What Happens When You Can No Longer Commingle Your Dirty Cash? The Stories Behind the Data

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The Covid pandemic shaped the financial crime landscape in many ways. The U.S., like many other countries, saw a surge in suspicious activity reporting, mostly related to fraud. But this unprecedented uptick in fraud cases masks an interesting phenomenon that emerged in the early months of the pandemic and has continued since. With many cash-intensive businesses shut down in the Spring of 2020, banks and money service businesses began to see a statistically significant uptick in structuring activity. This suggests that prior to the pandemic criminals were likely commingling a lot of their illicit cash revenue through cash-intensive businesses, and then when those businesses closed, they had to resort to other methods of placing their dirty cash. It became more difficult for them to have a plausible reason for making cash deposits, forcing them to structure more cash deposits below the $10,000 threshold, thereby setting off red flags. By examining SAR submissions to FinCEN over the past ten years, this study delves deeper into some of the hidden stories that lie beneath the surface, with important implications for law enforcement and private sector compliance professionals.

As Oliver Bullough (Bullough, 2023) discussed at last year's conference, while most consumers around the world are migrating away from cash toward digital payment platforms, the amount of cash in circulation keeps increasing, and is likely being used by criminal organizations, "facilitating the global epidemic of financial crime." Ken Rogoff and Jessica Scazzaro (Rogoff, 2021) have also examined the paradoxical increase in demand for paper currency in several major economies; paradoxical because the percentage of cash transactions in the formal economy has been steadily falling. All of this points to a robust and increasing demand for cash in the informal and illicit sectors, some of which is invariably used for purchasing illegal goods and services, bribery, tax evasion, evading capital controls, etc.

If cash is still widely used in the informal and illicit sectors, this presents a money laundering challenge when criminals wish to place these funds into the formal economy. When presenting cash at a bank, money service business, or casino, questions will be

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asked (or should be asked) and amounts above the reporting threshold will necessitate filling out forms that require a lot of information, something criminals normally do not wish to provide. Hence the need to break the cash down into smaller increments, sometimes referred to as smurfing, but more properly called structuring. But structuring requires time and expense. Trusted "smurfs" need to be hired, money mule accounts need to be set up, and the structured amounts shouldn't be too obvious. It's easier to get "caught" or at least reported as "suspicious activity" to a country's financial intelligence unit.

If criminals can avoid the tedium of structuring funds into money mule accounts, they will try to do so. One common method of laundering, or "placing," cash into the formal financial system without having to structure it is called *commingling*. This occurs when cash from criminal activity is commingled with the revenue of cash intensive businesses ranging from restaurants to concert venues (USAO Maryland 2022, USAO Florida 2023).

But what happens when those restaurants and concert venues, *and casinos*, shut down because of a pandemic? This is what we aim to examine in this paper.

Financial institutions are always on the lookout for structuring of deposits below the cash reporting threshold ($10,000 in the U.S.). They are adept at detecting and reporting it, too. Screening algorithms can easily capture not just the amount and frequency of deposits made at multiple branches, but also other variables that point toward structuring activity. It's so easy to spot and report, that filling out structuring-related SARs is viewed as somewhat of a "nuisance" by the compliance community (Gurdak 2023).

Commingling criminal cash receipts with legitimate business activity, on the other hand, is more difficult to detect, especially if these businesses have successfully garnered a currency transaction report (CTR) exemption status. Earning exemption status excuses the business from having to fill out a new form every time they make a cash deposit over $10,000. But even if they don't have an exemption, commingling illicit revenue with legitimate revenue is a useful disguise.

Our hypothesis is that if criminals find it more difficult to commingle dirty cash with legitimate cash-intensive businesses, they will gravitate towards the riskier method of structuring cash deposits into money mule accounts.

When the Covid-19 pandemic became more widespread by March 2020 and businesses began to shut down, cash-intensive businesses shut down, too. Suddenly it was more difficult for money launderers to commingle their dirty cash. There were no legitimate receipts among which to hide. That left money launderers with few choices, forcing them to take more risks when depositing cash with banks and making more frequent cash transactions at money service businesses.

To test this hypothesis (that there would be more reported structuring activity after the pandemic hit), we looked at structuring-related SARs filed by depository institutions, money service businesses, and casinos over a ten-year period (FinCEN, 2023).

DATA

We examined ten years of monthly data from FinCEN's Suspicious Activity Report Statistics database, broken down by sub-category and reporting institution. To measure structuring activity, we included all structuring-related SARs submitted by depository institutions and money service businesses. This included all suspicious activity related to structuring, including the following categories:

- Transaction(s) below BSA recordkeeping threshold
- Transaction(s) below CTR threshold
- Alters or cancels transaction to avoid BSA recordkeeping requirements
- Alters or cancels transaction to avoid CTR requirements
- Suspicious inquiry by customer regarding BSA reporting or recordkeeping requirements
- Other Structuring

In addition to looking at SARs related to the placement of dirty cash, for comparison purposes we also looked at total SARs and fraud-related SARs. Fraud-related SARs include suspicious activity believed to be related to ACH fraud, Advance Fee fraud, Business loan fraud, check fraud, consumer loan fraud, credit/debit card fraud, health insurance fraud, mail fraud, mass-marketing fraud, ponzi and pyramid schemes, securities fraud, and wire fraud, but not mortgage fraud, which the forms treat as a separate category.

