Reassessing a cocaine shock: a contrary narrative from Rabo de Peixe*

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Abstract

This work seeks to analyze the effects of an exogenous shock increase in the supply of cocaine using São Miguel Island, Portugal as a case study. Located in the Azores archipelago, the island is politically organized as an autonomous region. In January 2001, half a ton of cocaine unexpectedly washed ashore on Rabo de Peixe, São Miguel, leading to media reports of various alterations on the island, such as a surge in drug dealers and a significant reduction in the drug's price. These events even formed the basis for a documentary and a Netflix series. However, my comprehensive analysis utilizing a Synthetic Control approach paints a contrasting picture. I aimed to examine the short and medium-term repercussions of the increased accessibility of cocaine on São Miguel's crime rates, unemployment, and deaths. Contrary to the narrative constructed by the media and popular culture, I found no significant effects on these outcomes. This study challenges existing media narratives and provides a robust, data-driven insight into the actual impact of this incident on São Miguel.

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 their impact by finding a relationship between drug use and different outcomes, such as unemployment, consumption, etc. (see Miron 2001). The flaw in this strategy is self-evident: in societies with poor economic performance, individuals are more likely to resort to drugs, thereby reversing the causality. 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.

In the context of the experiment explored in this study, a unique incident occurred in January 2001 on São Miguel Island, Portugal.[1] Amid a cocaine trafficking operation, an unexpected turn of events led to half a ton of cocaine washing ashore, significantly increasing the local supply of the drug. This occurrence resulted in numerous reports of changes on the island, such as a surge in drug dealers and a significant reduction in drug prices, as reported by media outlets.

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. Although the term "natural experiment" is used inconsistently in the economic literature 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 depending on an external factor." In this

*For most recent version click here.

[1] https://www.theguardian.com/society/2019/may/10/blow-up-how-half-a-tonne-of-cocaine-transformed-the-life-of-an-island

sense, not only does the case study here constitute a natural experiment, but it would also be the first of its kind to explore such a considerable increase in cocaine in such a short period of time.

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), surpassing the number of deaths from amphetamine overdose (0.06). Studies have demonstrated that cocaine users have a higher mortality rate than non-users (Peacock et al. 2021). In particular, deaths attributed to cocaine use are often due to heart failure (Pergolizzi Jr et al. 2021, Havakuk, Rezkalla, and Kloner 2017).

In 2001, half a 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 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. Unfortunately for the smugglers, the waves dislodged the cocaine packages that ended up reaching the coasts of São Miguel. According to news reports[2], since this event, many islanders became small distributors of the drug."Reports also indicated that the price of cocaine collapsed, with distributors selling glasses containing 150 grams of cocaine for 17 euros, an extremely low price. These reported outcomes have been relayed through anecdotes from officials and citizens of the island, as well as in popular media through a documentary titled "Azores on Cocaine" and a Netflix series named "Rabo de Peixe". However, there has been little effort to document these changes more rigorously and empirically.

Located in the Atlantic Ocean, São Miguel is part of the Azores Archipelago, which includes a group of nearby islands (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 necessarily directly impact another. Furthermore, the increase in cocaine occurred at a particular point in time and not over multiple periods. These factors collectively enable the estimation of the causal effect of the aforementioned shock.

This work manages to contribute to various pieces of literature. First, the work proposes to find short and medium-term effects that drugs have on society. As will be discussed, while similar works examine exogenous variability in drug supply, most focus on supply reduction rather than 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 field of study that investigates the effects of specific episodes over time is known as 'persistence literature.

[2] https://www.cmjornal.pt/portugal/detalhe/alguns-pensavam-que-podiam-voar-testemunhas-recordam-o-dia-em-que-rabo-de-peixe-foi-inundado-de-droga

