level of compliance Aruba could have in total, and finally multiplied by 100.

$$SCI_t = \frac{\sum_{i=1}^{43} S(r)_t}{43*3} * 100 \tag{1}$$

Figure 1



Note. This figure demonstrates the trend of Aruba's Status of Compliance over the years 2008 through 2014. SCI is shown as a percentage of the total compliance to all 43 recommendations.

This will give us the overall percentage of compliance Aruba has in a given year. Figure 1 shows how SCI changes throughout the time period of the data. It started in 2009 when the initial report was given and ended in 2014 when Aruba no longer had to give progress reports. We will also multiple SCI by our dummy variable for exposure, so there is no effect in counties that have no exposure.

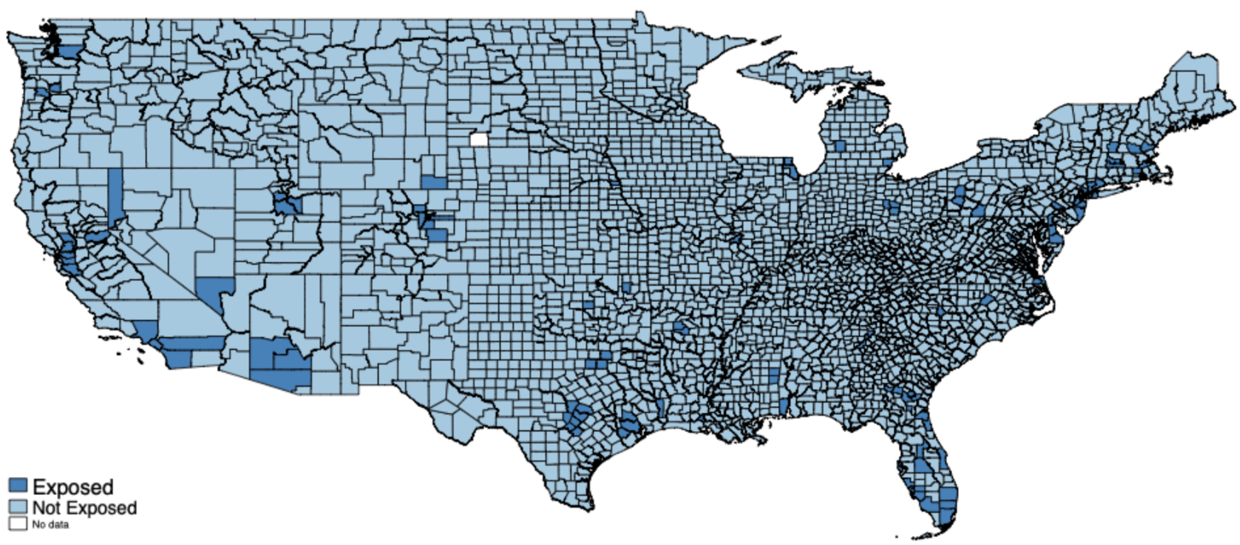
When deciding whether a county is listed in the data as "exposed," this paper looks for only one connection from that county to an offshore account in Aruba. The method used to find links to offshore accounts is from (Maskus, Peri & Rubinchik, 2021), however in that paper they weigh the level of exposure by how many links a county has. Since this paper is only using one country, I consider a county exposed if it has at least one link. To find counties in the United States that are exposed to offshore accounts in Aruba, databases from the Panama Paper leaks are used. The main database finds connections through three types of ways; entities, officers, and addresses. Entities represent firms, corporations and trusts that are associated with Aruba. Officers are owners or shareholders to an entity. And finally, addresses provide a zip code to where the officers or entities' mailing addresses are located. There are separate data sets for each of the three categories that give information such as which jurisdiction an entity is in, which country an officer is located, and the county an address is in. Entities are then linked to officers through their unique ID, and each is connected to an address.

To find counties in the United States that are exposed, I looked for entities with an associated jurisdiction in Aruba that have a U.S. mailing address, or officers connected to those entities with a U.S. mailing address. I also looked at entities in Aruba that were connected to entities with a connection to an officer with a U.S. mailing address. An entity with a U.S. mailing address is considered a direct link while the other connections are considered as indirect links. The connections that I found between Aruba entities and U.S. mailing addresses were all indirect links, where the entity is connected to a U.S. mailing address through its connection to another entity. This connection is illustrated in Figure 2 located in the Appendix A, and tracks the way the entity in Aruba is connected to a U.S. mailing address. These connections can be even more evidence of money laundering, since criminals tend to layer the money in order to make it more difficult to be connected back to them.

