Investors By Another Name:
Demand for Job Creation and Proliferation of Money Laundering in the United States

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Abstract

Money laundering allows money used in illegal activity to enter the conventional banking system. Money laundering networks enable terrorism, conflict, human trafficking, and other illegal enterprises to generate profits that can then be used to buy things in the legitimate economy. These illicit enterprises depend on money launderers to sustain and grow their operations; without them, illicit operations can be easily tracked and eliminated. In order to understand how money laundering props up illicit enterprises, we have to understand how money laundering operations work. In this paper, we ask: what attracts money launderers? We argue that money laundering is a natural consequence of public demand for job creation. That is, we argue that money laundering arises in response to the development of an illicit economy. The key role of money laundering is to hide the illicit origin of money using legitimate-seeming businesses. As such, we argue that constituent demand for politicians to attract businesses and create jobs should attract money launderers and also create incentives to allow existing money laundering to continue. We test the implications of this theory using a novel data set of money laundering allegations, collected from English-language news sources and government reports. In this paper, we present our preliminary results.

Introduction

Globalization, technological advancements, and other economic forces reshaping the United States economy and labor market have led to significant constituent demand for politicians to attract investment and "create jobs". This constituent demand creates strong incentives for politicians at the state and local levels to take steps to attract and retain business investment. These efforts to attract jobs can involve investment incentives (Jensen et al., 2014; Jensen and Malesky, 2018), digital infrastructure investment (Atkinson et al., 2009), tax employment incentives (Hanson and Rohlin, 2011) , public subsidies (Girma et al, 2008), and programs easing start up barriers to small businesses and entrepreneurs (Decker et al., 2014).

Yet these efforts to create jobs by attracting business investment may not attract strictly legal, above-board business investment. Many businesses also operate in illegal activities. Some of these activities are legal in some states or countries but not in others (e.g., marijuana dispensaries) whereas other illegal enterprises engage in activities that are illegal in many or most jurisdictions (e.g., prostitution). Despite differences in the legality of their business activity, these businesses also have similarities. Both types, for instance, typically need to hire and pay workers, acquire a space in which to operate, and carry out their business activities. Further, these businesses are often created in an explicit effort to appear legitimate. We expect that any policies that encourage business creation and growth will do so for both legal and illegal businesses.

The crucial difference between the operation of legal and illicit businesses is in their access to the banking system. Legal businesses can directly engage with the conventional banking system. This means they can save their money, apply for credit, invest, and spend their money within the legitimate economy. Any paperwork or oversight within the banking system is an expected part of their operation. Illegal businesses do not have this option; any information about their funds may reveal the illegal nature of their origins. These businesses need an intermediate step between their illegal activities and banking in order to obscure the origins of their funds. To avoid drawing any attention to their activities, businesses can launder their money to remove any ties to illegal activities. Often this money is laundered through a business that is ostensibly engaging in legal business activity (e.g., a pizza place or a laundromat), although primarily functioning to recirculate and "clean" the dirty money. The money laundering networks, opportunities, and resources that emerge to fill this intermediate step make it easier, and more profitable, to conduct illegal activity. This includes the funding of armed conflict, terrorism, black market sales, and human trafficking. Knowing that a jurisdiction might permit money laundering may attract additional money laundering operations, which then attract other actors who need to launder money.

In this paper, we connect these dots and argue that constituent demand for job creation, and the attributes of an economy that lead to that demand, may inadvertently also attract money laundering. We argue that there are two reasons why this is true. First, some regulatory changes that relax constraints on legal businesses in an attempt to attract them can also enable money laundering. If it's easy for legal businesses to do business, it's also easier for money launderers and their 'fake businesses' to do business. And second, demand for job creation is rarely specific to jobs in the legal sector. Since illegal businesses also create jobs, constituent demand for job creation should create incentives for politicians to turn a blind eye to the money laundering that allows the illegal economy to function.

In the next section, we provide more background on money laundering. Then we explain our theoretical framework in more detail. Following that, we describe our data collection efforts and methods. Finally, we discuss our preliminary results and conclude with parting thoughts and areas for future research.

Background and Theory

In recent decades, the opening of markets, rise of globalization, and overall liberalization of trade has been generally good for consumers, but less good for workers in the United States. Production of many goods has moved to countries where labor commands a lower average wage, resulting in falling costs for consumer goods, but also job losses as workers in the United States compete for jobs with less-expensive labor abroad (see, e.g., Owen and Johnston, 2017).

These job losses have led constituents across the United States to pressure their elected officials to "create jobs", often by attracting new business investment which is, in turn, expected to hire and pay workers (Jensen 2014, Jensen and Malesky 2018, Feng, et al., 2019). In response, elected officials at the federal, state, and local levels have put substantial effort into changing the rules and regulations that govern business, in an attempt to create a more 'business-friendly' investment atmosphere. In addition to overall changes to the state's regulatory and tax environment, governments have also offered specific companies investment incentives in exchange for creating jobs.

Although evidence suggests that the investment incentives do not 'work' as intended to attract companies (Jensen and Malesky 2018), they are at least targeted -- the broader changes to a jurisdiction's regulatory and tax environment are *not* targeted. This means, on one hand, that they benefit all participating companies equally and do not discriminate among them. On the other hand, it also means that they may have unintended consequences. This is because regulatory changes are a public good -- they are, at least in principle, non-rival, meaning that one person taking advantage of them does not forbid another from doing so, and they are also non-excludable. Just as birdseed set out to attract birds may attract not only birds but also squirrels and chipmunks, broad regulatory changes may attract legitimate business investment as well as other metaphorical woodland creatures, including illicit businesses such as money launderers.