We also looked at SARs submitted by casinos to gauge the extent to which they might be used to place dirty cash; both the total number of SARs submitted by state-licensed casinos and tribal casinos, as well as the following categories of transactions:

- Minimal gaming with large transactions
- Transaction(s) below BSA Recordkeeping Threshold
- Transaction(s) below CTR threshold
- Other structuring
- Customer cancels transaction to avoid BSA reporting and recordkeeping requirements
- Suspicious inquiry by customer regarding BSA reporting or recordkeeping requirements

METHODOLOGY

All SAR data were analyzed in time series. For initial descriptive evaluation, monthly data trends (Figures 4 and 5) were produced using moving averages, employing a symmetric moving window with equal weights.

Visual inspections of resulting plots were used for initial determination of whether substantial shifts in the mean number of submissions were likely to be present. For both banks and MSBs, at least one major change in the mean number of submissions was deemed likely. These changes were verified using a changepoint detection algorithm (Hinkley 1970) to test for changes in a time series using the R package *changepoint* (Killick & Eckley 2014).

Changepoint Detection

Changepoint detection may focus on changes in the mean, variance, or another aspect of a given time series. We elected to use the series mean, as that seemed most likely to be revelatory in the trend plots. Briefly, we employed a cumulative sum (CUSUM) test (Csorgo & Horvath 1977). The CUSUM test is a sequential test that uses Maximum Likelihood Estimation (MLE) to detect the likelihood of a single change in the mean of a time series. It works by calculating the cumulative sum of the differences between the observed data and the expected mean. If the cumulative sum exceeds a certain threshold, then the test rejects the hypothesis that the mean is constant and identifies the point of departure. The resultant plots (Figures 6 and 7) illustrate the results.

One critical aspect of changepoint detection is the assumption of the number of changepoints that are present in a series. Although initial inspection of plots seemed to indicate a single changepoint was present, this assumption was further verified through a similar algorithm known as Bayesian regime detection, using the *depmixS4* package in R.

Bayesian Regime Detection

Bayesian regime detection is an unsupervised machine learning algorithm that is also commonly used for the purpose of tracking and detecting changes in the dynamics of a time series. These models are gaining in popularity due to their statistical rigor, utility in a variety of fields and distributional assumptions, and their relative computational efficiency. Specifically, regime detection is becoming more common in tracking and monitoring fluctuations in financial data, though it has been applied to a variety of other disciplines, such as economics, environmental science, and health- related fields.

The regime detection algorithm was run to test multiple scenarios (different numbers of changes in the regime state). A regime state is a period of time during which the series is relatively stable. We tested the assumption of 2, 3, 4, 5, and 6 changes in the regime state. The resulting solutions were compared using the Bayesian Inference Criterion (BIC) to evaluate for the best fit in each of the two series (bank submissions and MSB submissions).

The regime detection algorithm we used employs Hidden Markov Models (HMMs) to describe the behavior of a time series. HMMs model time series data using two sets of variables: latent or “hidden” states and observed states (i.e., counts of posted reports). The hidden states are not directly observable, but they influence the observed data.

HMMs are defined by two probability matrices: the transition probability matrix and the emission probability matrix. The transition probability matrix specifies the probability of transitioning from one hidden state to another. The emission probability matrix specifies the probability of emitting an observation given a hidden state.

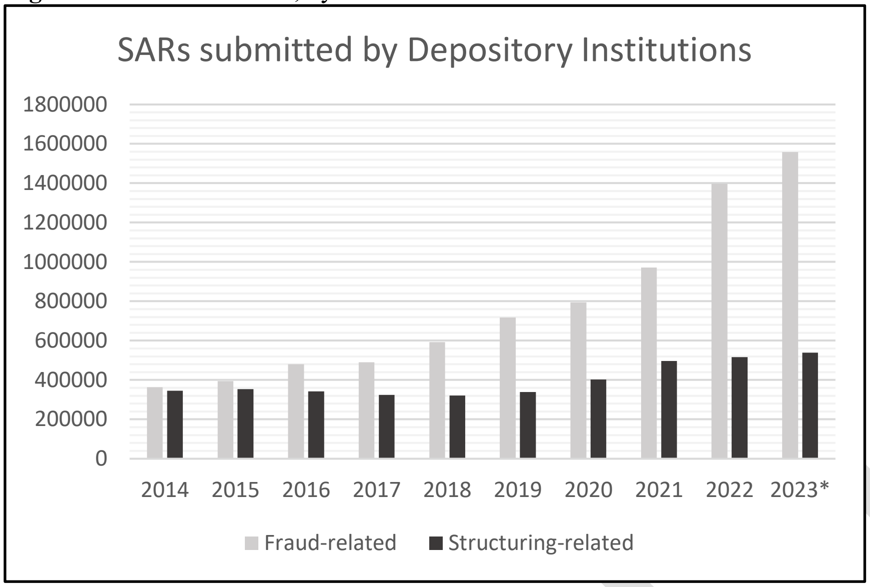
The Bayesian regime detection method works by fitting an HMM to the time series data and then applying an expectation maximization algorithm to estimate the parameters of the HMM. Once the HMM parameters have been estimated, the model is used to compute the probability of being in each regime at any given time (i.e., posterior probabilities). The posterior probabilities calculated by the model are then used to identify the regimes present in the time series (Figures 8 and 9), as indicated by the periods of time when the probability of being in a particular regime is high.

