Snowblind: Short and Medium-Term Effects of a Cocaine Supply Shock

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Abstract

This work seeks to analyze the effects of an increase in the supply of cocaine using an exogenous increase shock in São Miguel Island, Portugal as a case study. São Miguel is located in the archipelago of the Azores which is politically organized as an autonomous region that includes nine islands. In January 2001, half a ton of cocaine reached the shores of the island of São Miguel. According to news reports, this event was a trigger for many changes on the island, such as an increase the number of active drug dealers and an extreme reduction in the price of the drug. Through Synthetic Control, I seek to study the short and medium-term impact of an increase in the availability of cocaine in São Miguel on crime, unemployment, and health.

Introduction

For many years, scholars from various disciplines have investigated the impact that drugs have on society as a whole. Drugs have both direct effects (for example, deaths by overdose), and indirect effects, such as an increase in unemployment due to addiction. Many authors attempted to identify the impact by finding a relationship between drug use and different outcomes, such as unemployment, consumption, etc (see Miron 2001). The problem with this strategy does not need further explanation: those societies with the worst economic performance tend to contain individuals who resort to drugs, so the causality is reversed. The present work will use a natural experiment to estimate the causal effect that an increase in the supply of cocaine has on unemployment, health, and crime.

The natural experiment proposed in this work allows us to rule out the hypothesis of reverse causality because the economic performance of São Miguel did not cause the cocaine to reach the island. The term "natural experiment" is used inconsistently in the economic literature, but Titiunik 2020 proposes a definition that tries to clarify what we call a natural experiment. A natural experiment occurs when "the treatment assignment mechanism (i) is neither designed nor implemented by the researcher, (ii) is unknown to the researcher, and (iii) is probabilistic by virtue of depending on an external factor." In this sense, the case study treated here constitutes a natural experiment.

Cocaine is generally classified as a "Hard Drug", due to its addictive potential and its ability to cause harm, both to the consumer and to third parties (Janik et al. 2017). Through a multicriteria analysis, Nutt, King, Phillips, et al. 2010 ranks cocaine in a high position in terms of the damage it can cause. In terms of potential damage, it is located above tobacco, Cannabis, amphetamine, ketamine, etc. At a global level, cocaine causes a total of 0.09 deaths per 100 thousand inhabitants (Ritchie 2018), in these terms, surpassing the number of deaths from amphetamine overdose (0.06). This work **would be the first to use a natural experiment that exploits such a considerable increase in cocaine in such a short period of time**.

In 2001, half ton of cocaine got into São Miguel, Portugal. The yacht that was carrying the cocaine from Venezuela had planned to go to Spain, however weather conditions forced it