Money laundering refers to the process of making illegal funds look legitimate.The goal is to `clean' money so that it is not connected to any illegal activity and is therefore again usable as legal tender.[2] This protects the people engaging in illegal activities by obscuring the origin of the funds. This makes money laundering a necessary intermediate stage between businesses engaging in illegal activities and the legitimate banking and financial sector.

One of the most common forms of money laundering is by reporting profits through legitimate businesses. For example, profits from human trafficking cannot be deposited directly into a bank account without running the risk that they could be identified and traced back to the offender. So, the money is reported as additional profits for a legally established business. The origin of

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[2] Historically, money launderers used legitimate businesses like car washes, laundromats (from which the term 'money laundering' is derived), or pizzerias to smuggle money into the economy by reporting proceeds from illegal operations as profits or turnover from the legitimate business (Schieder, 2013). Now, as the magnitude of proceeds has grown, launderers can filter funds through property dealings, front companies, false loans, and trade invoices.

those funds is, as a result, significantly more difficult to trace, and the profits can be marked as legal funds and are able to cross over into the licit economy.[3] Once the money looks like it was legally obtained, it can be stored in a bank account and accessed without fear of repercussions.

Often, money is laundered through businesses that appear to be legal and legitimate, such as pizza places and laundromats. These businesses share many things in common with actual legal businesses: they must hire and pay people in order to carry out the ostensible legal activity (in addition to hiring and paying people to engage in the illegal activity), they must operate within many of the confines of a legitimate business (e.g., renting out a storefront), and they must adhere to the laws of legal businesses. Further, these businesses are created with the purpose of appearing legitimate, which means that they want to closely imitate, at least on paper, the operations of a legitimate business. Maintaining these money laundering fronts is easiest and least expensive -- and therefore most attractive -- in places where the barriers to opening and operating a business are low. In places where it is difficult or expensive to open a laundromat or a pizza place, for instance, it may not make financial sense to launder money.

In understanding where money launderers choose to "invest", there are two considerations. The first is a need to launder money. Jurisdictions that classify more activities as illegal ought to have more money laundering than those that classify fewer activities as illegal, all else held constant, because legal businesses do not need to launder money and illegal businesses do. For example, consider the sale of marijuana within the United States. In Texas, the sale of marijuana within the range of 7 grams to 5 pounds is considered a felony, and will result in a mandatory jail sentence (Texas Norml, 2019). Travel north to Colorado, and the sale of the substance is legal as long as the retailer is licensed and does not conduct sales with anyone under the age of 21 (Colorado State Portal, 2016). Thus, all proceeds made through marijuana sales in the state of Texas would be considered illegal as the activity itself is considered 'criminal' (Masciandaro, et al., 2007). However, within the borders of Colorado any proceeds are reported as legitimate business profits.[4] This means that anyone aiming to sell marijuana in Texas likely needs to launder their proceeds in order to use their money and not face prison time, whereas money laundering for that purpose is not necessary in Colorado.

The second consideration is the ease of operating, and ease of operating is why we argue that demand for job creation attracts money laundering: any changes that make it easier for *legitimate* enterprises to do business within a state can also make it easier for *legitimate-seeming* enterprises to operate within that state. The more relaxed a regulatory and

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[3] Money laundering consists of three phases: placement, layering, and integration (Jojarth, 2009; Schieder, 2013). In the first stage, money is moved from its source to the financial system. A simple example is taking cash proceeds from drug sales and depositing them into a bank account. In the second stage the launderer works to obscure the origin of the money. This is done through a series of financial transactions. Once the pathway of the funds is obscured, the funds are then filtered into the legitimate economy. This is the third and final stage of money laundering.

[4] This example gets significantly more complex if dispensaries in Colorado want to store their profits in a national banks, which are subject to federal regulations. Prior to late 2020, this meant that federally, any profits from marijuana sales were still considered illicit since marijuana was considered an illegal substance at the federal level. As a result dispensaries that were operating legally still could not store their business revenue in most banks without being flagged for illegal activity.

tax environment is, for instance, the more inviting it is to all businesses, regardless of the legitimacy of their operations. Reduced reporting requirements mean fewer administrative costs for both legitimate businesses and a lower risk of discovery for money launders, as well as less paperwork they need to forge. In sum, reducing the legal steps needed to run a business in order to attract new business growth means that it takes less work for money launderers to appear legitimate, and therefore regulatory changes intended to attract business investment are likely to also attract money launderers.

Additionally, demand for job creation may make money laundering easier because it may encourage governments to look the other way and not intervene. This is because, although money laundering comes with attendant negative consequences[5], it also produces benefits, especially for local economies. Money laundering and the kinds of illegal enterprises that require it also create jobs, provide safety nets against recessions, employ people with entrepreneurial and managerial skills, and add to the wealth (and therefore economic growth) from the profits spilling over into the licit economy (Williams, 1994).[6]

In other words, money launderers create legitimate-seeming businesses to hide their illegal money. In order to seem legitimate, these businesses operate much like legitimate ones. They may hire employees and often rent property. Further, if the money is properly laundered, someone whose income comes from illicit enterprises will spend just like someone whose income comes from licit enterprises. They will pay for housing, food, transportation, and entertainment, just like their peers who are paid by legal enterprises. Illegal businesses still spread money into the local economy. The novel Black Bottom Saints illustrates the positive role that criminal activity can play in a local economy, speaking of a man who ran a gambling ring in Detroit that resulted in over 40 arrests: "The courts say John was a criminal. I say John White was a saint. White used [gambling] to create jobs, to create wealth, to create community, and to create models of invisible communication." (Randall 2020, p. 282)

Taken together, governments feeling pressure from their constituents to create jobs have incentives to relax restrictions on businesses that attract legitimate business but also attract money launderers, and also have fewer incentives to crack down on illegal enterprises and the money laundering that allows them to exist. This leads us to our first hypothesis:

H1: As constituent demand for economic growth and jobs increases, so too does money laundering.