RESULTS

So much attention has been focused on the surge in fraud in the last three years of the pandemic, it’s easy to overlook what is happening in other areas of financial crime, and particularly in other subcategories of SAR filings. While not exactly hiding in plain sight, SAR filings have seen a statistically significant uptick since the Covid pandemic began.

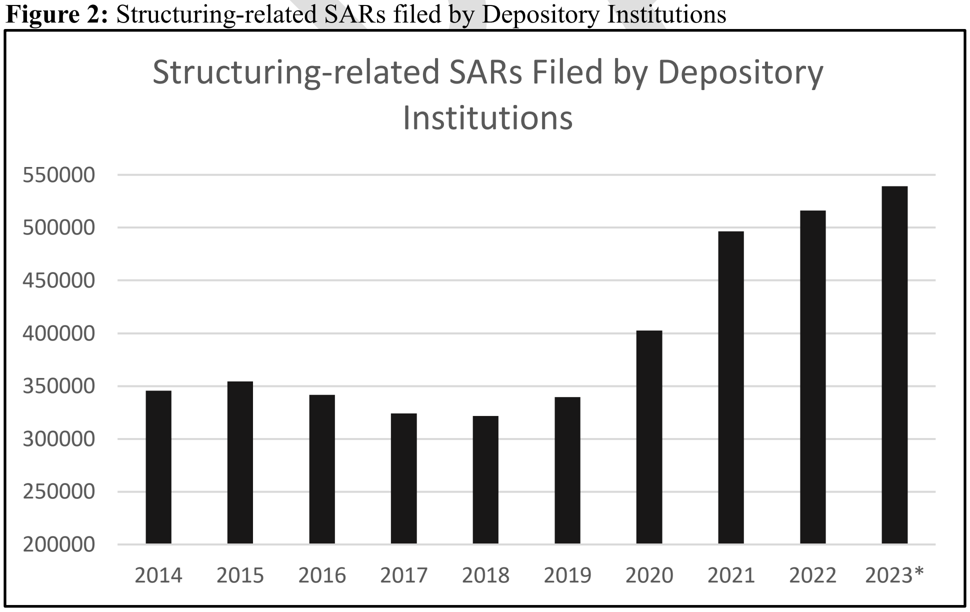
If we look at SAR filings from depository institutions (mostly banks) over the past ten years (Figure 1), we can clearly discern the dramatic increase in reported fraud-related transactions. While this is often assumed to be a direct result of Covid-relief funding and no-bid government contracts for personal protective equipment, the upward trend in reported fraud began before the pandemic, from about 2018. The Covid pandemic merely turbo-charged it.

Figure 1: Submitted SARs, by theme



If we take a closer look at and focus only on structuring-related SARs, cropping the vertical scale (Figure 2), we can begin to appreciate that something is probably going on that is not a statistical aberration. It is certainly not as dramatic as the nearly exponential increase in reported fraud, but it is nevertheless a phenomenon worth exploring.

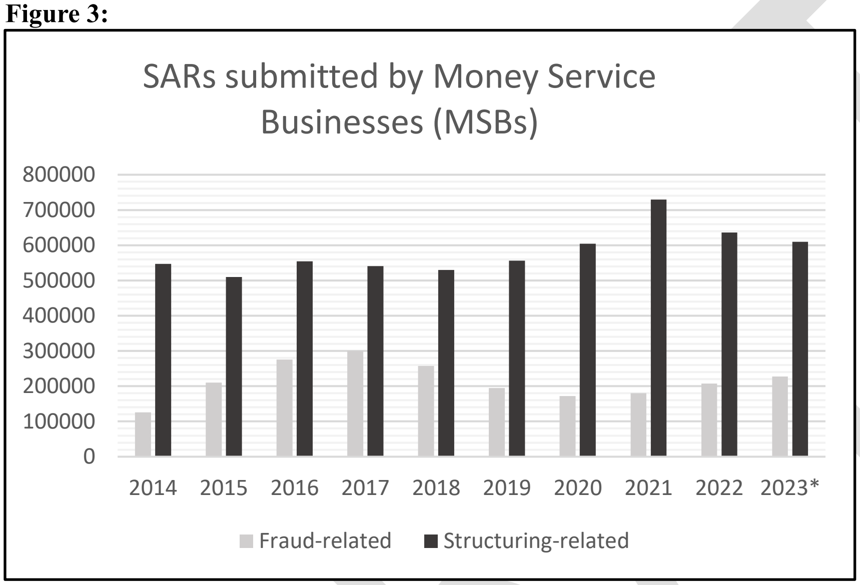
Figure 2: Structuring-related SARs filed by Depository Institutions



Looking at money service businesses, which includes everything from check-cashing services to money remitters and even cryptocurrency exchanges, we see that they were filing more structuring-related SARs than depository institutions over this ten year period (Figure 3). Fraud-related filings were far less significant, which makes sense given the nature of their typical transactions.

