Identifying the General Equilibrium Effects of Narcotics Enforcement

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Abstract

I analyze the demand side impacts of a supply side intervention into the market for illegal drugs in what has been described as America's largest open air drug market. Beginning in 2018, the Pennsylvania Attorney General's office and the Philadelphia Police Department engaged in an ambitious effort to shut down the drug market in Philadelphia's Kensington neighborhood. The intervention involved increased police presence in the targeted area alongside a series of targeted "kingpin" sweeps which were intended to remove the most pervasive operators from the market. I employ highly granular Safegraph cell phone location data to track changes in traffic flows between census block groups, observing that the initiative led to sizable and persistent reductions in traffic flows to the target area. Additionally, in contrast to substitution effects observed in other work, I observe that the initiative led to reductions in traffic flows to other regional drug markets and large declines in overdose mortality in the Philadelphia metropolitan area as a whole, suggesting a genuine reduction in the demand for illegal narcotics. With a combination of theory and empirics, I argue that this reduction in regional demand is able to be achieved due to the initiative disrupting a supply-chain that data indicates flows from the target area outwards to smaller satellite markets. Together this all suggests that, despite the inelastic demand for narcotics, regionally linked markets can be impacted broadly by location specific interventions.

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1 Introduction

Between 2015-2021, the opioid epidemic has claimed the lives of approximately 500,000 Americans. As heroin and prescription opioids have been replaced by the far more potent opioid, fentanyl, overdose deaths have continued to increase, rising in each year since 2016. In 2021, more than 100,000 Americans died as a result of drug overdoses, making drug overdoses the leading cause of death among American adults below the age of 50. Since 2020, overdose deaths have been higher in this age group than deaths caused by COVID-19, cancer, murder and suicides, combined.

In seeking to curtail the market for illegal narcotics social planners have sought to address both sides of the market. On the demand side, policymakers have invested in the traditional public health solutions to drug-related mortality: treatment, regulation of the pharmaceutical industry[1], and education. These tools have enjoyed modest success but have not been sufficient to stave off the extraordinary rise in overdose deaths caused by fentanyl, which is more addictive and considerably more toxic than other narcotics that have driven prior drug epidemics. Supply side interventions, on the other hand, have been consistently unsuccessful and have largely served to exacerbate the problems they sought to address. Here, I document a supply side initiative that works, a targeted series of law enforcement efforts aimed at tackling the largest operators in an illegal drug market that serves as the epicenter of a regional epidemic.

I argue, with theory and empirics, why this initiative was different and in turn why it was able to reap positive benefits where others have failed. The problem of the inelastic demand for narcotics doomed previous supply side initiatives.[2] Alpert et al. (2018) provides

[1] Alpert et al. (2022) discusses the origins of America's opioid crisis, tracing variation in its impact to differences in state policies regarding prescribing that in turn spurred geographic variation in Oxycontin's initial introduction.

[2] The problem of inelastic demand has also seemingly doomed several public health initiatives aimed at taming the ill effects of the opiate epidemic. Doleac & Mukherjee (2022) show that increasing naloxone access created a moral hazard problem, which led to increases in drug use. Packham (2022) documents syringe exchange programs leading to increased overdose mortality through a similiar moral hazard mechanism.

evidence that an abuse "deterrent" reformulation of a commonly abused pharmaceutical opioid led users to substitute to more dangerous heroin. Likewise, Soliman (2022) shows, at more granular local levels, that the removal of over-prescribing doctors similarly pushed users towards heroin. Ray et al. (2023) show that arrests of street level dealers spur spikes in overdoses as users engage in costly search behavior, in an effort to replace their now lost supplier. However, in this paper I demonstrate that intentionally targeted law enforcement effort can disrupt entire regional markets, spurring the sorts of positive impacts that policy makers hope for.