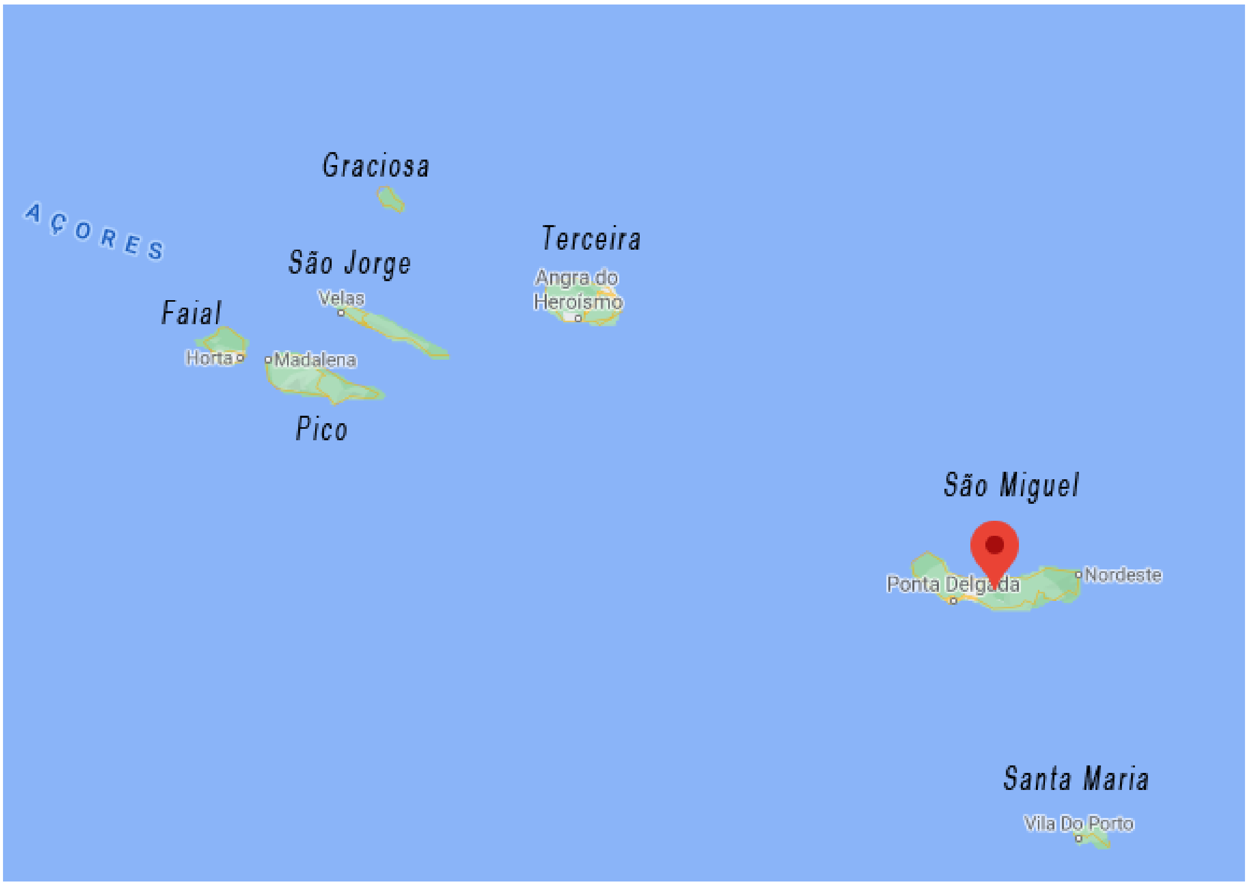

Figure 1: São Miguel and nearby islands in the Azores archipelago

to have to make a stop in São Miguel. Before arriving at port, the experienced sailor had to hide the cocaine he was carrying. The members of the crew tried to hide the cocaine in a cave in the north of São Miguel, with fishing nets and an anchor. But unfortunately for the smugglers, the waves dislodged the cocaine packages that ended up reaching the coasts of São Miguel. According to news reports, since this event, many islanders became small distributors of the drug. It was also commented that the price of cocaine completely collapsed to the point of distributers selling glasses with 150 grams of cocaine for 17 euros, which was extremely cheap. Although these results were documented through anecdotes from officials and citizens of the island, little has been done to document changes in a more rigorous way.

Located in the Atlantic Ocean, São Miguel has a group of nearby islands that are part of the Azores Archipelago (Figure 1). These islands have similar characteristics in terms of climate because they are close to each other, but because they are separated by water, a shock that impacts one will not directly impact another. Furthermore, the increase in cocaine occurred at a particular point in time and not over multiple periods. **All this makes it possible to estimate the causal effect of the aforementioned shock.**

This work manages to contribute to various literatures. First, the work proposes to find short and medium-term effects that drugs have on society. As it will be seen below, there are similar works in the sense that they examine some type of exogenous variability in the supply of drugs, but the majority do so through a reduction in the supply and not an increase. On the other hand, this work tries to investigate the impact of a particular episode that could have significantly changed the destiny of an entire population. The literature that is responsible for investigating effects that have particular episodes over time is known as persistence literature. If lasting effects are found, this work is also contributing to this type of literature.

Related Literature

The literature related to the effects of changes in the supply of drugs can be divided into at least two categories, one includes a reduction in supply, while the other includes an increase in supply. These two relevant literatures will be detailed below.

Drug Impact

Reduction in the Supply of Drugs

Studying shocks in the drug market in Colombia Abadie, Acevedo, et al. 2014 found evidence that a reduction in the supply of cocaine tends to produce an increase in violence. They argue that this could be due to an increase in disputes to capture the rents that are associated with cocaine sales.