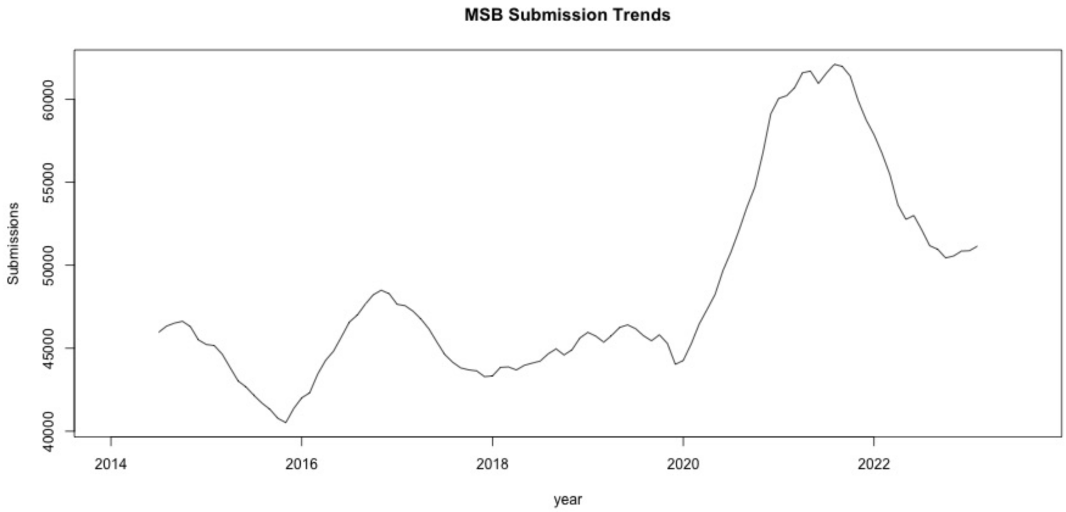
Here, too, we see an uptick beginning during Covid, reaching a peak in 2021, before returning to 2020 levels. It still represents a lot of reported structuring activity. Money service businesses in the U.S. are on track to file approximately 600,000 structuring-related SARs in 2023.

Figure 3:



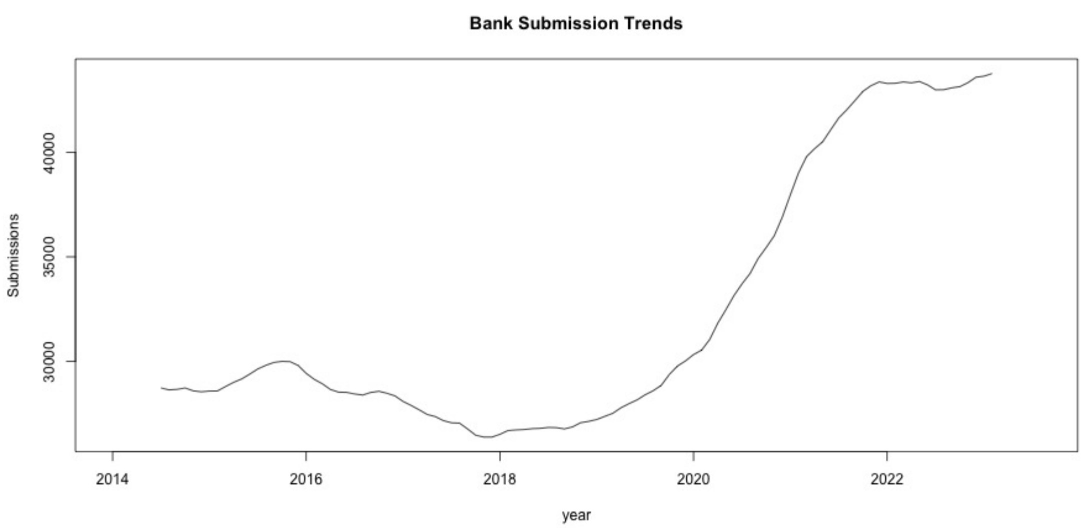
Next, we examined monthly SAR filings. There was naturally a lot of expected variation month to month (as seen later in Figures 6 & 7), so we smoothed the data. Smoothed data (using moving averages) reveal what appears to be an abrupt increase in SAR submissions by MSBs that begins in year 2020 (Figure 4).