Here, I examine an intervention in what is arguably America's largest market for illegal narcotics. This paper considers the broad regional demand side impacts of a location-specific supply side intervention. Beginning in 2018, the Pennsylvania Attorney General's office and the Philadelphia Police Department engaged in an ambitious effort to shut down the drug market in Philadelphia's Kensington neighborhood. The intervention involved increased police presence in the targeted area alongside a series of targeted "kingpin" sweeps which were intended to remove the most pervasive operators from the market. Over the course of seven major sweeps, around 115 individuals were arrested. I employ highly granular Safegraph cell phone location data to track changes in traffic flows between census block groups, observing that this attempted market shut down led to a sizable and persistent reduction in traffic flows to the target area, as well as reductions in traffic flows to smaller drug markets throughout the metropolitan area. I argue that the initiative's impacts on these areas that were not directly targeted were driven by the disruption of a supply chain flowing from Kensington, the targeted market, to satellite markets throughout the region, and interpret large reductions in traffic flows between Kensington and these alternative markets as evidence of this mechanism that is in line with the theoretical framework that I develop. Following these disruptions to Kensington's drug market, the initiative appears to have led to a significant decrease in drug overdose mortality across the Philadelphia metropolitan area.[3] I observe a 20% reduction in overdose mortality across the metropolitan area following the initiative's onset, with a 30% reduction observed in parts of the metro that were not at all directly targeted by the initiative. All together this suggests that there is a linkage between markets across the region and that well targeted highly localized interventions, like the initiative I study here, have the potential to spur broad regional impacts.

While drug enforcement has various goals including reducing violence in the drug trade, addressing quality of life concerns in communities where drugs are commonly bought and sold and ensuring adherence to the rule of law, the leading justification for the war on drugs is to save the lives of drug users themselves by reducing the number of overdose deaths. Supply-side interventions can have beneficial effects and a number of case studies, including a notable case study in Australia, suggest that law enforcement – through its ability to interdict drugs – is not powerless to reduce drug-related crime and mortality (Moore & Schnepel, 2024). This is, however, especially difficult to do in the United States which shares long land borders with its neighbors to the north and south and which is home to a number of the largest ports of entry in the world. The task of border authorities is made yet more difficult by the potency of fentanyl. It has been speculated that a single truck full of fentanyl could transport enough product to kill every last man, woman and child in the United States. Here I show that well targeted locally-specific law enforcement interventions, after the narcotics have already made it through the border, can reduce overdose mortality across a much broader region by curtailing regional supply.

Since the opioid epidemic has ravaged the United States, thousands of articles have documented its proliferation, its social and economic impacts and the effectiveness of various types of treatment in curtailing opioid use and overdose deaths. However, far less is known about the effects of what remains the most prolific and well-funded tool to intervene in drug

[3] In the supplemental appendix, I present evidence that the impacts may have stretched beyond the Philadelphia metropolitan area- as reductions in overdose mortality were also observed in the Baltimore metro.

markets: law enforcement. The academic literature that I have at my disposal suggests that supply sides shocks or disruptions, such as increases in street level enforcement effort, will contribute to increased prices in the markets for illegal narcotics (Reuter and Kleiman 1986).[4] Dobkin and Nicosia (2009) document this effect in methamphetamine markets with short lived impacts, as an intervention that targeted low level manufacturing led to an increased reliance on sourcing from larger scale manufacturers.[5] Caulkins (1992) argues that dealers may adapt to enforcement efforts, relocating or changing means of delivery. That argument is in line with the findings of Dobkin et al. (2014) who documented no changes in methamphetamine consumption following interventions that reduced the number of clandestine laboratories, as once again sourcing simply shifted to larger foreign manufacturers. My theoretical framework captures the essence of this tendency towards relocation, substitution, and search common throughout the literature, but instead emphasizes how regional supply chain disruptions can prevent the offsetting effects of mobile users.

Further, while all of the existing literature regarding supply side efforts to disrupt the markets for illegal narcotics either observes outcomes that are proxies for consumer demand (such as rehab admissions, arrests, or overdoses) or reported price data of dubious reliability, ours is the first study to seek to more directly observe consumer demand in these illegal markets. Several other recent studies have employed Safegraph mobility data as a means to more directly measure consumer demand, including Fe and Sanfelice (2022) and Babar et al. (2023). I am the first to extend this same logic, of foot traffic to establishments being a measure of demand, to illegal markets. Further, I nest the positive relationship between enforcement effort and prices for illegal narcotics, that all of the aforementioned studies rest upon, into my theoretic framework.

Beyond its contribution to the immediate area of policy interest, this research contains

[4]Some earlier literature failed to detect a relationship between high level seizures and illegal drug prices. Dinardo (1993) uses the total weight of cocaine seized as a proxy for enforcement effort. Yuan and Caulkins (1998) test for Granger causality and fail to find evidence of any relationship between illegal drug prices and high level seizures by federal agencies.