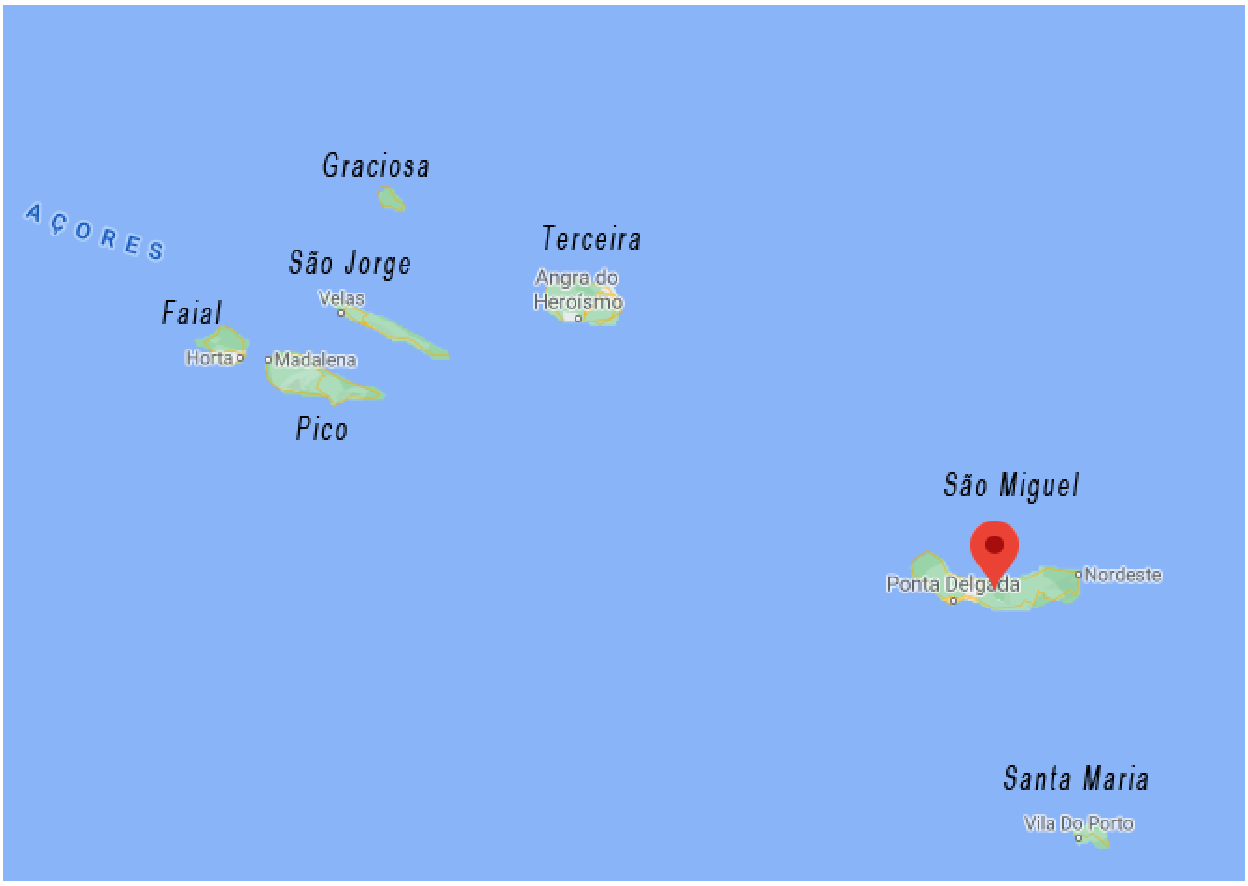


Figure 1: São Miguel and nearby islands in the Azores archipelago

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 pertinent categories of literature are detailed below.

Drug Impact

Reduction in the Supply of Drugs

Studying shocks in the drug market in Colombia Abadie, Acevedo, et al. 2013 found evidence that a reduction in the supply of cocaine tends to produce an increase in violence. They argue this increase in violence could be due to heightened disputes over the profits associated with cocaine sales.

Castillo, Mejía, 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."Similarly, Cunningham and Finlay 2016 noted that a reduction in illegal market drug supply tends to increase street prices, alongside substitution effects among different drug types.

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. For example, 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 concerning heroin use. In the same spirit, Meinhofer 2016 researched the effect of a reduction in the supply of oxycodone. Their research reveals that increased prices in the informal market led to a substitution effect, significantly impacting heroin overdoses but showing no measurable effect on crime rates.

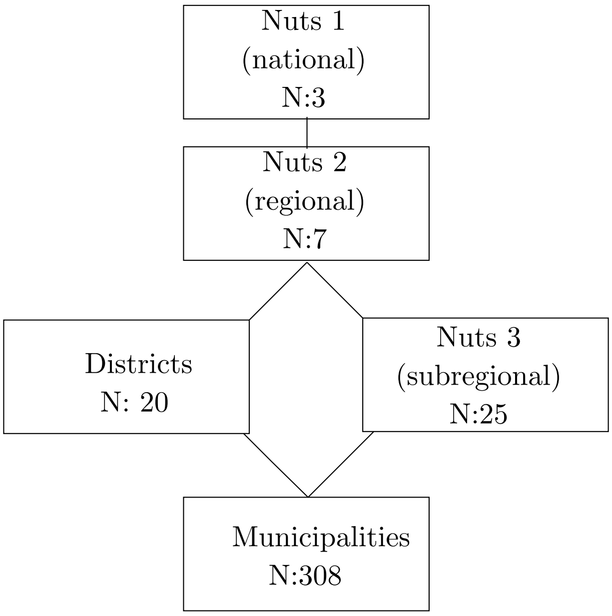
Increase in the Supply of Drugs

Finding exogenous increases in the supply of drugs is more difficult than finding decreases. An exception is the study by Beeder 2020, which utilizes an exogenous increase in cocaine supply to analyze subsequent violence in Colombia. The study found that cheaper cocaine production leads to an increase in violence. This result suggests that in the case of São Miguel, there could 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.

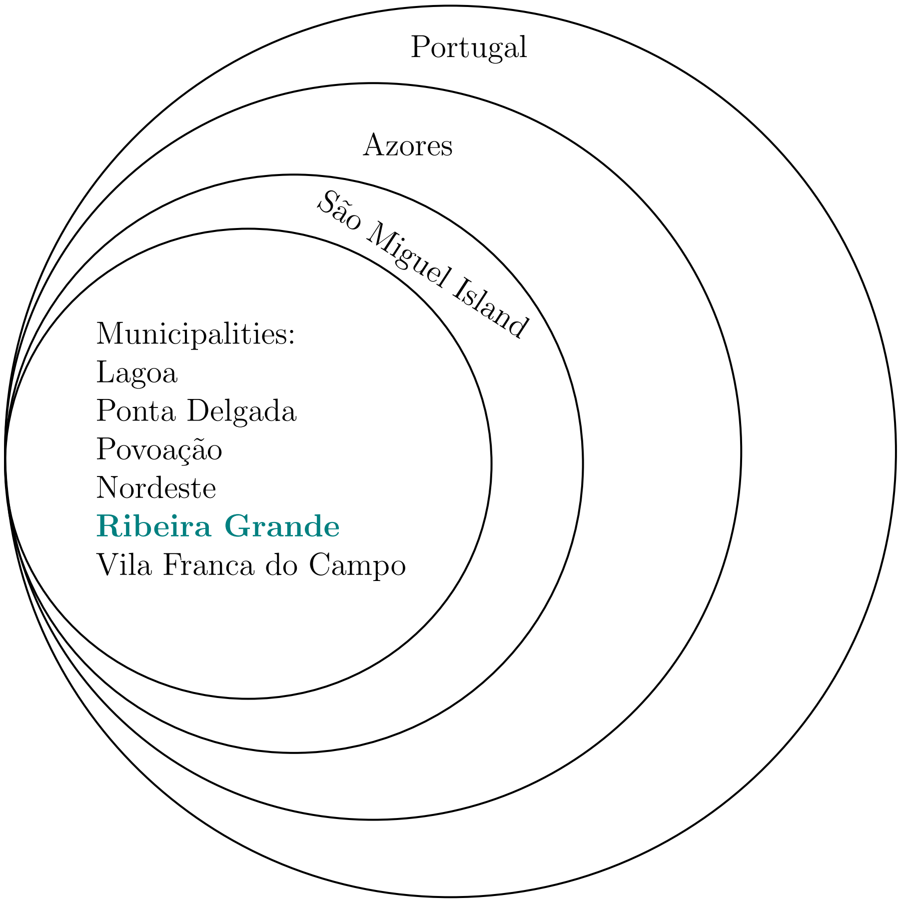
Persistence Literature

In the past few years, there has been a growing body of research on persistence in economics. This refers to studies that investigate the impact of a particular event and how it shapes the destiny of a specific city or country in the subsequent 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, studies of this nature primarily concentrate on long-term effects (see for example the seminal work of Acemoglu, Johnson, and Robinson 2001), but some 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).