Castillo, Mejıa, and Restrepo 2020 examined the role of a reduction in the supply of cocaine in the increase of violence in Mexico. Studying seizures in Colombia the authors found that a reduction in the cocaine supply could account for a 10% increase in violence in Mexico. In a similar vein, Cunningham and Finlay 2016 pointed out that a reduction in the supply of drugs in illegal markets tends to increase the street price of drugs, and there are also substitution effects between different types of drugs.

Regarding changes in the supply of other drugs, we can find some studies that suggest that there are substitution effects between drugs, as the last study cited above. Alpert, Powell, and Pacula 2018 studies the effect of a supply disruption in abusable opioids in the United States, which could have caused a substitution effect with respect to heroin use. In the same spirit, Meinhofer 2016 conducted research on the effect of a reduction in the supply of oxycodone. The study finds that prices in the informal market are rising and that there is a substitution effect that appears to have caused a dramatic increase in heroin overdoses, but no impact on crime.

Increase in the Supply of Drugs

Finding exogenous increases in the supply of drugs is more difficult than finding decreases. Most of the previous literature studies the effects of a decrease in the drug supply. An exception is Beeder 2020 which makes use of an exogenous increase in the supply of cocaine and analyzes the subsequent violence in Colombia. The author found that when cocaine production becomes cheaper, violence increases. This result suggests that in the case of São Miguel there would be a similar effect in terms of crime rates. Taken together, the evidence would suggest that both an increase in the supply of drugs and a reduction could lead to an increase in crime.

Persistence Literature

In the past few years, there has been a growing body of research on persistence in economics. That is, studies that investigate the impact of a particular event and how it shapes the destiny of a particular city or country in the following years. As shown in Nunn 2009, empirical evidence has supported the claim that some historical events can have long-lasting effects in different variables such as economic performance, culture, or even gender differences. Generally, works of this type focus on long-term effects (see for example the seminal work of Acemoglu, Johnson, and Robinson 2001), but there are also those that study the short and medium-term consequences of certain shocks (for example, Jones and Olken 2009). The work presented here would evaluate short and medium-term effects (around 10 years).

The direct relationship with this type of literature will depend on the effect found. That is, it is possible that the effects disappear too soon and therefore this study would not constitute a contribution to persistence literature.

Data

For the purpose of this study, the data will be obtained through the National Institute of Statistics of Portugal, which contains disaggregated data for the different regions of the country. It has data on, for example, crime, hospitalizations, and unemployment. In principle, the available data are not high frequency. But if necessary, high frequency data could be requested (in the case of hospitalizations and crime, we wish we had daily data).

If for some reason it is not possible to obtain some of the explanatory variables of interest, a close proxy would be sought. For example, there may not be data with such a high frequency for hospitalizations, but it is more likely to obtain data of this type with regard to deaths, the impact on health would then be studied through this last variable.

The synthetic control method provides the possibility of using covariates to construct the pre-treatment paths of the outcome variables of the donors. These covariates will be chosen based on the availability of data and on how good a predictor they can be of pre-treatment path. That is, they are not decided in advance. In an extreme scenario the exercise could be carried out without covariates, simply using lagged values of the outcome variables.

Methodology

Causal relationships can be defined through potential counterfactual results that cannot be observed. Lewis 1974 was one of the first authors to make this explicit: "The proposal has not been well received. True, we do know that causation has something or other to do with counterfactuals. We think of a cause as something that makes a difference, and the difference it makes must be a difference from what would have happened without it. Had it been absent, its effects-some of them, at least, and usually all-would have been absent as well".

The ideal scenario to evaluate the impact of an increase in drug availability in a region is to take a certain number of regions (the more the better) and randomize the application of the treatment (increase in the supply of drugs). Such an experiment cannot be carried out easily. But considering such an experiment can be helpful in finding a valid source of exogeneity Angrist and Pischke 2008, p. 4.

Given the above, it is necessary to find a counterfactual of what would have happened without the increase in the supply of cocaine in São Miguel. Once this counterfactual is found, according to Rubin's Causal Model (Rubin 2005) the difference between what is observed and what would have happened in the absence of the shock would be the causal effect of interest. There are different ways of constructing counterfactuals, in this case, because we only have one treated unit and several untreated units are not necessarily similar, the method to use will be synthetic control.