[5]Adda et al. (2014) examine an opposite setting to ours in which sanctions are reduced in a specific local area, finding crimes associated with decriminalized marijuana increase following depenalization.

valuable lessons for thinking about general equilibrium effects in other illicit markets, including markets for illegal guns, stolen goods and human trafficking. In each of these contexts, local law enforcement finds itself on the front lines in countering criminal activity that feeds these markets.My research suggests that the ability of local law enforcement to counter regional, national or even international problems like drug addiction and overdose deaths is less limited than other criminal justice research might suggest. Place-based initiatives such as hot spots policing (Braga et al 2019), greening vacant lots (Branas et al 2011), restoring blighted properties (Branas et al 2018; MacDonald et al 2021) and investing in enhanced street lighting (Mitre et al 2022) have enjoyed a great deal of success in controlling garden-variety street crimes in large part because many offenders have strong economic and social ties to place (Weisburd 2015; Chalfin et al. 2022). In other words, while it might be rational for offenders to relocate when the probability of apprehension increases in their area of operation, most research finds that this tends not to happen. While buyers in illicit markets presumably also have social and economic connections to particular places, they also appear to have much less elastic demand for their desired outcomes meaning that, in this context, there is a broader scope for place-based initiatives to be defeated by general equilibrium effects and the relocation of buyers. However, if markets are linked through their supply chain, place-based initiatives are able to have downstream impacts that can reverberate regionally, allowing for general equilibrium effects to counteract the consumer tendency towards search and geographic substitution.

I further contribute to the growing literature documenting the down stream impacts of supply chain disruptions in the markets for illegal drugs. Dell (2015) demonstrates that cartel crackdowns lead to increases in violence and diversions of drug traffic to alternative routes. Deiana et al. (2020) demonstrate that reductions in Afghan opium prices lead to increases in opiate prescribing in the United States. Castillo et al. (2020) document down stream increased competition and violence following seizures of cartel cocaine, and Beeder (2023) documents increases in violence when the costs of an input into the cocaine production process drops. My work is the first in this young literature to examine the regional demand effects of extremely local, place-based, supply shocks in this sort of illegal market.

The remainder of the paper is organized as follows. Section II explains the key points of a small general equilibrium toy model (derived more fully in the supplemental appendix) that provides a context for thinking about my subsequent results. In Section III I describe the Kensington Initiative and the tools that were employed to disrupt the drug markets in Kensington. Section IV describes my primary data and analyzes impacts on traffic flows into the target area and alternative drug markets in the region and includes results demonstrating reductions in traffic flows between the initiative's target area and alternative markets. Section V analyzes drug overdoses and Burprenorphine dispensing (a drug used to treat opiate use disorder), important second order effects of the initiative, and Section VI concludes.

2 Theoretical Framework

I motivate with this paper with a simple toy model, derived more fully in the supplemental appendix. The logic of this model is quite simple and provides an explanation for how an effectively targeted location specific intervention, such as the initiative I examine empirically, can avoid the adverse outcomes spurred by the sorts of substitution effects that plague other supply side interventions.

The basic logic of the model is as follows. There are two opposing markets for a single illegal drug located at either end of a city.[6] Sellers in either market compete on price and consumers are faced with transit costs that are a function of distance and have different probabilities of being aware of either market. If the costs sellers face in either market are merely functions of police effort in that market (along with other exogenous factors), then

[6]This assumption of a single illegal drug is fairly realistic in practice. There is no viable substitute product for the current "street opiate". Heroin has been supplanted by a mixture of fentanyl analogues and tranquilizer. Fentanyl pressed pills have largely replaced diverted pharmaceuticals. There is no viable substitute drug that users are able to substitute to during periods of supply chain disruptions to fend off the mal-effects of opiate withdrawal. To this point, in 2022 in Philadelphia opiates were present in 83% of fatal drug overdoses. Fentanyl or a fentanyl analogue was present in 96% of those overdoses in which an opiate was present (Philadelphia Department of Public Health, 2023).

a crack down in that market will be felt as a supply shock, driving down local demand and pushing consumers to the alternative market. However, if there is a linkage between the two supply chains (i.e. that the drugs sold in alternative markets are in fact sourced in the Kensington market), the costs to sellers in the alternative market would be functions of police effort in both markets. In this state, an increase in police effort in the source market would have an ambiguous effect on demand in the alternative. The direction of the effect depends on differentials in price transmission. Particularly, a decrease in demand in the alternative market will only be observed if the pass-through rate in the alternative market is greater than that in the shocked source market. Thus, given that my Kensington Initiative treatment only directly impacts the targeted Kensington area, an estimated decrease in demand in alternative markets would provide empirical evidence of a supply chain linkage in which illicit narcotics flow from Kensington outwards to alternative markets, with a pass through rate greater in these satellites than in their source market.