Data[3]



[3]Note that there are minor discrepancies in the data reported on ine.pt compared to other sources. Specifically, while other sources may report eight subregional levels for the NUTS 2 classification, ine.pt lists seven. For detailed information on the localities included within each aggregation, refer to Appendix 1.



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, hospitalisations, deaths, and unemployment.

If it is not possible to obtain certain explanatory variables of interest, a closely related proxy will be sought. For instance, high-frequency data on hospitalisations may not be available, but data on deaths are more likely to be accessible. In this case, the impact on health would be studied through the latter 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 selected based on data availability and their effectiveness in predicting the 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 on 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. However, conceptualizing such an ideal experiment can aid in identifying a valid source of exogeneity, as Angrist and Pischke 2008, p. 4 suggest.

Therefore, it is essential to establish a counterfactual scenario to understand what would have occurred in São Miguel without the increase in cocaine supply. Once this counterfactual is established, the causal effect of interest, as per Rubin's Causal Model (Rubin 2005), can be determined by the difference between the observed outcome and what would have occurred in the absence of the shock. One approach to constructing counterfactuals in this situation, where there is only one treated unit and several untreated units that are not necessarily similar, is to use the synthetic control method.

The first work that used the synthetic control method was Abadie and Gardeazabal 2003. In their seminal paper, they examine the effect of terrorist conflicts in the Basque country. Their work spawned an entire literature, asserting that to estimate causal effects, one must present a single treated unit and a pool of donor units to construct a synthetic control. This method gained such significance that Athey and Imbens 2017, p. 9 declared, 'the synthetic control method is arguably the most important innovation in the policy evaluation literature in the last 15 years'.

First, we define the unobservable causal effect of the treatment, that 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.

The key step in the synthetic control method is the minimization of the distance between the treated unit and the synthetic control unit. This distance is typically measured using a weighted sum of the differences between the treated unit and the control units on the pre-intervention outcome variable of interest, such as GDP or employment. The selection of weights in this distance measure aims to ensure that the synthetic control unit accurately represents a weighted average of the control units, closely matching the treated unit in terms of the pre-intervention outcome variable. The minimization problem can be formulated as follows:

$$\underset{w}{\text{minimize}} \sum_{t=1}^{T} \left(y_t - \sum_{j=1}^{J} w_j y_{jt} \right)^2 \text{ such that: } w_j \geq 0, \sum_{j=1}^{J} w_j = 1$$

where y_t is the outcome variable for the treated unit at time t, y_{jt} is the outcome variable for control unit j at time t, w_j is the weight assigned to control unit j, and T is the number of time periods. The minimization problem ensures that the synthetic control unit is a weighted average of the control units that closely match the treated unit on the pre-intervention outcome variable.

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. While initially, it may seem logical to include the entire pre-treatment path of the outcome as a predictor, Kaul et al. 2015 indicates that this approach renders other predictors irrelevant and can lead to estimator bias. The key takeaway from Kaul et al. 2015 is the existence of two viable alternatives: either include all lagged values of the outcome variable without including covariates or include covariates but not all lagged values.

Building Synthetic Control

As previously mentioned, a synthetic control is a method for constructing a counterfactual in cases where no unit similar to the treated one exists, but several somewhat similar units, that did not receive the treatment, are available. The latter are called donors. Using the islands near São Miguel as a starting point, we will create a weighted average of the variables of interest to minimize the disparity between the data 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. A challenge with this approach is that concurrent shocks during the period of interest could confound the effects, making it difficult to isolate the specific effect under study.

The first step to performing synthetic control is to define the outcome of interest (in this case the outcomes will be hospitalisations, 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 before 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). 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, there is no evidence that cocaine ships 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.

Results

Several variables in the donor pool exhibit numerous missing values, complicating the generation of reliable pre-treatment matching. However, when examining descriptive graphs for variables such as internments or hospitalisation days, no clear effect is observable (see appendix 4).

Death rate

By disaggregating data to the municipal level, the most detailed level possible for our variables of interest,[4] and using Ribeira Grande as the treated unit, we observed a decline

[4] In the datasets utilized for this study, a negligible proportion of data points—specifically, less than 0.001% of the total were identified as missing. To ensure a balanced panel and maintain data integrity,

in the mortality rate in the year of the shock. This observed decline is succeeded by an increase; thus, in the most favorable scenario, should there be any impact of the cocaine supply shock, it might be posited that this led to reduced death rates. However, the theoretical foundation to support such a hypothesis is notably lacking.

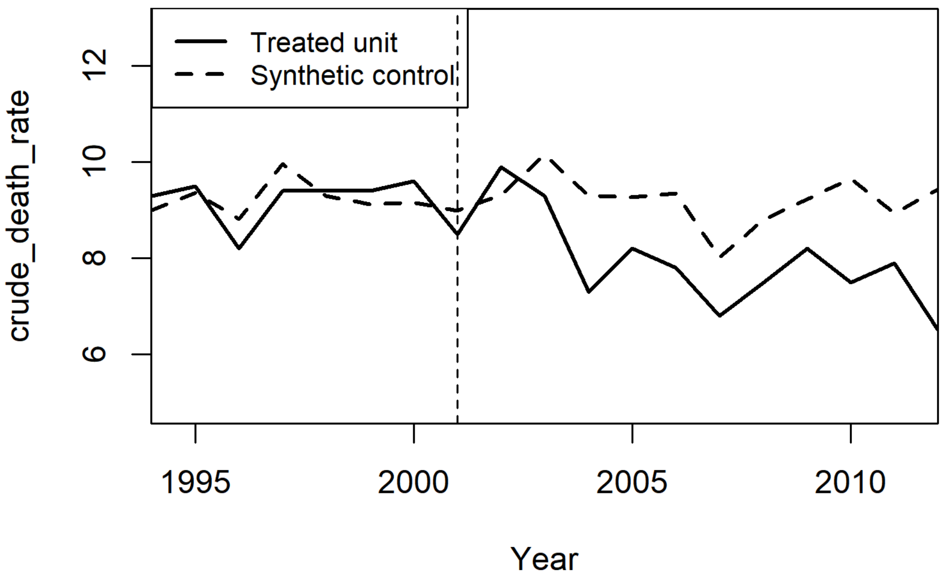


Figure 2: Synthetic control using municipalities aggregation

In terms of weights, the donors with the highest contributions are Lousada, Vila Franca do Campo, and Arcos de Valdeve, bearing weights of 0.45, 0.34, and 0.20, respectively, all the other donors received a weight less than 0.001. This allocation is particularly reasonable for Vila Franca do Campo, given its location on the same island and likely similar characteristics. Some of the variables used include sex ratio, fertility rate, average population, and energy consumption. For a complete list, please refer to the appendix 5.