The first work that used the synthetic control method was Abadie and Gardeazabal 2003. In their seminal paper, Abadie and Gardeazabal 2003 examine the effect of terrorist conflicts in the Basque country. Their seminal work generated a whole new literature in which, to estimate causal effects one has to present only one treated unit and a pool of donors to construct a synthetic control. It acquired such relevance that Athey and Imbens 2017, p. 9 state that "the synthetic control method is arguably the most important innovation in the policy evaluation literature in the last 15 years".

Building Synthetic Control

A synthetic control is a way of constructing a counterfactual in a case where there is no unit similar to the one that receives a treatment, but there are several units that have a certain similarity and did not receive the treatment. The latter are called donors. Starting from the islands near São Miguel, a weighted average of the variables of interest would be created in such a way as to minimize the gap between the series of our treated unit and the synthetic control. One of the alternatives to synthetic control would be to perform a before and after analysis with a trend. That is, the current result is compatible with the value that the variable would have taken if it had followed the trend and it is assumed that in the absence of treatment that would have been the result. The problem with this is that during the shock of interest there could have been various shocks that muddle the effect and therefore do not allow us to distinguish the effect of interest from others.

The first step to perform synthetic control is to define the outcome of interest (in this case outcomes will be hospitalizations and crime and unemployment rates). Next, we will define the predictors of each outcome. And finally, we will decide the period in which the difference between the treated and synthetic regions will be minimized (the largest number of years prior to 2001 for which data is available).

The synthetic control method requires the choice of donors, these donors can be chosen based on a decision according to the similarity between the donors and the unit treated or a data-driven approach can also be carried out, where donors are selected through methods like LASSO (Amjad, Shah, and Shen 2018). To carry out this work, two alternatives will be considered.

Donors could be chosen based on their proximity to the island of São Miguel, as well as other observed characteristics (if they are very different, it would not make sense to include them). Fortunately, no cocaine ships were got on the other islands at the time of the shock to the island of São Miguel. If another island had received the same treatment, it would have to be removed from the donor list.

Causal Effect

The unobservable causal effect of the treatment is $\Delta_{1t} = Y_{1t}(1) - Y_{1t}(0)$. The problem is that $Y_{1t}(0)$ is not observable (it is the potential outcome if the treated unit was untreated). We approximate $Y_{1t}(0)$ using a weighted average of donors, so the estimated causal effect is: $\hat{\Delta}_{1t} = Y_{1t}(1) - \sum_{j=2}^{J+1} w_j Y_{jt}(0)$ for $t = T_0 + 1, \ldots, T$. Abadie, Diamond, and Hainmueller 2010, p. 496 shows that $\hat{\Delta}_{1t}$ is an unbiased estimator of Δ_{1t} even if we have data from only one pre-treatment period.

At the time of constructing the $Y_{jt}(0)$, the outcome predictors can be other relevant variables as well as lagged values of the outcome. In principle it seems reasonable to add the entire pre-treatment path of the outcome as a predictor, but Kaul et al. 2015 shows that this makes all other predictors irrelevant, this can cause the estimator to be biased. The conclusion derived from Kaul et al. 2015 is that two alternatives can be followed; include all lagged values of the outcome variable and do not include covariates or do not include all lagged values and include covariates.

Expected Results

The expected results include a radical change in the trend of the outcome variables. From the date of the increase in supply, unemployment would be expected to increase, and in terms of persistence, its level is not expected to revert for at least 10 years. In terms of crime and health, the expected effects would be short-term and would tend to dissipate over time.