More formally, to begin I assume a linear city of length 1 with a drug market located at either end. There are consumers located uniformly across the city's length. Consumers can only purchase from one of the two markets. One of the markets is denoted k and represents the Kensington drug market agglomeration. The other market is denoted a and represents a smaller alternative drug market. This is a simple Hotelling model in which full information demand for each market can be determined by equating the cost to the marginal consumer for purchasing from either market. Consumers are price takers and a monopolistic seller in either market seeks to maximize their own profit through price competition, selecting an optimal p_k or p_a that consumers purchasing in either market will face.[7] Each market has a separate marginal cost. Since market k represents the Kensington agglomeration, I will assume that $c_k < c_a$.[8] To derive the demand side, I assume a marginal consumer located

[7] Much of the "supply side" of this model's framework is similar to that found in Poret (2002), where a monopolist is seen as distributing narcotics wholesale to oligopolistically competing distributors. My framework is quite similar with the influence of the monopolist wholesaler modeled as an exogenous input into the retailers' cost functions.

[8] I can assume that $c_a = c_k + \omega$, where ω is some additional fixed cost entailed for operating outside of Kensington.

at some point in the linear city, x. I include transit costs as a function of other exogenous factors:

$$t_k = \frac{1}{\psi_k} x \quad and \quad t_a = \frac{1}{\psi_a}(1-x) \tag{1}$$

The ψ_i variables represent the ease of transportation between locations. These variables in themselves could be functions of other exogenous variables, such that the ψ_i variable's value increases as more transit infrastructure is introduced, effectively lowering the cost of movement to location i.

Bare in mind that $x : \{x|0 \leq x \leq 1\}$ and $\psi_i : \{\psi_i|0 < \psi_i \leq 1\} \ \forall \ i$.

Prices selected by the monopolist in either market are functions of some cost faced by sellers that is a function of enforcement effort in that market and a constant parameter, b_i. Thus, $c_i = c(e_i, b_i)$ such that:

$$\frac{\partial \ \ c_i(e_i, b_i)}{\partial e_i} > 0 \tag{2}$$

Since the b_i component is fixed I neglect this notation from further derivations for readability. Increases in police effort in either market, e_i, increase the marginal cost of operating in that market.

Now, solving the Hotelling model for demand under full information:

$$D_k(p_k, p_a, \psi_k, \psi_a) = -\frac{((p_k - p_a)\psi_a - 1)\psi_k}{\psi_k + \psi_a} \tag{3}$$

And:

$$D_a(p_k, p_a, \psi_k, \psi_a) = \frac{((p_k - p_a)\psi_a - 1)\psi_k + \psi_k + \psi_a}{\psi_k + \psi_a} \tag{4}$$

Both of these are strictly positive for $\frac{1}{\psi_a} > p_k - p_a > \frac{-1}{\psi_k}$.

Introducing an information dynamic, there is an exogenous probability ϕ_k that an agent is aware of the Kensington market and a probability ϕ_a that an agent is aware of the alternative market. For simplicity, all agents have a uniform probability of being aware of either market. Some proportion of the agents are aware of both markets. Thus, using the solutions from the full information setting:

$$D_k() = \phi_k[(1-\phi_a) + \phi_a(-\frac{((p_k-p_a)\psi_a-1)\psi_k}{\psi_k+\psi_a})] \tag{5}$$

And:

$$D_a() = \phi_a[(1-\phi_k) + \phi_k(\frac{((p_k-p_a)\psi_a-1)\psi_k+\psi_k+\psi_a}{\psi_k+\psi_a})] \tag{6}$$