Figure 3 shows a map of the United States and marks exposed counties in dark blue. Table 1 located in Appendix B shows the amount of exposed and non-exposed counties, including the amount of exposed counties in both metro and non-metro areas. In total I found 113 counties with at least one link to an offshore account in Aruba, and 33 states containing at least one exposed county. This means that the data set includes a large variety of different states and counties exposed, making it a good representation of the United States as a whole.

Figure 3

United States Map of Exposed Counties



Note. Exposed counties are represented by dark blue. All U.S. States are included minus Hawaii and Alaska in order to see the map clearly. This does not mean there are no exposed counties in these states, as they will be included in the final data sheet.

To obtain data on yearly business establishment counts for each county, I used the Quarterly Census of Employment and Wages taken from the U.S. Bureau of Labor Statistics. This provided data on the annual average of quarterly establishment count for a given year in a county. In my data sheet each county-year establishment count is logged for the regression. The control for county income level was taken from the SAIPE data sets provided from the U.S. Census Bureau, and I choose to control it by log of the median household income for each county in a given year. Lastly, I used the National Cancer Institute to categorize metro and non-metro counties. The final data sheet includes the log of yearly establishment count, SCI for exposed counties, categorization of metro and non-metro counties and the log of the median household income level. In total there are 11 variables and 21,951 observations.

4 Methodology

The main X variable that will represent the shock from the AML regulations in Aruba to exposed counties in the United States is shown in equation (2). By summing all of the scores for each recommendation in a given year and then dividing that by the best overall score Aruba can have, we will get a percentage on the overall level of compliance. This is represented in equation (2) as SCI_t, which was derived in equation (1). As Aruba puts policies into place and improves on their AML regulations, this number will increase leading to a "shock". Finally, we will take this number and multiply it by our dummy variable for exposed counties.

$$Shock\text{-}SCI_{c,t} = E_c * SCI_t \tag{2}$$

The dummy variable, E_c, is equal to 1 when the county is exposed and equal to 0 when the county is not exposed. This way the shock from AML regulations will only affect the counties that are exposed to agents with connections to offshore accounts in Aruba, because those counties are the only ones that our X variable should affect.

The years included in the data are 2008 through 2014. Since the first SCI score was given in 2009, because that was when Aruba was first evaluated by the CFATF on their AML policies, there is no official SCI score for the year 2008. Because the CFATF did not present the 49 recommendations to improve AML policies until the year 2009, we can assume that there were no significant changes in Aruba to AML regulations between the years 2008 and 2009. With this assumption, 2008 is given the same SCI score as 2009 and is included in the regression model.

The regression equation that is used to capture the effect of AML regulations in Aruba on the number of business establishments in exposed U.S. counties is shown by equation (3).

$$Y_{c,t} = \beta_\theta + \beta_1 Shock\text{-}SCI_{c,t} + d_c + d_{s,t} + X_{c,t} + \epsilon_{c,t} \quad (3)$$

$Y_{c,t}$ is the main outcome variable, and represents the log of the number of business establishments by county year. By taking the log of this value, the model will show the percent change in the amount of business establishments due to each of the variables in the regression. The main focus of the regression will be β_1. This tells us the effect of the key X variable, the shock of AML regulations in Aruba on exposed U.S. counties, on the percent change in business establishments.

The model controls for county-fixed effects, d_c, to capture both observable and unobservable county characteristics that affect the amount of business establishments in a county. For example, smaller more rural counties will naturally have less business establishments then a large county in a city. This control will capture this effect in the regression. The model next controls for state-year fixed effects in the variable $d_{s,t}$. This variable controls for any time varying effects in each state that can contribute to a change in business establishments. Finally, $X_{c,t}$ controls for county income level. This variable is represented by the log of median household income in a county. The regression will include both the variable for median household income and the interaction between the dummy variable for exposed counties and median household income. A county's income level can have a major effect on the amount of business establishments the county has. Higher income levels lead to more business establishments, and lower income levels lead to less business establishments. Finally, there is an error term $\epsilon_{c,t}$, which captures all other unobserved controls that are not included in the model.

In order to ensure that the deviation between the change in the number of business establishments in exposed counties and non-exposed counties is strictly caused by the change in our SCI variable, I will be using a regression to determine the trend in the change of business establishments before the treatment was put into place. The data contains the log of the number of business establishments in each county, starting from 2004 and ending in 2010 where SCI makes its first significant change.

$$Y_{c,t} = \beta_\theta + \beta_i(Year * Exposed) + d_c + d_{s,t} + X_{c,t} + \epsilon_{c,t} \tag{4}$$

In this regression, the same controls from equation (3) are used in addition to a variable for the interaction between year and the dummy variable for exposure. The focus of this regression is β_i, which shows the difference in log of business establishments between exposed counties and non-exposed counties in a given year. Before running our main regression, we must first show that there is no significant difference between the number of business establishments in exposed counties and non-exposed counties before SCI begins to change.