The implication of this goes beyond the effect of public opinion -- if this logic is correct, it should also be the case that any political or economic phenomenon that is expected to lead to

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[5] Often, we associate money laundering and illicit finance with its costs at the country level, which include undermining legitimate businesses (McDowell and Novis, 2001; Brennan-Galvin, 2002), stunt capital market growth (Quirk, 1997), corrode financial institutions (Levi, 2002), and destabilize domestic markets (McDowell and Novis, 2001; Tsingou, 2005).
[6] Looser financial regulation and breaks for foreign investors also ease entry into the market, and can kick start a financial sector (Simmons, 2001).

constituent demand for job creation should also be causally linked to increased money laundering. The causes of constituent demand for job creation, namely state unemployment, experiences with globalization and job losses, lead constituents to feel economically imperiled. This leads a demand for elected officials to intervene to preserve and create jobs. Politicians then create a business environment that will attract both legitimate businesses and money laundering operations. This suggests two additional hypotheses:

H2: States with greater increases in employment should have more money laundering.

H3: States that have lost more jobs to offshoring and international trade should have more money laundering.

Data
Money Laundering
The goal of money laundering is to make illicit funds appear legitimate. When done appropriately, this means that there is no observable difference between a money laundering operation and a standard business. Once we are able to identify money laundering, it is no longer able to pass off illicit funds as legitimate, meaning that it is no longer able to launder the money. Gathering systematic data on the enterprise is then a practice of identifying the unobservable. This dynamic leaves researchers with two options. They can either build models to estimate flows of money laundering, or they can rely on observations of failed money laundering.

The most prominent model is the Walker/Unger Gravity model (Walker and Unger 2014; Joras et al., 2020). Gravity models are based on the idea that attraction between two objects depends on their mass, their distance, and gravity. Building off of the use of gravity models to understand bilateral trade flows (Eichengreen and Irwin, 1998), the Walker/Unger model estimates the flow of illicit finance from one country to another. In the most recent iteration of this model (Joras et al., 2020), they define the mass of each country using a combination of economic variables (GDP, GDPpc) and variables indicating a 'favorable' environment for laundering money (conflict, corruption, tax haven status, and Egmont classification). The distance between any bilateral pair is defined by both physical (shared border, physical distance), cultural (common language, religion, history), and economic (common currency, trade value) attributes.

Modeling the flow of illicit finance or money laundering faces one key challenge: validation. Because there is a dearth of definite records of money laundering flows, empirically validating the results of these models can rarely be done outside of a specific case. Even then, there exists no 'gold standard record' of instances or amounts of money laundering for us to compare these estimates against. Further, because these models are conditioned on the information that they are given, validation efforts or analysis with the estimates can often result in a feedback loop. For example, if we want to use these estimates to understand what is causing differences in money laundering flows, we cannot use any of the variables included in our estimate of money laundering flows. While models such as these can provide us valuable insight to where

we would expect money laundering to happen, they are just that: a quantification of our own expectations.

Alternatively, researchers can use the money laundering operations that we do know about, or suspect, to give an indication of the broader flows within and between countries. As financial transparency has become more of a priority for governments, particularly since the start of the `War on Terror' in the United States and the regulatory reckoning that followed the 2008 Global Financial Crisis, information regarding discovered cases of money laundering has become more readily available. Data regarding Suspicious Activity Reports (SARs)[7] has been released by offices of financial oversight, like the Financial Crimes Enforcement Network (FinCEN) within the US Department of the Treasury. Organizations like the Global Financial Integrity Index have used available trade data to track trade misinvoicing,[8] while others, like the Financial Action Task Force (FATF) create `blacklists' or provide indicators of the absence of financial transparency (Cobham, et al., 2015). Further, leaked banking records, like the Panama Papers (ICIJ, 2016) or the FinCEN files (ICIJ, 2020), have given researchers and reporters insight to potential money laundering operations.

However, among these different data sources, there is no one source that records instances of money laundering. SARs only denote suspicious or irregular activity, which includes fraud and corruption, and provide no evidence that the activity actually indicated a crime occuring. Trade misinvoicing only provides us with insight to one of many outlets for money launderers. Blacklists and secrecy indices tell us more about regulatory convergence than the actual occurrence of money laundering. Leaked banking records provide information regarding institutional practices and failures, but can only help us identify specific operations within the institution. While this data is useful for understanding particular cases of money laundering, it does not give us the ability to actually examine broad trends, let alone try to explain them.

With this in mind, we estimate money laundering using data on "failed" money laundering, money laundering operations that have been detected by law enforcement and therefore pass into the observable world. There are a number of reasons that this type of data has not been assembled in the past. First, various law enforcement groups report money laundering cases as they are being tried. However, these reports rarely stretch beyond a single country's border unless an international institution, such as Interpol, is one of the investigators. Furthermore, the fluidity of money laundering as a crime often means that there is not a single institution within a country that investigates all cases. For example, money laundering investigations within the United Kingdom can be handled by three national agencies: The National Crime Agency, Border Force, and UK Police. This does not account for the potential involvement of local or state law enforcement, both of which may also release reports on money laundering cases. A result of this large pool of investigators is that tracing money laundering cases solely by country is nearly

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[7] SARs are the reports made by financial institutions to report `suspicious activity' to the federal government. While the exact determinants of what constitutes a `suspicious activity' are not publicly known, some examples include large transactions, high frequency transactions, or erratic transactions.
[8] Trade invoicing is the practice of falsifying the prices on the goods of imports and/or exports on trade invoices, thereby allowing companies to use the difference from the true price as a way to move illicit funds into or out of a country.

impossible. Instead, individual institutions must be the source for cases, and unless collaborative efforts were made these entities are unlikely to unify their data across the board.