Now, the maximization problem of the monopolist seller in market k can be represented as:

$$\max_{p_k\geq 0}\{\phi_k[(1-\phi_a) + \phi_a(-\frac{((p_k-p_a)\psi_a-1)\psi_k}{\psi_k+\psi_a})]\cdot(p_k-c_k(e_k))\} \tag{7}$$

The seller in market a faces a symmetric optimization problem. These yield optimal price vectors that can be expressed as functions of exogenous parameters and used to solve for the equilibrium demand in either market.

$$D_k()^* = \frac{((c_a(e_a)-c_k(e_k))\phi_a\phi_k\psi_a + (2\phi_a-1)\phi_k\phi_a)\psi_k + ((\phi_a-1)\phi_k+\phi_a)\psi_a}{3\phi_a\phi_k\psi_a + 3\phi_a\phi_k\psi_k} \tag{8}$$

And

$$D_a()^* = -\frac{((c_a(e_a)-c_k(e_k))\phi_a\phi_k\psi_a + (-\phi_a-1)\phi_k+\phi_a)\psi_k + ((-2\phi_a-1)\phi_k+\phi_a)\psi_a}{3\phi_a\phi_k\psi_a + 3\phi_a\phi_k\psi_k} \tag{9}$$

While these demand functions are not quite tractable, I am able to compute a few comparative statics that are important for motivating my analysis:

$$\frac{\partial D_k()}{\partial e_k} = -\frac{\psi_a \psi_k}{3\psi_a + 3\psi_k} \cdot \frac{\partial c_k()}{\partial e_k} \quad and \quad \frac{\partial D_k()}{\partial e_a} = \frac{\psi_a \psi_k}{3\psi_a + 3\psi_k} \cdot \frac{\partial c_a()}{\partial e_a} \tag{10}$$

$$\frac{\partial D_a()}{\partial e_k} = \frac{\psi_a \psi_k}{3\psi_a + 3\psi_k} \cdot \frac{\partial c_k()}{\partial e_k} \quad and \quad \frac{\partial D_a()}{\partial e_a} = -\frac{\psi_a \psi_k}{3\psi_a + 3\psi_k} \cdot \frac{\partial c_a()}{\partial e_a} \tag{11}$$

Unsurprisingly, demand in each market moves negatively with levels of police effort in that market through impacts on marginal costs in that market. If, as I have assumed, cost in each market is merely a function of police effort in *that* market, an increase in effort in either market will predictably drive demand to the alternative market. However, if instead the two markets are linked such that the product in one market is sourced from the other, costs in the subordinate market will also be function of effort in the chief market. For example, if the product in the alternative market is sourced from the Kensington market (such that $\frac{\partial c_a(e_a,e_k)}{\partial e_k} > 0$), demand in the alternative can be expressed as:

$$D_a()^* = -\frac{((c_a(e_a, e_a) - c_k(e_k))\phi_a\phi_k\psi_a + (-\phi_a - 1)\phi_k + \phi_a)\psi_k + ((-2\phi_a - 1)\phi_k + \phi_a)\psi_a}{3\phi_a\phi_k\psi_a + 3\phi_a\phi_k\psi_k} \tag{12}$$

I represent alternative market costs here as a function of police effort in the directly targeted market rather than as a function of prices in that market intentionally, to keep the model more generalizable. In this set up, I am able to capture the essence of a market in which product in the alternative markets are directly sourced from retailers in Kensington as well as the possibility that the exogenous supplier to both markets is physically operating in that market at some level above retail (as suggested by DEA reports describing Kensington as a major transit point for Mexican cartels). The marginal effects of changes in enforcement effort in the alternative market on alternative market demand remains unchanged while the marginal effect of changes in enforcement effort in the Kensington market on alternative market demand can be expressed as:

$$\frac{\partial D_a()}{\partial e_k} = (\frac{\partial c_k()}{\partial e_k} - \frac{\partial c_a()}{\partial e_k}) \cdot \frac{\psi_a \psi_k}{3\psi_a + 3\psi_k} \tag{13}$$

The direction of this effect is determined by differentials in price transmission. If the price pass through rate in the alternative market is less than that in the source market, demand will still increase in the alternative, but to a lesser extent than if the two markets were not linked. If instead the impact on costs is amplified through the supply chain, and the pass through rate in the alternative exceeds that of its source, the alternative market would see a *decrease* in demand. Thus, given that my Kensington Initiative treatment only directly impacts the targeted Kensington area, an estimated decrease in demand in alternative markets would provide empirical evidence of a supply chain linkage in which illicit narcotics flow from Kensington outwards to alternative markets, with a pass through rate greater in these satellites than in their source market. A slightly more formal derivation of this model is presented in the online-only supplemental appendix.