In the context of utilizing São Miguel Island as a whole, as opposed to specifically Ribeira Grande, as the treatment unit through the aggregation of all municipalities on the island, it becomes evident that achieving an optimal fit is problematic. However, there isn't any discernible impact either.

these missing values were imputed with the mean of the available data.

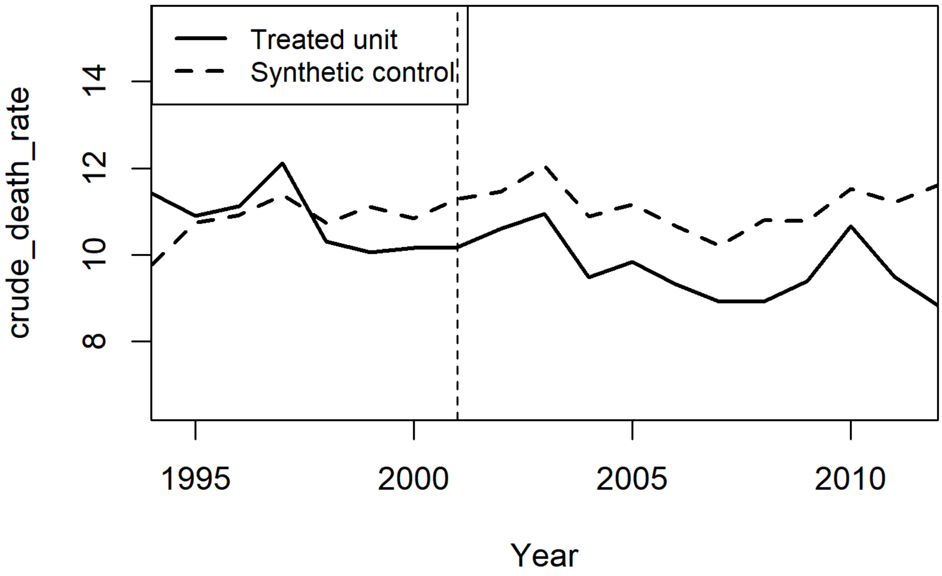


Figure 3: Synthetic control using municipalities aggregation but São Miguel Island as the treated unit

Crime rate

For the crime rate, information was available at the NUTS 2 aggregation level. In the context of the NUTS 2 aggregation, the Azores serve as the treatment unit, with São Miguel Island accounting for 54% of the Azores' total population. In this case, no immediate effects were noticed in the shock year. However, a reduction in the crime rate was observed in the year after the shock, but it then returned to its original trend.

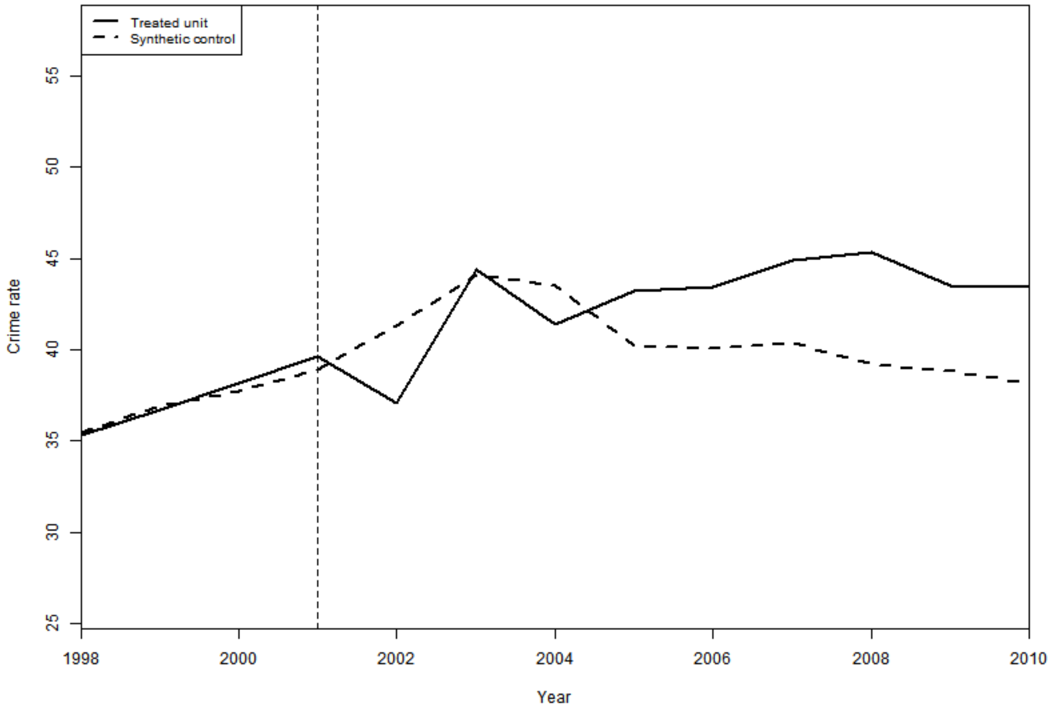


Figure 4: Synthetic control using NUTS 2 aggregation

Most contribution from the donor pool was done by Região autónoma da Madeira (0.6), Alentejo (0.27) and Algarve (0.27). The significant contribution from Região Autónoma da Madeira is justifiable, given its geographical proximity to the Azores. Examination of the graph indicates a diminution in the crime rate immediately after the shock, followed by an augmentation post-2005. This latter increase cannot be construed as a consequence of the shock, given the substantial temporal interval that elapses between the initial shock and this subsequent rise.