Figure 4: Moving average of structuring-related SARs submitted by MSBs



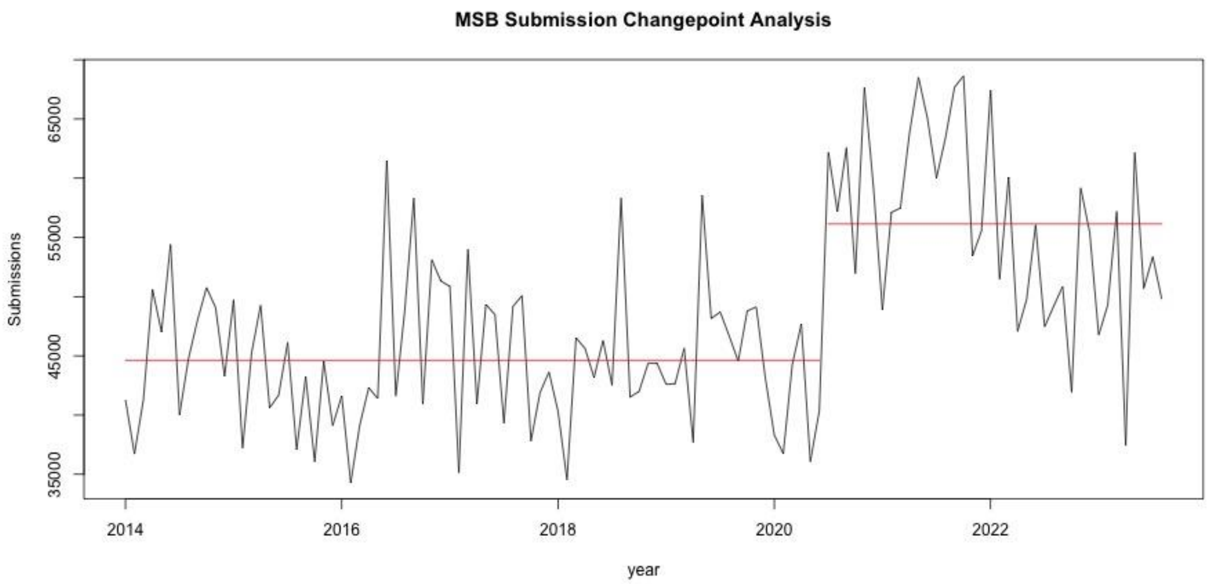
Bank submissions of SARs follow a similar trend (Figure 5), though the smoothed trend appears far less volatile than was evident among MSBs. In both cases, there appears to be a pronounced increase in SARs beginning in year 2020 and, in the case of banks, persisting thereafter.

Figure 5: Moving average of structuring-related SARs submitted by depository institutions



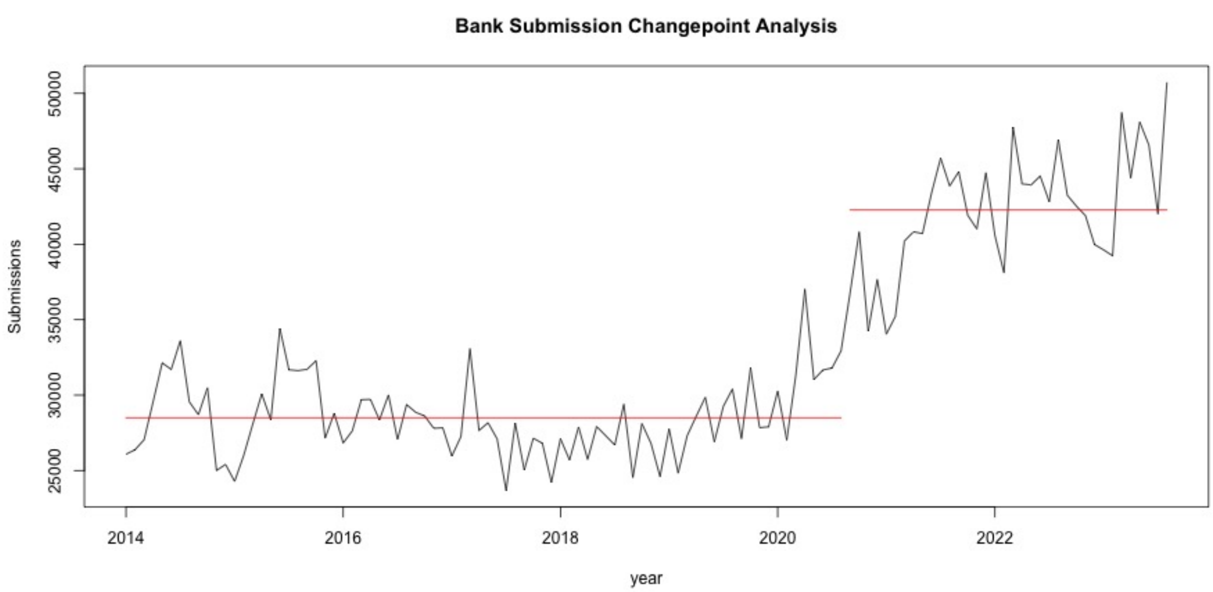
In order to verify with clarity the significance and timing of these changes, we employed changepoint detection. Changepoint detection indicated June 2020 as the likely date for a shift in the time series of MSB submissions. The horizontal red line in Figure 6 presents the mean of the raw time series. The series mean shifts to a greater value for MSBs in June 2020

Figure 6: Changepoint results for MSB submissions of structuring-related SARs



For banks, the likely date for change in the series mean was determined to be August 2020 (Figure 7), despite an initial increase in April.