Table 2 displays the P-value of β_i in a given year. Column 1 includes all United States counties, and shows a significant difference between exposed and non-exposed counties in all years leading up to the treatment. In Column 2, all non-metro counties are dropped and only metro counties are included. When only including metro counties, we find that there is no significant difference between exposed counties and non-exposed counties until the year 2010, which is the first year of the treatment. Finally, Column 3 shows the p-value of β_i when only using non-metro counties. Each year shows a higher p-value than metro counties, until it approaches the treatment year where the non-metro counties show no significant difference between the exposed counties and non-exposed counties.

Table 2

P-Value on the Difference in Business Establishments Between Exposed and Non-Exposed Counties

Year (Pre-treatment)	(1) All Counties	(2) Metro Counties	(3) Non-Metro Counties
2005	0.003*	0.541	0.010*
2006	0.004*	0.586	0.053
2007	0.007*	0.442	0.137
2008	0.006*	0.329	0.185
2009	0.000**	0.093	0.233
Year (Post-treatment)	(1) All Counties	(2) Metro Counties	(3) Non-Metro Counties
2010	0.000**	0.024*	0.222

Note: Table includes the p-value of the difference between log of business establishments in exposed counties and non-exposed countries leading up to the treatment year, shown in equation (4). A significance on the 95% level is represented by * and a significance on the 99% level is represented by **. 2009 is the first year Aruba is rated on their AML policies and 2010 is the first change in the SCI variable.

When including non-metro counties in the sample, we see a significant difference in the number of business establishments in exposed counties and non-exposed counties before the SCI variable begins to change. This means that the regression will not represent the actual effect of the change in Aruba's AML regulations on the number of business establishments in exposed counties. To make sure that there are no significant differences between exposed and non-exposed counties before the treatment year, the sample will be limited to only metro counties when running the regression shown in equation (3). This will allow us to accurately show the change in business establishments in exposed counties caused by a change in the SCI variable, and will eliminate any differences between the two that will lead to a bias estimator.

5 Results

We start by using equation (3) to estimate the effect that SCI has on exposed counties, restricting the sample to metropolitan counties. Table 3 provides results on β_1 starting with a basic OLS regression and then adding fixed effects and other controls. Column 1 gives results when regressing only $Shock\text{-}SCI_{c,t}$ on the log of establishment count. It found that Shock-SCI has a significant positive effect on the number of business establishments in exposed counties. The coefficient β_1 is equal to 0.0148, which means that for every additional unit SCI increases by, the number of business establishments in exposed counties are predicted to increase by 1.48% compared to non-exposed counties. This value is biased however since we are not controlling for any other variables and the regression does not have any fixed effects. This can be seen in the R-squared value, which shows that the model only captures 15.19% of the variance in the Y variable.

In Column 2, both county-fixed effects and state-year-fixed effects are added to the regression removing some of the bias from the coefficient in Column 1. After adding fixed effects, the coefficient for Shock-SCI drops down to 0.0003, leading to a predicted 0.03% increase in business establishments in exposed counties compared to non-exposed counties for every additional unit of SCI. However, even with such a big drop in percentage the coefficient is still statistically significant meaning that there is still a significant positive correlation between SCI and the number of business establishments in exposed counties. The R-squared value is 0.9997 which shows that now 99.97% of the variance in Y is shown by the model. This shows that the presence of fixed effects has increased the effectiveness of the model leading to the coefficient for Shock-SCI to be much less biased and an accurate representation of the effect of AML regulations on the number business establishments in exposed counties.

Table 3

Effect of AML Regulations in Aruba on Log Business Establishments For All Metro Counties

	OLS (1)	FE Controls (2)	Income Controls (3)
Shock-SCI	0.014764** (0.000)	0.0003087** (0.000)	0.0002968** (0.000)
Household Income			0.0634721** (0.000)
Exposed * Household Income			0.0610702 (0.082)
FE	No	Yes	Yes
Observations	8,154	8,147	8,147
R-Squared	0.1519	0.9997	0.9997

Note: Column 1 regresses the main X variable with no other controls. Column 2 adds both county-fixed effects and state-year-fixed effects. Finally Column 3 estimates the full regression in equation (3). The sample used includes all metro counties from 2008 to 2014. A p-value<0.05 is represented by * and a p-value<0.001 is represented by **.