Our dataset is an attempt to use failed money laundering while sidestepping the challenges associated with collecting it directly from law enforcement. To do this, we recorded every instance of money laundering mentioned in an English-language newspaper or government report from 2012-2020. The resulting sample we drew money laundering reports from included a combination of big newspapers (New York Times, Washington Post, etc…), local newspapers, and government reports (FBI White Collar Crimes Database, United States Department of Justice News Release, etc…). Reports from questionable sources, such as tabloids, were removed. (For more details on our data collection, see Appendix B.)

We recognize that collecting data in this manner may introduce a form of selection bias, since we only have reports on money laundering operations that we can observe, which suggests that they are no longer active. We argue that while failed money laundering operations might differ in their efficacy from successful ones, the launderers themselves do not have a systematic difference in their preferences. Both failed and successful money launderers want to succeed, and look for environments where they think this is possible. While they might go about laundering money in different ways, they both look for the same opportunities. To this end, because we are focused on the external environment that entices money laundering, failed money laundering operations are equally able to give us insight to successful ones.

A second potential concern is that these data actually run counter to our theory, since we argue that politicians have an incentive to ignore money laundering, which might imply that we would not see money laundering in states where it flourishes. Fortunately for our purposes, tracking and prosecuting money laundering is a function of the federal government in the United States. Since we are looking at federal investigations and reports by national newspapers, we have no reason to believe that money laundering is more likely to be monitored or reported on unevenly.[9]

Other Data
To test the hypothesis about demand for job creation, we use data from the American National Election Studies (ANES) 2012 and 2016 surveys. In each survey, we calculate the percent of respondents from each state who reported that jobs[10] were the most important issue facing the country. In the absence of yearly data, we assume

For our hypotheses about the correlates of demand for job creation, we use seasonally-adjusted unemployment from the Bureau of Economic Analysis for January of the recorded year and

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[9] Although the federal government has regional branches working on the issue, the people involved in these cases are separate from the politicians at the state level of whom job creation is demanded. While it is possible that there are interactions between these two groups of people, such that state politicians might pressure federal agents to also ignore money laundering, we think it is unlikely this happens frequently and we do not believe it is consequential for our analysis.

[10] In 2012 the relevant response was "jobs" and in 2016 it was "employment". We consider these to be the same for our purposes.

Trade Adjustment Assistance claims from Public Citizen Trade Adjustment Assistance Database[11] as a proxy for job losses due to globalization. We control for the government's ideology of each state using the Berry et al. (1998) NOMINATE scores updated through 2018. We also control for state population, using data from the US Census.

Figure 1 shows the distribution of money laundering per state for each individual year. What is immediately evident from these figures is that money laundering "hot spots" are not stable across time. In other words, it is not the case that money laundering flows exclusively and consistently into the same handful of states. Although some states, such as North Dakota, Montana, and Minnesota, rarely attract money launderers, many other states have many records in one year and few the next. Table 1 lists the top five states for reported money laundering,[12] and Figure 2 reinforces what we learn from the maps: even the states with the most laundering have this boom and bust cycle, suggesting money laundering does not strictly flow into a handful of states consistently. This is consistent with the image of money laundering as an illegal activity that is nimble and constantly moving to avoid law enforcement. It also highlights the necessity of our question: if money launderers are constantly moving, where might we expect them to move to?
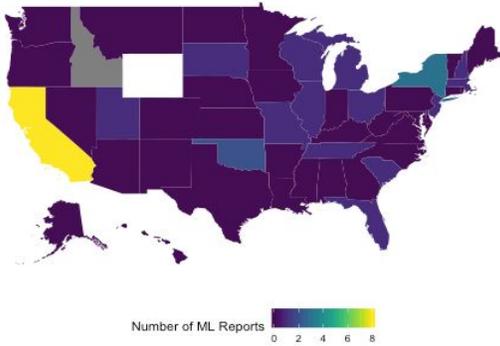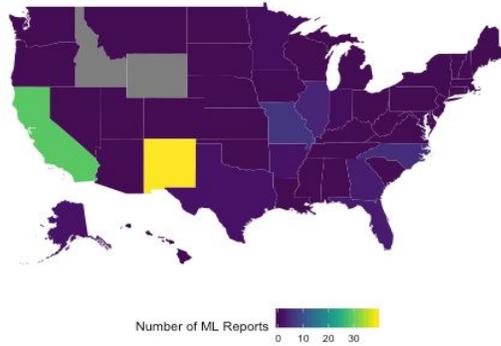
Figure 1: State Year Maps, 2012 - 2019

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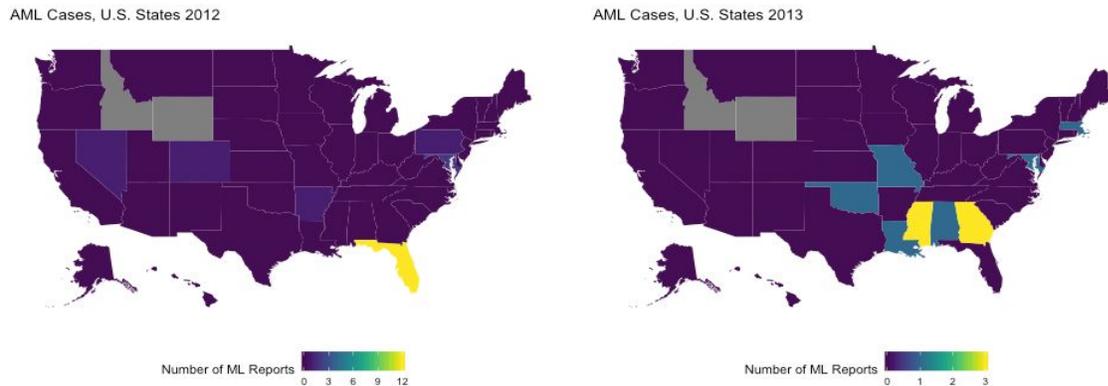
[11] https://www.citizen.org/article/trade-adjustment-assistance-database/
[12] The counts for all 50 states are provided in the appendix.