The logic of this simple model provides the mechanism by which supply side enforcement efforts can have real tangible impacts in the markets for illegal drugs- despite the inelastic demand of users. Interventions that are geographically targeted at areas that are central to regional supply chains can effectively cut off the down stream market, reaping positive effects similar to those seen when an island is cut off from its supply as in Moore & Schnepel (2024).

3 The Kensington Initiative

In August 2018, Pennsylvania's Attorney General implemented a place-based effort to curb a well known market for illegal drugs in Philadelphia, Pennsylvania (Harding et al. 2021). This effort, the Kensington Initiative (hereafter simply referred to as the "initiative"), brought a law enforcement based approach to tackling drug activity in the Kensington neighborhood, increasing police presence, allowing for greater coordination between state, local, and federal law enforcement agencies and prosecutors, and implementing intelligence efforts aimed at taking down the large scale drug trafficking organizations in the market while seeking to foster increased community engagement with law enforcement.[9] This effort seeded a coordination between Pennsylvania's Attorney General's Office, the Philadelphia Police Department, the city of Philadelphia's Managing Director's Office, Homeland Security, and the Drug Enforcement Administration.(Harding et al. 2021). Appendix A1 provides preliminary evidence that in the immediate short term, upon the start of the initiative, the target area saw an increase in narcotics arrests, while no change in prosecutorial behavior (in regard to the target area) was observed.

The initiative was solely a *supply-side* intervention, it did not seek to address the demand-side underlying causes of drug addiction in the area. As such, by examining the *demand-side* effects of this intervention I am able to gain a deeper understanding of how consumers in the markets for illegal narcotics respond to shocks in the supply chain.

Kensington is a neighborhood in Philadelphia, locally referred to as the "Badlands". It is infamous for its open-air drug markets and the high concentration of drug users found in the area (Johnson et al. 2020; Lawrence 2023; Porreca 2023). The area has received significant media attention internationally, where it has been dubbed "the Walmart of heroin".[10] This neighborhood, and the drug market it houses, attracts drug users from the greater-Philadelphia metropolitan area, and beyond, with heroin linked to suppliers in the neighborhood showing up in overdoses in surrounding counties (Johnson et al. 2022). The area is viewed as being the epicenter of drug overdoses in the states that comprise the metropolitan area (Scavette 2019).

The location of the initiative's focus area within the broader eleven county Philadelphia metropolitan area is depicted below. For the purposes of this project, the metropolitan area

[9] See the appendix for some discussion of these large scale "kingpin" sweeps that were part of the initiative.

[10] See `https://www.nytimes.com/2018/10/10/magazine/kensington-heroin-opioid-philadelphia.html` for a New York Times piece examining the Kensington heroin market.

is defined as being composed of the following counties: Burlington, Camden, Gloucester, and Salem in New Jersey, Bucks, Chester, Delaware, Montgomery, and Philadelphia in Pennsylvania, New Castle in Delaware, and Cecil in Maryland. This is the Metropolitan Statistical Area as defined by the US Government's Office of Management and Budget. [11]