Employment rate

For the employment rate, data was available at the NUTS 2 aggregation, in this case, we don't see any effects in the year of the shock nor subsequent years.

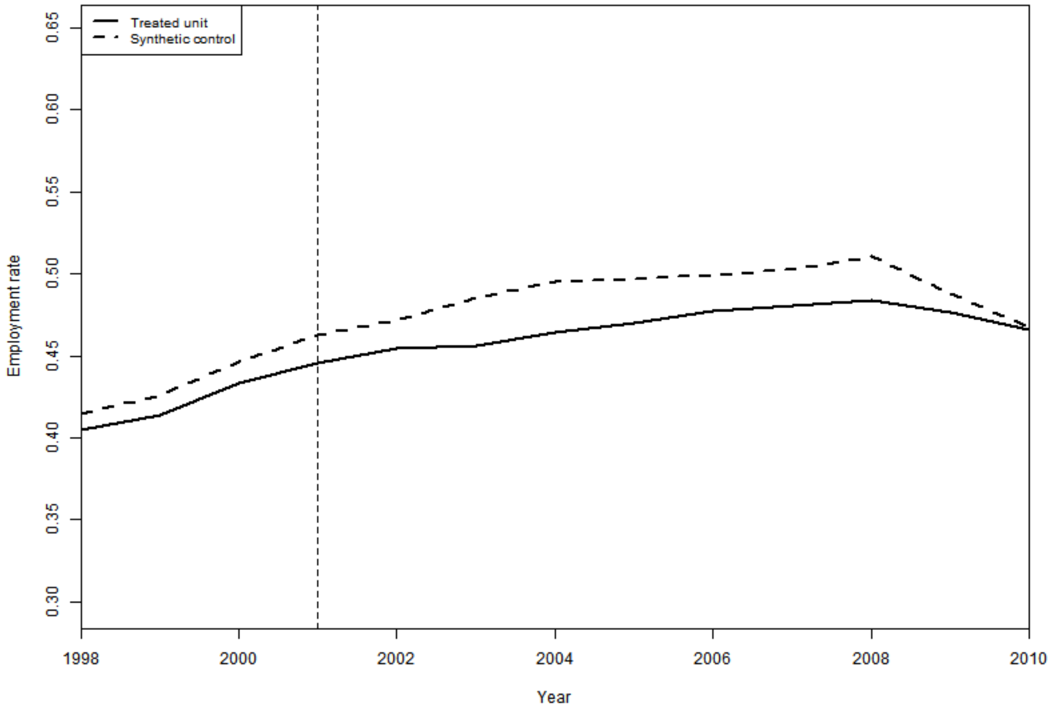


Figure 5: Synthetic control using NUTS 2 aggregation

Most contribution from the donor pool was done by Algarve (0.8) and Norte (0.138).

Main findings

The findings suggest a lack of short-term effects from the shock, with even less evidence of long-term impacts. The supply shock does not appear to have impacted the analyzed variables, even when conducting a graphical analysis without considering p-values. Subsequently, I will make an attempt to account for or understand why this result may be meaningful.

- First and foremost, all the news covering this event report the arrival of cocaine as a catastrophe or something that deeply impacts the island. For instance, this is suggested by over 10 sources, including newspapers from countries beyond Portugal.

- Secondly, the previously cited studies demonstrate that there usually are effects from an increase or decrease in drug supply in a specific country or territory. The scarcity of research yielding similar conclusions may stem from publication bias, where studies showing significant effects are more likely to be published, while those with null effects often receive less attention and fewer citations (Brodeur, Cook, and Heyes 2020, Blanco-Perez and Brodeur 2020, Auspurg and Hinz 2011, and Weiß and M. Wagner 2011). It is worth considering that the null effects found in our study might be due to cocaine being a novel substance in São Miguel. Unlike regions with established cocaine use, where fluctuations in supply could significantly affect crime rates by disrupting existing market dynamics, the sudden influx of cocaine in São Miguel might not have resulted in immediate or substantial shifts in crime rates. This divergence emphasizes the influence of regional sociocultural and economic contexts on the relationship between drug supply dynamics and crime rates, offering an alternative explanation for the observed null effects.

Explaining null effects

One possible explanation for the absence of significant health or crime effects observed in this study could be that individuals did not develop an addiction to cocaine after a single increase in its supply. Cocaine addiction is a process that may take time and repeated exposures to the drug to develop. While addiction can, in rare instances, arise from a single exposure to cocaine, such cases are less common. If individuals in São Miguel were only exposed to a single dose of cocaine, it is plausible that they did not experience sufficient effects to develop an addiction.

In addition, the short-term effects of cocaine can vary significantly among individuals. Some people may experience intense euphoria, while others may feel anxious or even depressed. Therefore, if the island dwellers in the study did not experience significant short-term effects, it's plausible that they were not notably affected by the single dose of cocaine.

The likelihood of developing addiction from cocaine consumption will depend on the method of administration. It is well known that the probability of addiction is not the same when cocaine is snorted as compared to when it is smoked in the form of crack or injected. The latter two methods of administration often carry a greater risk of addiction (O'Brien and Anthony 2005). Although the probability of developing cocaine dependence is higher than with drugs like marijuana, it may not have been sufficient to cause a noticeable increase in addiction among users in São Miguel. For example, estimates are showing that 5 to 6 percent of individuals who have tried cocaine become dependent within the first year (F. A. Wagner and Anthony 2002). This percentage, although not zero, may not be high enough to generate statistically significant effects on the analyzed variables.

Becker and Murphy's theory of rational addiction

According to Becker and Murphy's rational addiction model, we can comprehend why the shock in São Miguel did not generate a widespread addictive effect from cocaine. One of the main conclusions of the model is that there is an inverse relationship between the future price of the good and its demand (Becker and Murphy 1988). Since the shock that the island received is a one-time event, this means that scarcity will prevail in the future and therefore prices will rise. If individuals anticipate higher prices in the future, they may reduce their current demand for the drug, influencing the overall addiction rates. Higher prices in the near future, therefore, make demand not high enough to achieve a large number of addicted individuals.