Figure 1: State Year Maps, 2012 - 2019 (cont.)

AML Cases, U.S. States 2014

Number of ML Reports
0 2 4 6 8

AML Cases, U.S. States 2015

Number of ML Reports
0 10 20 30

AML Cases, U.S. States 2016

Number of ML Reports
0 10 20 30

AML Cases, U.S. States 2017

Number of ML Reports
0 4 8 12 16

AML Cases, U.S. States 2018

Number of ML Reports
0 20 40 60

AML Cases, U.S. States 2019

Number of ML Reports
0 3 6 9 12
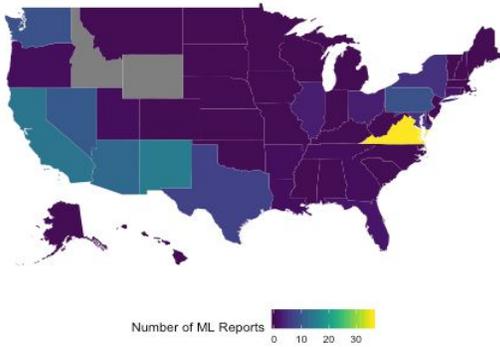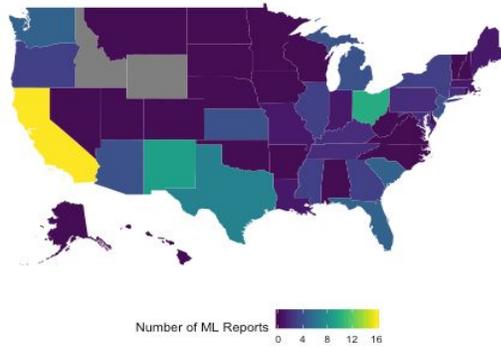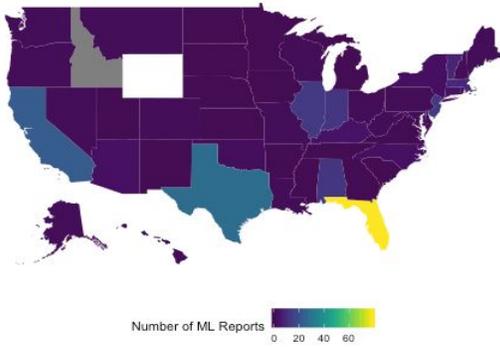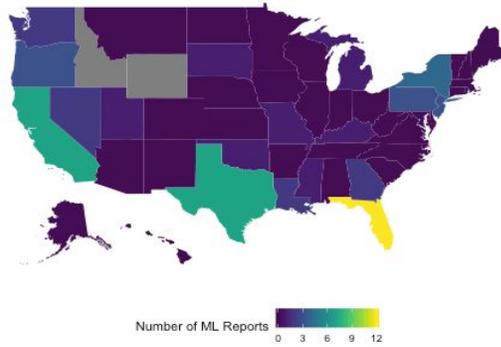
Table 1:

Top 5 States, 2010 - 2020

State	Count, per year	Total Count
Florida	79	115
California	29	97
New Mexico	39	63
Texas	28	51
Virginia	36	36

Figure 2: Money laundering per state over time

Count of ML Reports, Florida 2011 - 2020

Count of ML Reports, California 2011 - 2020

Count of ML Reports, Texas 2011 - 2020

Count of ML Reports, New Mexico 2011 - 2020
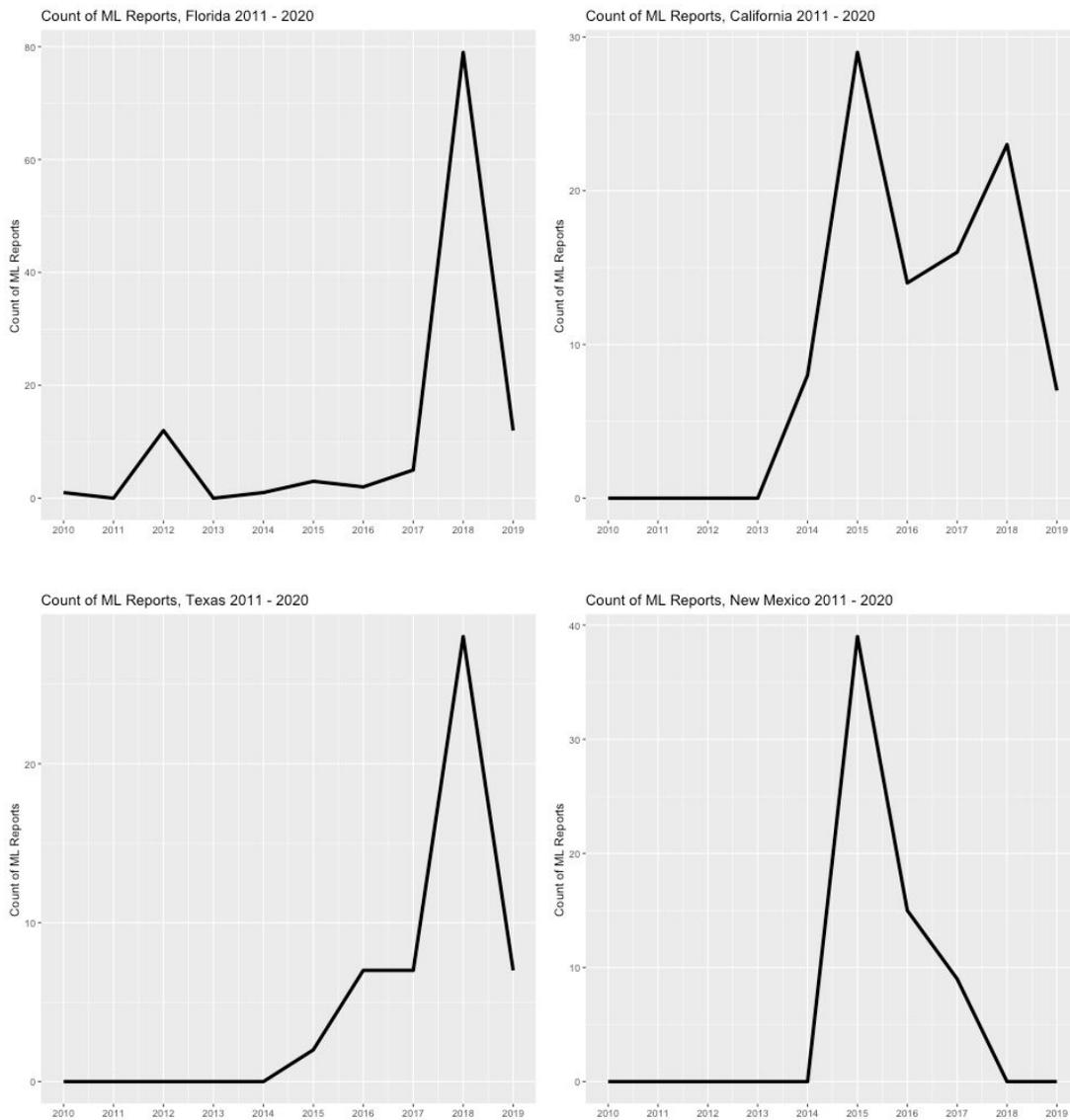
Analysis and Discussion