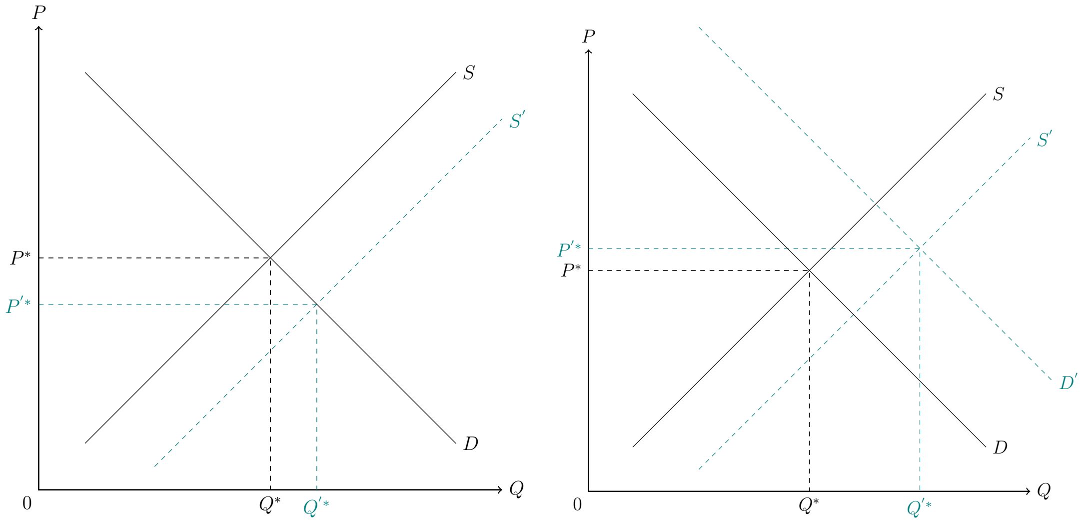

Figure 2: Supply curve shift and a possible after-effect of increased demand

As stressed before, there are many studies that suggested that the reduction in the supply of illegal drugs tends to generate violence due to conflicts related to the increase in rents from the sale of drugs (see Mejia and Restrepo 2013). Notwithstanding, it does not seem to be expected that in this case there will be a reduction in crime, because although there will be a decrease in rents associated with the illegal sale of cocaine, the number of agents who participate in the illegal drug sales market may increase.

The mechanisms behind the cocaine surge shock can be thought of as a shift in the supply curve. In the new equilibrium, we would obtain a lower price, with higher exchanged quantities, as shown in the left graph in Figure 2. After the shock, there could be an increase in the demand for cocaine, represented by a shift in the demand curve. This effect could be explained by an incipient literature that deals with the topic of updating preferences (Delaney, Jacobson, and Moenig 2019). After tasting cocaine, agents may update their preferences, leading to an increase in demand.[1] The final result could lead to an increase in both price and exchanged quantities, this will depend on which effect is greater.

Robustness Tests

It is necessary to carry out robustness tests once a certain result has been obtained. In the case of synthetic control, there are various possible tests. The best known are detailed below.

Changing the Date of Shock

This test consists of assuming that the shock occurred on another date and seeing if there are significant consequent changes. For example, one can choose the same month but a previous year. As at that time there was no such shock, one would expect that the series

[1] The slope of the curve could have also changed, but to keep the analysis simple, the curve is only shifted.

will not have a significant change from that moment on (that is, that the two series do not differ from each other).

Synthetic Control for Each of the Donors

This test consists of assuming that the donors are treated and calculating different controls with each of the donors using all the other observations. In the ideal scenario, what we should find is that none of the donors shows the same behavior as the treated unit. If we see, for example, that on the date of treatment, a donor presents a significant change with respect to its synthetic control, then this would cast doubt on the exercise.

Leave-Out Test

This test is based on using the synthetic control methodology but removing donors. Iteratively, a donor is removed each time and the same exercise is performed. Ideally, there should be no significant changes, suggesting that the results do not depend on a single region.

Cross-validation to choose V Weights

To construct the pre treatment path, one could use a linear combination of covariates. Those are weighted through a V matrix. One way to construct V weights is through cross-validation Hastie, Tibshirani, and Friedman 2009, pp. 241–245. This method allows us to avoid overfit problems since it uses a part of the sample to estimate and another to test. In general, 5-fold cross-validation (Breiman and Spector 1992) or 10-fold cross-validation (Kohavi et al. 1995) is recommended, but this will depend on the number of pre-treatment periods available. The method will divide the sample into k parts, one of these parts will be used for testing and the rest for estimating, then the following will be done with another partition and successively all partitions will take the role of test and train. This procedure will allow us to evaluate the robustness of the estimated gap while at the same time showing how well the synthetic control adjusts in the regions through different validation periods.

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