Operant conditioning

Operant conditioning refers to the process of learning in which the consequences of a behavior influence the likelihood of the behavior being repeated in the future. In the context of drug use, if the experience of using a drug increases the probability of using it again, the drug is considered a reinforcer. Primary reinforcers, such as drugs, are intrinsically rewarding, similar to food or sex. In contrast, secondary reinforcers are only rewarding because they have acquired some learned value, such as money. The value of money is learned through its ability to provide primary reinforcers like food and other necessities.

However, not all experiences are reinforcing. Some individuals may find the first experience with a drug unpleasant, which may lead to the avoidance of the drug in the future. This is an example of punishment, as the unpleasant experience discourages drug-taking behavior. In the context of São Miguel, these factors – satiation, immediacy, contingency, and stimulus size – may have influenced the reinforcing power of cocaine and affected the likelihood of repeated use.

Satiation refers to the state of being "full" or satiated. In the context of food, it is evident that food is more rewarding when an individual is hungry, and less rewarding when they are satiated. Similarly, the rewarding nature of drug use may be heightened when other sources of pleasure, such as relationships, work, or hobbies, are absent in an individual's life. Additionally, the particular effect of the drug may influence satiation. For instance, caffeine is more rewarding when an individual is tired and needs a boost.

In this sense, it could happen that factors such as the context have caused diverse individuals to not become addicted simply because they did not have a good experience (or good first experiences) with the consumption of cocaine. Conversely, if individuals' lives are already enriched with sources of pleasure, the consumption of cocaine may not provide additional satisfaction. (Edwards 2016).

Other reasons

Finally, we can consider certain factors that are related to the quality of the cocaine.If the cocaine was sufficiently adulterated, as sometimes occurs, this could have diminished its addictive potential among users. Alternatively, in the context of São Miguel, if user preferences leaned towards other types of drugs, such as depressants over stimulants, this might explain the lower demand for cocaine.

Conclusion

In conclusion, this study aimed to analyze the impact of a shocking increase in the supply of cocaine on an island in Portugal using the synthetic control method. Contrary to what was suggested in various news reports, series, and documentaries, our study, employing the synthetic control method, found no significant impact on any of the analyzed variables. This suggests that the increase in the supply of cocaine did not lead to any observable changes in drug-related behaviors or outcomes on the island. These findings highlight the importance of rigorously evaluating claims made in news reports. Our findings demonstrate that not all claims made in media reports are necessarily supported by substantial empirical evidence.

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Appendix 1

NUTS 1 aggregation
continente
região autónoma da madeira
região autónoma dos açores

NUTS 2 aggregation
alentejo
algarve
área metropolitana de lisboa
centro
norte
região autónoma da madeira
região autónoma dos açores

NUTS 3 aggregation
alentejo central
alentejo litoral
algarve
alto alentejo
alto trás-os-montes
ave
baixo alentejo
baixo mondego
baixo vouga
beira interior norte
beira interior sul
cávado
cova da beira
dão-lafões
douro
entre douro e vouga
grande lisboa
grande porto
lezíria do tejo
médio tejo
minho-lima
oeste
península de setúbal
pinhal interior norte
pinhal interior sul
pinhal litoral
região autónoma da madeira
região autónoma dos açores
serra da estrela
tâmega

Municipalities list (1/3)		
abrantes	águeda	aguiar da beira
alandroal	albergaria-a-velha	albufeira
alcácer do sal	alcanena	alcobaça
alcochete	alcoutim	alenquer
alfândega da fé	alijó	aljezur
aljustrel	almada	almeida
almeirim	almodôvar	alpiarça
alter do chão	alvaiázere	alvito
amadora	amarante	amares
anadia	angra do heroísmo	ansião
arcos de valdevez	arganil	armamar
arouca	arraiolos	arronches
arruda dos vinhos	aveiro	avis
azambuja	baião	barcelos
barrancos	barreiro	batalha
beja	belmonte	benavente
bombarral	borba	braga
bragança	cabeceiras de basto	cadaval
caldas da rainha	calheta (r.a.a.)	calheta (r.a.m.)
câmara de lobos	caminha	campo maior
cantanhede	carrazeda de ansiães	carregal do sal
cartaxo	cascais	castanheira de pêra
castelo branco	castelo de paiva	castelo de vide
castro daire	castro marim	castro verde
celorico da beira	celorico de basto	chamusca
cinfães	coimbra	condeixa-a-nova
constância	coruche	corvo
covilhã	crato	cuba
elvas	entroncamento	espinho
esposende	estarreja	estremoz
évora	fafe	faro
felgueiras	ferreira do alentejo	ferreira do zêzere
figueira da foz	figueira de castelo rodrigo	figueiró dos vinhos
fornos de algodres		

Municipalities list (2/3)

freixo de espada à cinta	fronteira	funchal
fundão	gavião	góis
golegã	gondomar	gouveia
grândola	guarda	guimarães
horta	idanha-a-nova	ílhavo
lagoa	lagos	lajes das flores
lajes do pico	lamego	leiria
loulé	loures	lourinhã
lousã	lousada	mação
macedo de cavaleiros	machico	madalena
mafra	maia	mangualde
manteigas	marco de canaveses	marinha grande
marvão	matosinhos	mealhada
mêda	melgaço	mértola
mesão frio	mira	miranda do corvo
miranda do douro	mirandela	mogadouro
moimenta da beira	moita	monção
monchique	mondim de basto	monforte
montemor-o-novo	montemor-o-velho	montijo
mora	mortágua	moura
mourão	murtosa	nazaré
nelas	nisa	nordeste
óbidos	odemira	odivelas
oeiras	oleiros	olhão
oliveira de azeméis	oliveira de frades	oliveira do bairro
oliveira do hospital	ourém	ourique
ovar	paços de ferreira	palmela
pampilhosa da serra	paredes	paredes de coura
pedrógão grande	penacova	penafiel
penalva do castelo	penamacor	penedono
penela	peniche	peso da régua
pinhel	pombal	ponta delgada
ponta do sol	ponte da barca	ponte de lima
ponte de sor		