Table 2 presents our initial attempt to answer this question. Using a negative binomial model, we estimate the expected number of money laundering reports for each state-year.[13]
Our dependent variable is the number of money laundering records for each US state in the years 2012-2019.[14]

Table 2: Money Laundering Reports

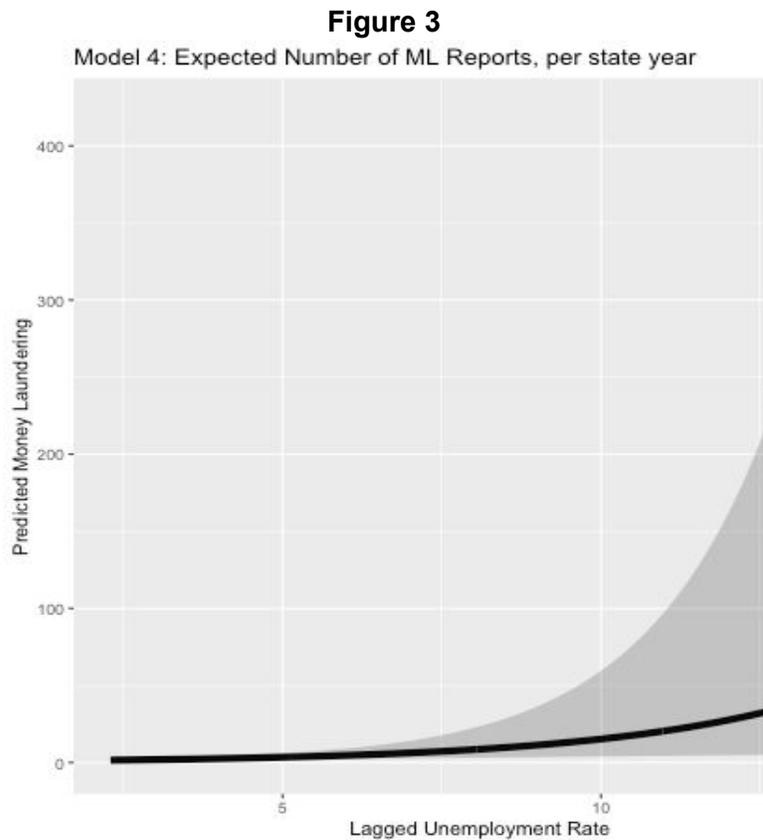|	Dependent variable:				
	Number of Money Laundering Reports				
	(1)	(2)	(3)	(4)	(5)
Lagged Unemployment	**0.325*** **(0.098)**			**0.297*** **(0.111)**	-0.302 (0.208)
Log(Lagged Job Losses)		-0.128 (0.094)		-0.102 (0.098)	**-0.356*** **(0.121**)
Lagged Demand for Jobs			-1.909 (2.877)	-0.827 (3.075)	**12.619** **(5.366)**
Lagged Ideology	-0.0001 (0.007)	0.002 (0.007)	0.001 (0.007)	0.001 (0.007)	-0.011 (0.020)
Log(Population)	**0.669*** **(0.129)**	**0.891*** **(0.169)**	**0.757*** **(0.128)**	**0.724*** **(0.185)**	11.810 (10.804)
Constant	-49.478 (5,213,976)	-50.169 (9,536,355)	-12.852*** (2.035)	-14.118*** (2.333)	-157.599 (145.773)
Fixed Effects	Year	Year	Year	Year	State-Year
Observations	384	371	288	279	270
Log Likelihood	-446.191	-443.880	-423.551	-413.652	-364.900
theta	0.354*** (0.050)	0.333*** (0.047)	0.346*** (0.049)	0.371*** (0.054)	0.743*** (0.126)
Akaike Inf. Crit.	914.381	909.759	865.102	849.305	845.801

Note: * $p<.01$; **$p<.05$; ***$p<0.01$. Negative binomial model coefficients in cells. Standard errors in parentheses below.

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[13] Our data includes all 50 states plus the District of Columbia.
[14] Our 2020 data are incomplete, as data collection was ongoing in the summer of 2020.