Figure 7: Changepoint results for bank submissions of structuring-related SARs



The actual point of change for the mean value of the time series can be empirically difficult to assess. After all, changes in the series mean may be gradual, making it difficult to determine at which point the series may be considered to have shifted. Among bank submissions, the observed trend in submissions begins its increase in early 2020 (Figure 5). But algorithms such as changepoint detection are prone to select the midpoint in the initial slope of the increase as the inflection point that allows us to differentiate between one state to another.

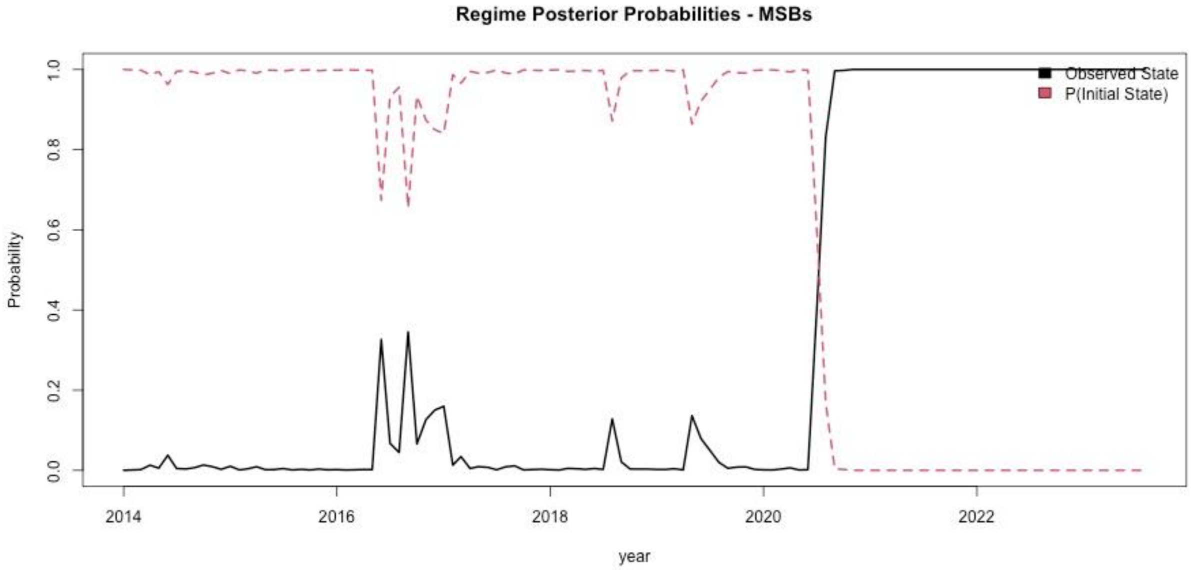
The difference between empirical observation and mathematical estimation is what makes it important to employ a variety of methods for assessing the changes in time series data. In this case, the changepoint analyses indicate the presence of a change and the point at which such a change is mathematically clear. Mathematical clarity is more likely once the value of the series increases past some *midpoint*. The time series trends, however, similarly clarify that such changes may be gradual. Plotting the trend and assessing the raw data allows us to assess a point at which the increase in submissions likely *began.* In the case of bank SAR submissions, raw data point to an initial jump in volume that begins in April 2020, in keeping with the start of the Covid pandemic business shutdowns. The trend plot (Figure 5) indicates that the increase in submitted reports persistently rises from that point.

The changepoint detection results illustrated in figures 6 and 7 were based on the assumption that only a single change exists in each of the two time series presented: MSB submissions and bank submissions. In the case of MSB submissions, particularly, that assumption may be suspect, given the amount of variability evident in the series. Regime detection allowed us to verify the results of the changepoint analysis and test whether three or more changes were a better fit for each time series we evaluated.

In each case, bank submissions and MSB submissions, the regime detection algorithm converged. Recalling that in this type of analysis a "regime" is a period in which a time series is relatively stable, various models were run for both MSB submissions and bank submissions under the assumptions that 2, 3, or more series regimes exist in the data set. The Bayesian Inference Criterion (BIC) was then used to compare relative fit between regime detection models.