Finally in Column 3 the control for county income level is added by the variable for median household income and its interaction with the dummy variable for county exposure.

Adding this control does not lead to as big of a change as the transition from Column 1 to Column 2, but we do see a slight decrease in the coefficient for Shock-SCI. The coefficient changes from 0.0003087 to 0.0002968 while keeping the same level of significance as Column 2. This shows that while controlling for both fixed effects and county income level, there is still a significant positive effect from the Shock-SCI variable on the number of business establishments between exposed counties and non-exposed counties.

In Table 4 located in Appendix B, non-metro counties are added back into the sample to compare to the results from Table 3. When all United States counties are included in the sample, the coefficient for Shock-SCI is larger than it was when limiting the sample to metro counties. Column 3 shows the coefficient is equal to 0.00034 when controlling for county income level and fixed effects, compared to 0.00297 when only using metro counties. This suggests that using all United States counties leads to a bias estimator that overestimates the effect of Shock-SCI on the number of business establishments in exposed counties. This is consistent with the results from Table 2, which showed that there was a significant difference between exposed and non-exposed counties when all counties were included in the sample. By taking out all non-metro counties we are able to get rid of this difference before the treatment happens, causing our estimator to be less biased.

Table 5 in Appendix B shows the effect of Shock-SCI when only non-metro counties are included into the sample. Columns 2 and 3 show the effect when controlling for fixed effects and income level, and express coefficients for β_1 that are insignificant on the 95% level. The only time we find a significant coefficient for β_1 is when Shock-SCI is regressed with no other controls, however this result contains a lot of bias. This shows that non-metro counties that are exposed do not experience a significant effect from the Shock-SCI variable, likely because these exposed counties are inherently different from exposed counties in metro areas. Excluding them allows for the model to accurately predict the effect from the change in AML regulations in Aruba on new business establishments in counties we expect to see changes in.

6 Conclusion

The results of this paper are very similar to the ones found in (Maskus, Peri & Rubinchik, 2021). When regressing equation (3) without fixed effects and the control for county income level, (Maskus, Peri & Rubinchik, 2021) found β_1 to be 0.023 compared to our result of 0.0148. When adding county-fixed effects and then additionally the control for county income level to the regression, the paper found coefficients for the main X variable equal to 0.00039 and 0.00036 compared to this paper's results of 0.0003087 and 0.0002968. This shows that the effect from AML regulations in this paper is slightly smaller than the effect found in (Maskus, Peri & Rubinchik, 2021). The most likely explanation for this is the decision to limit the sample to include only metro counties. When non-metro counties are added back into the sample, we find results closer to the ones found in (Maskus, Peri & Rubinchik, 2021).

This suggests that the effects from new AML regulations on new business establishments in exposed counties are consistent across different Caribbean countries. The results in this paper were similar when looking at only one country compared to (Maskus, Peri & Rubinchik, 2021) which looked at seven different Caribbean countries. With similar results, we can conclude that changes in AML policies will yield similar changes in new business establishments in United States counties that have links to offshore accounts, regardless of what Caribbean country these changes take place in. This also disproves that countries who start with lower levels of AML regulations will have a greater effect on new business establishments in exposed counties when they start implementing stricter policies. On average the change in policies will have similar effects regardless of where the country starts off in SCI.

The results in this paper provide evidence that as AML regulations in Aruba become more strict, there is a significant increase in the number of business establishments in counties with connections to offshore accounts in Aruba. Although this shows proof of an increase in new business establishments, we cannot confidently say how much of the increase is linked to business-based money laundering. As stated in (Pacini and Forbes, 2020), offshore accounts are not only used for money laundering and terrorist funding, but also used as a way to aviod taxes. One way of legally avoiding taxes or limiting the amount of taxes a person pays can be done through running a business. This means that it is possible that some of the increase in new business establishments can be from legal practices. Since it is impossible to know which businesses are being used for money laundering and which are used to legally reduce taxes, we cannot be certain of the magnitude of the effect on stricter AML policies on business-based money laundering.

Although the extent of the increase in business-based money laundering is unknown, we can assume that a percentage of the new businesses caused by AML regulations in Aruba are money laundering operations. This means that as it becomes harder to launder money through offshore accounts, we can expect an increase in business-based money laundering. There have been numerous studies done showing that organized crime and other illegal operations open up offshore accounts in countries like Aruba where there is a lack of efficient policies and enforcement against money laundering.