Since the counts are overdispersed, we expect the data generating process to roughly follow the negative binomial distribution, and thus we use a negative binomial regression model.[15] Additionally, because we suspect the reports of money laundering to vary over time, with older instance being more likely to be recorded due to the lag in reporting, each model includes a year-level fixed effects. Models 1 and 2 examine the impact of our key independent variables, a lagged measure of unemployment and a lagged measure of job losses, while controlling for state government ideology and population. Model 3 focuses on the public demand for job creation, aggregated to the state level. Finally Models 4 and 5 combine the three variables, with Model 5 including state-level fixed effects.

Figure 3

Model 4: Expected Number of ML Reports, per state year

These models present three interesting results. First, out of all our key independent variables, only unemployment has a stable impact on reports of money laundering. *Figure 3* presents the predicted number of money laundering points over the range of unemployment. While the error bands do not rule out a null effect, the increasing upward slope suggests that as unemployment increases, so too does the expected number of money laundering reports. This supports our

[15] The counts also have a lot of zeros, which suggests the necessity of a zero-inflated negative binomial (ZINB) model. We don't present ZINB results for two reasons. First, at present we have no firm theoretical grounding on which to base the logistic portion of that regression. Second, and perhaps more importantly, since our dependent variable is a count of reported money laundering cases, the vast majority of those zeros are likely not actually zeros. In other words, zeros in our data are more likely to reflect low levels of money laundering, but not actually the absence of money laundering.

second hypothesis, *H2*, which expects that states with greater increases in unemployment will have higher levels of money laundering. The graph does suggest that any expected increase in money laundering reports doesn't occur until unemployment reaches closer to 10%. This makes sense given our theory; the more desperate politicians are to create jobs, the easier it will be for money launderers to operate, and the more common money laundering operations will be.

Even though we treat the data as a count variable, it is worth noting that these are not exactly counts of money laundering. In using these data as our dependent variable, we assume that the data we collected reflects -- but does not accurately measure -- the underlying amount of money laundering within a state. States with a lot of money laundering should have more reported cases than states that have little. Yet it might well be the case that our data misstates the distinctions in degree. That is, a state with more money laundering might have *many more* reported cases than one with few, because the known presence of money launderers might mean there is more monitoring. It might also be the case that in states with many money launderers, finding one money launderer might lead to finding others, such that a single report might lead to a chain of several, whereas in a state with fewer money launderers, a single report would likely remain a single report. It could also be the case that money launderers learn from failed operations. This would mean that the occurrence of a money laundering report allows others to become better at avoiding discovery. This would depress our count as more and more operations are reported in the news.

This points to the difficulty of modeling this unobserved behavior: modeling the data generating process. In the models presented above, we are assuming that reports of money laundering operations happen in sequence (you must have 1 report before 2, 2 reports before 3, and so on). Further, by including fixed effects, we are accounting for but not modelling temporal or spatial dynamics. As a result, our estimates tell us the expected marginal impact on an additional instance of money laundering. However, we could also consider the number of reports not as counts but as indicators of the level of evidence. In this case, we could sort states into ordered categories based on their level of reported money laundering operations. This would require us to consider the impact of the business environment on the distinct levels of evidence for money laundering.

These initial findings, however, do provide us with insight into the relationship between state economic environments and money laundering. Our analysis suggests that money laundering operations are responsive to the economic environment. Therefore, we should expect that, looking forward, any adjustments to this economic environment by governments or policy makers has repercussions for their operations.

Conclusion and Future Work
While this paper provides only tentative evidence regarding where money laundering operations take place, it contributes to the growing interest in understanding the ways that money moves hidden through economies. By connecting these illegal operations to legitimate desires for job creation, we move to understand the ways in which the illegal and legitimate economies are not

only linked, but how they can support and benefit from each other. Our analysis provides a first step to understanding the consequences of this relationship over time and space.

In this paper we present a theory arguing that money laundering operations benefit from policies designed to attract legitimate businesses by creating a more business-friendly climate. We argue that policies and relaxed regulations put in place by politicians dealing with desperate economic conditions, and the perilous political conditions that result, attract not only legitimate businesses, but also illegal businesses that must operate a legitimate-seeming front. Our key expectation was that whenever politicians are incentivized to enact policies that create jobs, we should expect money laundering operations in the state to increase. To examine this expectation we created a novel dataset coding up news articles reporting instances of money laundering. We then aggregated the number of reports by state over the time period 2011-2019.

In future iterations of this project, we look to more closely model the way in which we think our data is actually occurring. This includes re-evaluating the assumptions that underlie our models, including considering our dependent variable as a count, accounting for spillovers over time and space, and dealing with the process by which reports of money laundering are generated, let alone how money laundering operations themselves are.[16] Further, our data set includes information at the city level as well as at the national level outside the US, although it is currently heavily skewed to reports within the US. As we move forward with this project, we aim to round out the dataset so that we can examine the variation in money laundering at these different levels of analysis over a wider range of time.