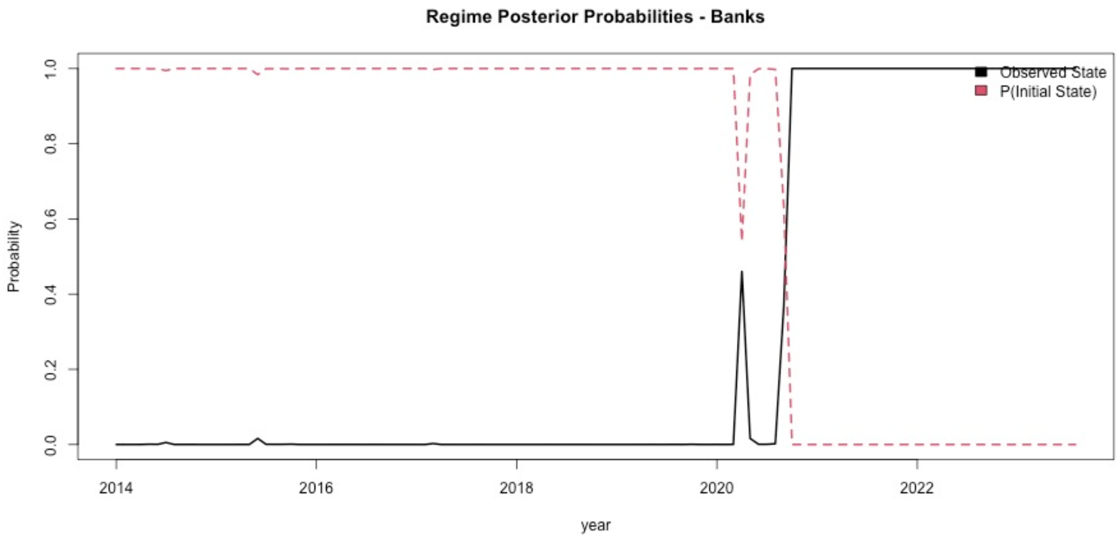
For both bank submissions and MSB submissions, a two-regime model provided the best fit. In other words, each time series consisted of an initial state (the first regime) and a changed state (the second regime). The volatility in the MSB submissions, in particular, had begged the question of whether two regimes provide the best description of changes within the series. As illustrated in figure 8, the clear delineation between the initial and second regime (solid black line) are a good, but not perfect representation of the two regimes, the dotted red line indicating the posterior probabilities that the series remains in the initial regime. Aside from some decreases in the probability values after 2016, the definitive probability that the series had entered into a new regime took place in 2020, with the initial regime ending at the end of June 2020.

Figure 8: Bayesian regime detection results for MSB submissions



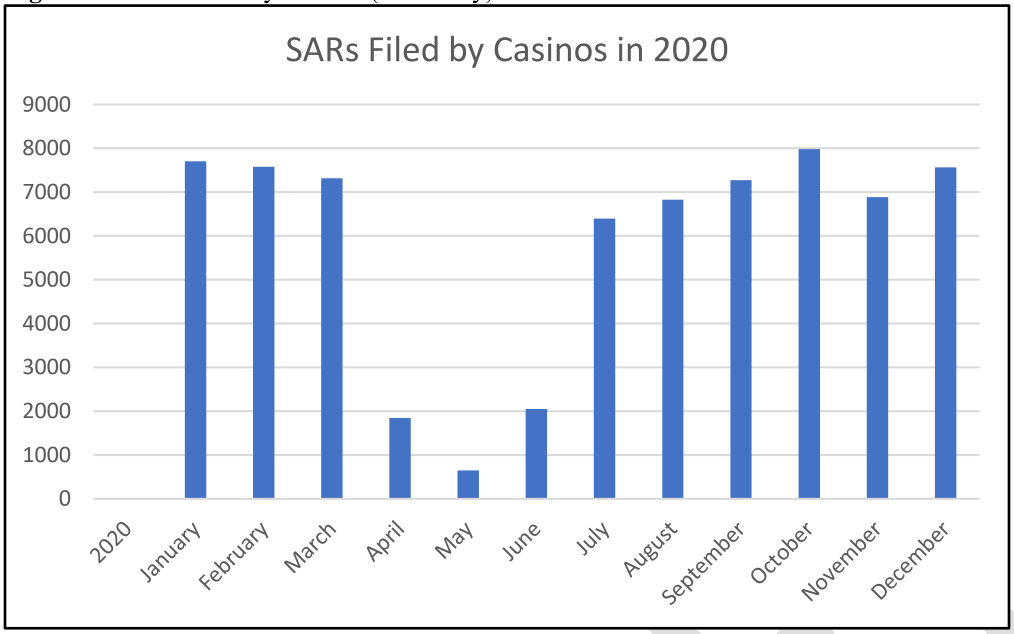
By comparison, bank submissions of SARs are more starkly delineated. The main difference is the substantial drop in probability occurring at the April 2020 time point, as indicated by the dotted red line. This corresponds with what we noted about the value of considering multiple forms of analysis when considering when a regime shift actually occurs. In this case, the regime change algorithm detects the initial shift, but does not assign probability of a regime shift until midway through the increase in the number of bank submissions that is visible in figure 5. Nonetheless, given these findings, it is reasonable to assume that the beginning of the upward shift occurred in April 2020.