Municipalities list (3/3)

portalegre	portel	portimão
porto	porto de mós	porto moniz
porto santo	póvoa de lanhoso	póvoa de varzim
povoação	proença-a-nova	redondo
reguengos de monsaraz	resende	ribeira brava
ribeira de pena	ribeira grande	rio maior
sabrosa	sabugal	salvaterra de magos
santa comba dão	santa cruz	santa cruz da graciosa
santa cruz das flores	santa maria da feira	santa marta de penaguião
santana	santarém	santiago do cacém
santo tirso	são brás de alportel	são joão da madeira
são joão da pesqueira	são pedro do sul	são roque do pico
são vicente	sardoal	sátão
seia	seixal	sernancelhe
serpa	sertã	sesimbra
setúbal	sever do vouga	silves
sines	sintra	sobral de monte agraço
soure	sousel	tábua
tabuaço	tarouca	tavira
terras de bouro	tomar	tondela
torre de moncorvo	torres novas	torres vedras
trancoso	trofa	vagos
vale de cambra	valença	valongo
velas	vendas novas	viana do alentejo
viana do castelo	vidigueira	vieira do minho
vila da praia da vitória	vila de rei	vila do bispo
vila do conde	vila do porto	vila flor
vila franca de xira	vila franca do campo	vila nova da barquinha
vila nova de cerveira	vila nova de famalicão	vila nova de foz côa
vila nova de gaia	vila nova de paiva	vila nova de poiares
vila real	vila real de santo antónio	vila velha de ródão
vila verde	vila viçosa	vimioso
vinhais	viseu	vizela
vouzela		

Appendix 2

Source	Language
El País	Spanish
Diario do nordeste	Portuguese
Ara	Spanish
Clarin	Spanish
Cultura Colectiva	Spanish
Noticias Ya	Spanish
The Guardian	English
Digismak	English
I Love Azores	Portuguese
Cadena Ser	Spanish
Yahoo Noticias	Spanish
Ardina News	Portuguese
Correio da Manhã	Portuguese

Table 1: Some sources that documented the event

Appendix 3

Table 2: Definitions of Variables

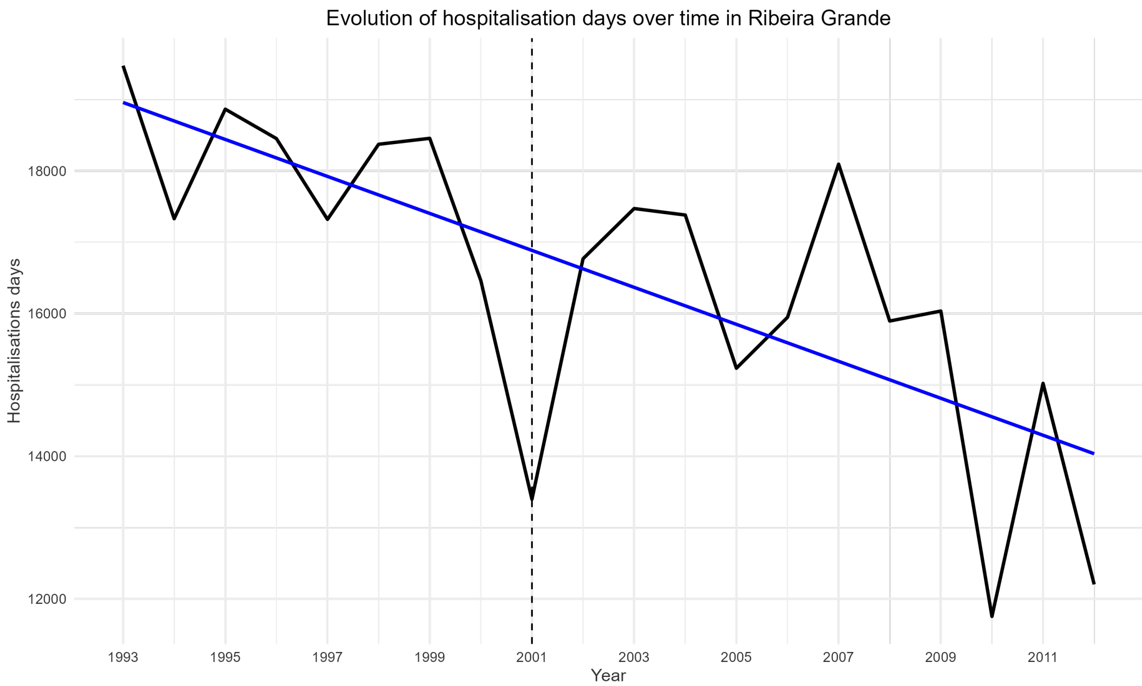
Variable	Definition
Aging ratio	The number of individuals aged 65 and over per 100 people of working age defined as those aged between 20 and 64.
Population	Population.
Hospital beds	Number of beds in hospitals.
Dependency ratio	The ratio of the elderly (ages 65 and older) plus the young (under age 15) to the population in the working ages (ages 15-64).
Energy consumption	Energy produced by hydroelectric, conventional thermal, nuclear, wave and tidal, wind and solar photovoltaic power plants.
Fertility rate	The mean number of children that would be born alive to a woman during her lifetime if she were to pass through her childbearing years conforming to the fertility rates by age of a given year.
Hospitalisation days	Total number of days spent by all patients formally admitted to the various hospital in-patient services, during a given period, excluding the days of discharge of these patients. Nursery stays or days under emergency observation are not included.
Internments	Number of internments in hospitals.
Migratory rate	The ratio of the net migration during the year to the average population in that year.
Progression of proceedings	[(Number of incoming cases - number of completed cases)/ Number of pending cases]*100.
Sex Ratio	The ratio of males to females in a population.
Women in childbearing age	Proportion of women aged 15 to 49 years old, considered the age range of women in childbearing age, in the total of female resident population.