In recent years, these countries have made efforts to limit the amount of illegal activity done through offshore accounts, making it more and more difficult for criminals to clean their money through the financial sector. As this paper has shown, this causes an increase in business-based money laundering in countries like the United States, where enforcement against laundering money in the financial sector is already high. Law enforcement and other government agencies should focus their attention on investigating suspicious activity in new business establishments, as other countries tighten their policies against offshore accounts.

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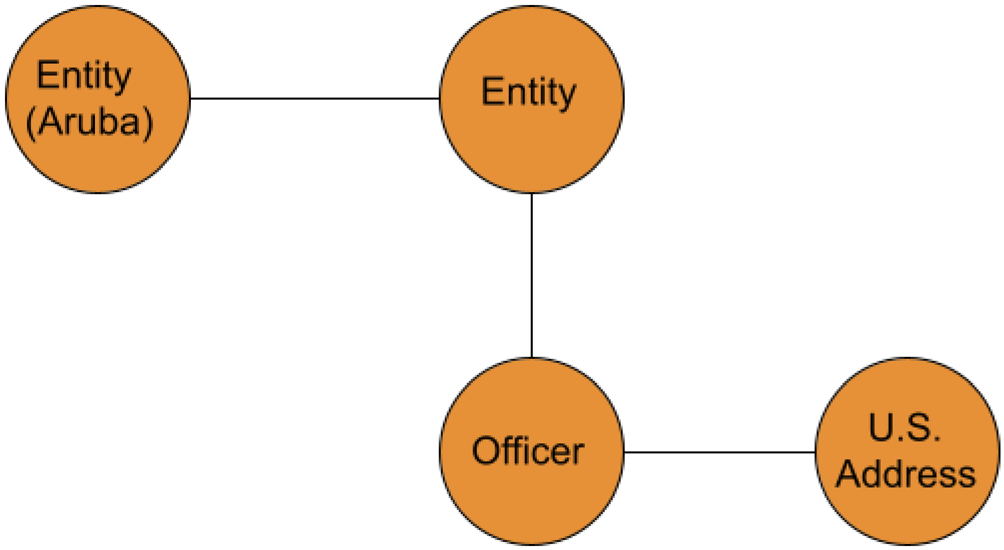
Appendix A: Figures

Figure 2

Connection From Entities in Aruba to U.S. Mailing Address



Note. This illustrates how we found connections between offshore accounts in Aruba to U.S. counties. The Entity that is not labeled as Aruba is located in an unstated country. Each exposed county in the sample is connected to Aruba in the way this figure shows.

Appendix B: Tables

Table 1

Number of Exposed and Non-Exposed Counties

	(1) All Counties	(2) Metro Counties	(3) Non-Metro Counties
Exposed	113	100	13
Non-Exposed	3,022	1,064	1,958

Note. Exposed counties are counties with connections to offshore accounts in Aruba. The table does not include counties in United States territories outside of the 50 states.

Table 4

Effect of AML Regulations in Aruba on Log Business Establishments For All Counties

	OLS (1)	FE Controls (2)	Income Controls (3)
Shock-SCI	0.0184551** (0.000)	0.0003354** (0.000)	0.0003419** (0.000)
Household Income			0.1253792** (0.000)
Exposed * Household Income			0.0191224 (0.598)
FE	No	Yes	Yes
Observations	21,951	21,951	21,944
R-Squared	0.1157	0.9994	0.9994

Note. Column 1 regresses the main X variable with no other controls. Column 2 adds both county-fixed effects and state-year-fixed effects. Finally Column 3 estimates the full regression in equation (3). The sample used includes all United States counties from 2008 to 2014. A p-value<0.05 is represented by * and a p-value<0.001 is represented by **.

Table 5

Effect of AML Regulations in Aruba on Log Business Establishments For Non-Metro Counties

	OLS (1)	FE Controls (2)	Income Controls (3)
Shock-SCI	0.0035968* (0.011)	0.0000448 (0.507)	0.0000848 (0.257)
Household Income			0.1652768 ** (0.000)
Exposed * Household Income			-0.0908021 (0.140)
FE	No	Yes	Yes
Observations	13,797	13,790	13,790
R-Squared	0.0018	0.9984	0.9984

Note. Column 1 regresses the main X variable with no other controls. Column 2 adds both county-fixed effects and state-year-fixed effects. Finally Column 3 estimates the full regression in equation (3). The sample used includes all non-metro counties in the United States from 2008 to 2014. A p-value<0.05 is represented by * and a p-value<0.001 is represented by **.