Figure 9: Bayesian regime detection results for bank submissions



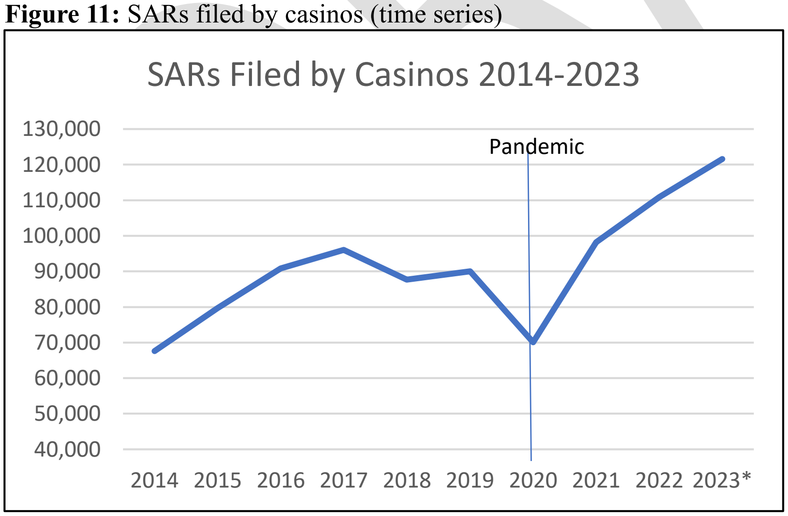
Since banks and money service businesses are not the only reporting entities likely to encounter physical cash transactions, we also looked at SAR filings from casinos in order to test the hypothesis that criminals may have migrated their placement activities during and after Covid (from commingling dirty funds with legitimate non-casino establishments to other methods.) Because state-licensed casinos were also temporarily shut down during the pandemic, they submitted fewer SARs in 2020. Casinos on tribal lands, on the other hand, had fewer restrictions, and did not experience as dramatic a drop in suspicious activity filings. Nevertheless, the total number of SARs submitted by all casinos fell significantly in April, May and June, reflecting reduced activity in March, April and May. Once casinos opened up again, SAR filings resumed at a regular clip similar to the first three months of the year.

Figure 10: SARs files by casinos (2020 only)



But something interesting happened after 2020. The number of SARs filed by casinos increased significantly and steadily. In state-licensed casinos, the number of SARs filed in 2023 is projected to be 23% higher than the pre-pandemic level in 2019. In tribal casinos there has been even more of an increase: 69% over pre-pandemic levels.

Figure 11: SARs filed by casinos (time series)



Finally, for the structuring-related SARs filed by depository institutions and money service business, we also examined seasonal variations to help account for that effect in our results. For example, if SAR filings normally fall in the Spring and rise in the Autumn, we would need to discount that from the impact of Covid in the Spring of 2020. We did not find any significant seasonal or monthly differences beyond the length of the month. For example, February had lower SAR filings every year, but this was consistent with the month being shorter. The average February filings of structuring-related SARs were 10% lower for depository institutions and 13% lower for MSBs.

DISCUSSION

The results of our analysis reveal interesting developments for which there may be several explanations. We can definitively say that structuring-related SARs have increased significantly for both depository institutions and casinos since the summer of 2020. While this metric is only measuring the number of reports and may not precisely measure the actual dollar value of structuring by criminal groups, it is nevertheless a good indicator of increased structuring activity. It's also possible that reporting institutions decided to ramp up their efforts at detecting structuring. While some of this may have happened, it's unlikely that better detection and reporting alone could account for a 53% increase in structuring-related SARs filed by depository institutions, and a 29% increase in SAR filings by casinos in the last three years. [c]

Some of the increase in SARs filed by casinos may be due to increasing pressure from regulators to be more proactive about detecting suspicious activity and reporting it. And perhaps they are now filing more SARs as a result, especially after the Cullen Commission findings in neighboring Canada (Cullen, 2022). But it isn't clear if that heightened response has also extended to casinos throughout the United States (Hendry, 2022).

The explanation that we are proposing is that money launderers, who are still dealing with large amounts of physical cash (notwithstanding the increase in crypto-related crimes and other digital crimes) encountered significant challenges when cash-intensive businesses shut down during the Covid pandemic in the Spring of 2020. Some of these businesses closed permanently. And those that did reopen were more likely to offer increasingly popular electronic payment methods. This in turn led money launderers to adopt alternative placement methods such as laundering cash through casinos, and structuring deposits through banks. These alternative money laundering placement methods are easier to detect than commingling, which we believe accounts for the increase in SAR filings.

[c] Average annual SAR filings for 2021-2023 compared to average annual SAR filings for 2014-2019.

This finding has broader implications and lessons for policy makers, FIUs, law enforcement and private sector compliance departments. For policy makers, this is yet another signal that criminals are still making heavy use of cash, while at the same time law-abiding consumers are moving away from cash. This has implications for the ongoing debate about when or whether to introduce a central bank digital currency as we transition towards a cashless economy. Also, given the increased incidence of structuring, perhaps there is a way to streamline those SAR filings while still retaining as much identifiable information about the suspects and accounts as possible. A recent piece in *ACAMS Today* (Gurdak, 2023) suggests that too many law enforcement investigators have "become reluctant to initiate any structuring investigations" because of discrepancies in actual transaction dates and times vs posted times, leading to "sloppy investigation optics." With increased adoption of machine learning, FinCEN could triangulate the data from these suspected structuring cases to build more promising investigative leads.

Hopefully law enforcement will take note and pursue such leads. Structuring is "the "reddest of the red [money laundering] flags" (Gurdak, 2023). Ignoring these SARs means leaving a lot of valuable intelligence on the cutting room floor. Few agencies, with the exception of IRS-Criminal Investigations, take full advantage of the BSA database. With more awareness and training, law enforcement can make accessing SAR data (and other BSA intelligence) a routine part of all of their investigations.

There are also lessons for financial institutions. The crushing weight of increased fraud cases and increased SAR filings for all categories of offenses has left many employees burned out. More sophisticated machine learning algorithms (and other promising AI-related applications) will hopefully make the job of a compliance investigator easier and more fulfilling. The goal should be more effective and actionable SAR filings; quality over quantity.

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