Table 3: Definitions of Variables

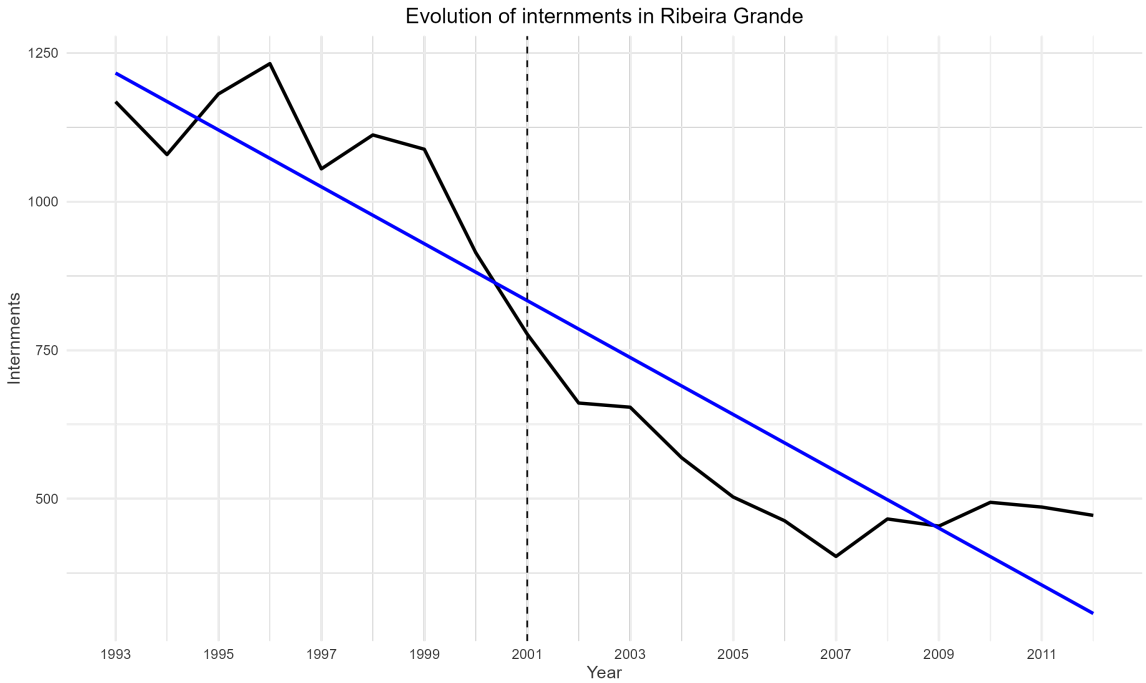
Variable	**Definition**
Young-age dependency ratio	The ratio of the number of young persons of an age when they are generally economically inactive (either under 15 or under 20 depending on the context) to the number of persons of working age (from 15 to 64 or from 20 to 59 depending on the context).
Crude death rate	The ratio of the number of deaths during the year to the average population in that year. The value is expressed per 1000 inhabitants.
Prices	Consumer price index growth rate.
Divorce rate	Divorces divided by average population and multiplied by 100
Early leavers	Resident population aged between 18 and 24 years old, with complete level of education until 3rd. cycle lower secundary education who not received any education (formal or non formal) in reference period divided by resident population aged between 18 and 24 years old and multiplied by 100
Graduates of tertiary education	Graduates divided by resident population aged between 20 and 29 years old, multiplied by 1000

Appendix 4

The trend for hospitalisation days is on a downward trajectory. Upon examining the year of the shock specifically, a significant decrease is observed. However, in the subsequent years, it returns to its original trend line.



Concerning internments, it appears there is no noticeable impact.



Appendix 5

Death rate

In terms of control variables, every available municipality was incorporated into the analysis. However, the municipalities contributing most significantly as donors were Lousada, Vila Franca do Campo, and Arcos de Valdevez, with respective weights of 0.45, 0.34, and 0.20. All other donor municipalities were assigned weights below 0.001. The detailed table has been excluded due to its extensive size.

Table 4: Distribution of v. weights

Variable	**v.weights**
Ageing ratio	0.066
Average population	0.04
Beds	0.102
Dependency ratio	0.057
Energy consumption	0.015
Fertility rate	0.054
Hospitalisations	0.009
Internments	0.013
Migratory rate	0.015
Proceedings	0.033
Sex ratio	0.06
Women child bearing age	0.51
Young age dependency ratio	0.026

For the synthetic control model with São Miguel Island as the treated unit, donors whose contributions exceed 0.001 include Lousada, Celorico de Basto, and Arcos de Valdevez.

Table 5: Distribution of v. weights with São Miguel Island as treated unit

Variable	**v.weights**
Ageing ratio	0.079
Average population	0.064
Beds	0.085
Dependency ratio	0.084
Energy consumption	0.085
Fertility rate	0.08
Hospitalisations	0.081
Internments	0.034
Migratory rate	0.089
Proceedings	0.085
Sex ratio	0.075
Women child bearing age	0.087
Young age dependency ratio	0.072

Crime rate

Table 6: Distribution of w. weights

Unit Names	W. Weights
Alentejo	0.215
Algarve	0.257
Área Metropolitana de Lisboa	0.000
Centro	0.000
Norte	0.079
Região Autónoma da Madeira	0.449

Table 7: Distribution of v. weights

Variable	V. Weights
Prices	0.051
Death Rate	0.002
Divorce Rate	0.073
Employment Rate	0.080
Early Leavers Rate	0.060
Energy Consumption	0.020
Graduate	0.035
Ageing Ratio	0.001
Population	0.049
Beds	0.001
Dependency Ratio	0.048
Hospitalisations	0.060
Internments	0.054
Fertility	0.039
Migratory	0.023
Proceedings	0.250
Sex Ratio	0.024
Women Child Bearing Age	0.008
Young Age Dependency	0.121

Employment rate

Table 8: Distribution of v. Weights

Variable	V. Weights
Prices	0.095
Death Rate	0.001
Divorce Rate	0.000
Early Leavers Rate	0.000
Energy Consumption	0.002
Crime	0.000
Graduate	0.021
Ageing Ratio	0.116
Population	0.082
Beds	0.005
Dependency Ratio	0.081
Hospitalisations	0.018
Internments	0.010
Fertility	0.046
Migratory	0.007
Proceedings	0.175
Sex Ratio	0.339
Women Child Bearing Age	0.000
Young Age Dependency	0.000

Table 9: Distribution of W. weights

Unit Names	W. Weights
Alentejo	0.028
Algarve	0.914
Área Metropolitana de Lisboa	0.000
Centro	0.001
Norte	0.000
Região Autónoma da Madeira	0.056