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[16] Here we pull from the event count literature, particular the work done to validate casualty data in civil conflict (Seybolt, Aronson, and Fischhoff, 2013; Bagozzi et al., 2018)

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Appendix

A. Data Description
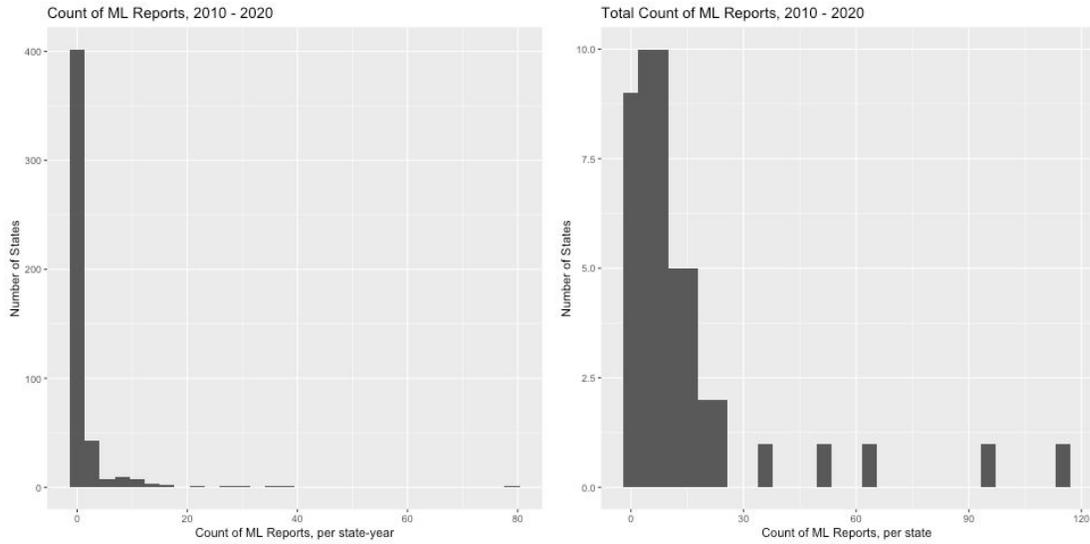
Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Money Laundering Reports, Count	480	1.423	5.295	0.000	0.000	0.000	1.000	79.000
Jobs Lost	476	2,398.137	2,591.244	0.000	537.750	1,611.000	3,237.750	13,988.000
Unemployment	496	6.034	2.324	2.300	4.200	5.500	7.500	13.900
Population	496	6,418,478	7,096,742	576,3050	1,852,350	4,588,2980	7,282,7300	39,512,223
Investment Incentives, Count	462	512.113	1,079.600	1.000	54.000	154.000	561.750	10,000.000

Reports of Money Laundering, by State

State	Max. Annual Reports	Total Reports
AK	2	2
AL	12	13
AR	2	4
AZ	12	19
CA	29	97
CO	1	2
CT	4	8
DE	1	1
FL	79	115
GA	3	12
HI	0	0
IA	0	0
IL	13	24
IN	12	14
KS	4	4
KY	4	7
LA	2	6
MA	9	12
MD	5	11
ME	1	2
MI	4	6
MN	1	1
MO	6	11
MS	3	7
MT	0	0
NC	5	8
ND	0	0
NE	0	0
NH	1	2
NJ	13	22
NM	39	63
NV	10	14
NY	5	18
OH	10	15
OK	2	6
OR	3	8
PA	9	16
RI	0	0
SC	5	6
SD	1	2
TN	2	4
TX	28	51
UT	1	3
VA	36	36
VT	8	8
WA	9	17
WI	1	2
WV	1	1

B. Details of Data Collection

Coders were assigned a specific year, ranging from 2012-2020, and asked to find articles reporting money laundering within their time frame in government reports and English language media by using library databases. By narrowing our search through an article published date, we hoped to achieve two things. First, we wanted to minimize duplicated reports across researchers. Second, as money laundering adapts with technological advances like online banking, by keeping our information current we can attempt to ensure that any notable patterns are relevant rather than a fluke of a changing system. Our researchers would then read through the article, search for the information we had broken down as necessary for our dataset, and code what they were able to find into their individual sheet. Any information that could not be found within an article was coded as NA. After several months, we adapted this formatting from individual sheets to a Google Form. This change ensured greater consistency across the board.

When the project began, we were coding for 17 variables. By the end of the data collection stage we had adjusted for a total of 27 variables. The expansion was a result of certain categories providing more information then we initially predicted, while others were nearly impossible to find within our available resource pool. Not including the story source or date published, the material can be broken down into 7 separate categories. The first is personal information about the accused. This includes the name, the type of money launderer, and what position they held. For the purposes of our research, type refers to whether it was an individual, company, or other organization that committed the act. Position refers to either the occupation of the individual or the main line of work done by the organization (i.e. bank, non-profit, etc...). This information gives us greater insight into potential employment fields with higher trends of money laundering incidents.

The next category addresses location in three parts. The location of the money laundering references where the crime took place. Location of the conviction indicates where the perpetrator faces charges. Finally, the location of the individual specifies where the accused was during the event. The specification of these allows us to track cases geographically, and also denotes incidents in which money laundering may have occurred in one jurisdiction, while the person committing the act resided in another. The third category accounts for networks associated with the money laundering case. Both numerical values, the country network denotes if more than one country fell victim to a money laundering scheme, with specific countries listed in the notes section. This section helps with recognition of international money laundering. Meanwhile, the company network indicates if more than one individual/company was involved in a scheme. Both of these also assist with identifying large-scale ploys. The next category marks the estimated amount of money laundered and the type of currency.

The fifth category deals with years. Under this section, coding was done for the estimated start of a money laundering scheme, the estimated end, and the point at which the incident was officially identified. All of these help reveal multi-year schemes, and potential patterns with certain time periods harboring greater amounts of money laundering. The next section

addresses investigators of the case. This was split up to include the U.S., State, International, and Non-U.S. Country agencies. There is an additional place to code for investigators that may not belong to any of those categories (i.e. local law enforcement, private investigators, etc…). This section highlights which agencies most often handle money laundering cases and allows for a quick analysis of those likely to be involved in international cases. The final category relates to the charges against those involved. The dataset includes if the defendant has been officially charged, who the charging entity is, and what charges were being tried. Patterns within the charges themselves are useful, as one can quickly note what other commonalities exist beyond the money laundering. Outside of these categories, our researchers were asked to include a summary of the article they read, and any additional notes that could prove to be helpful for future analysis.