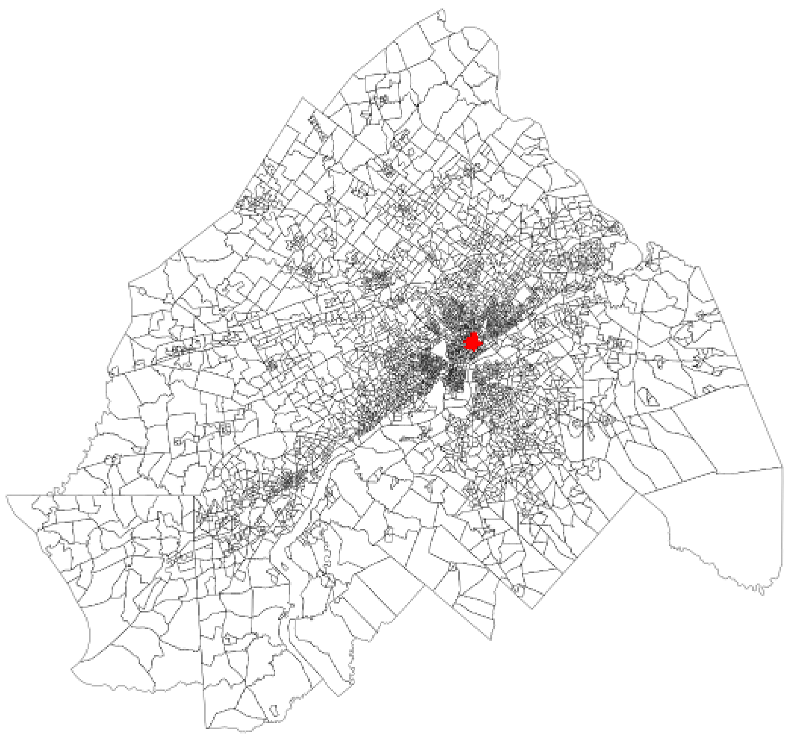


Figure 1: Figure depicting the location of the Kensington Initiative's focus area (in red) within the broader 11 county Philadelphia metropolitan area examined in this study. The borders depicted are the census block groups that compose the region.

Within this metropolitan area, a small section of the Kensington neighborhood was designated as the initiative's target area.[12] The designated area comprises 47 census block groups (out of the 1336 that compose the City of Philadelphia). This area of about 3 square kilometers or 1.2 square miles, within Kensington, was selected due to the high prevalence of illicit drug activity found there. To an extent I rely on this neighborhood's popular perception to defend one of my primary assumptions: that some non-negligible proportion of

[11] https://www.whitehouse.gov/wp-content/uploads/2018/09/Bulletin-18-04.pdf

[12] See Harding et al. (2021) for a street level map of the official target area.

individuals traveling to this area do so to engage in the illegal drug market. It is observed in the data that individuals travel to this area from nearly the entirety of the metropolitan area and from areas all over the eastern United States, despite the area having no notable tourist attractions or recreational opportunities. Two of the census block groups (CBGs) that make up the Kensington Initiative's focus area appear in the top 50 Philadelphia CBGs in terms of the diversity of metropolitan area visitor home CBGs. To put this in context, of the 4305 CBGs that make up the Philadelphia metropolitan area, more than 3200 are represented as the home locations of visitors to individual CBGs of the target area. The remainder of the top 50 Philadelphia CBGs include the city's central area, universities, sporting complexes, major retail hubs, and recreational areas.[13] There is no such intrinsic draw to the Kensington area. Examining the effects of this attempted drug market shut down at such a granular level in an environment such as this allows us to isolate within-neighborhood trends and identify changes in traffic flow patterns in extremely localized areas.

4 Measuring Impacts on Demand through Traffic Patterns

In this section, I analyze the impacts of the initiative on traffic flows throughout the region, operating under the assumption that changes in traffic patterns to the areas in which narcotics are openly sold are reflective of changes in the underlying demand for narcotics. I begin by showcasing reduced form estimates of the Kensington Initiative's impact on traffic to the target area. Next, I discuss how I determine alternative drug market areas in the region and provide some evidence of the validity of assessment before proceeding to demonstrate the Initiative's impact on those areas. Finally, I exploit traffic flow dyad observations,

[13] One of these Kensington CBGs includes McPherson Park (locally known as Needle Park), a well known area in which outreach organizations set up to shop to provide services for the area's homeless and drug addicted. See `https://www.inquirer.com/philly/columnists/mike_newall/mcpherson-square-library-heroin-needle-park-20170609.html` for more discussion of that park.

counts of unique individuals traveling between two localities, to showcase a particularly observable reduction in traffic between Kensington and the region's alternative drug markets- which I interpret as evidence of the supply chain disruption mechanism. In the supplemental appendix I proceed with a more structural approach, in which I specify a model of locational choice to highlight geographic heterogeneity in the response to the initiative.

4.1 Impacts on Target Area

The Kensington Initiative was intended to reduce overdoses and gun violence throughout Philadelphia, by directly slowing the underlying drug market. If these law enforcement efforts were to be successful, I should observe the Kensington market for illegal drugs itself shrinking, as users substitute to legal and illegal alternative supply sources- or as we would hope, are priced out of the market entirely. While, for obvious reasons, drug dealing is difficult if not impossible to observe directly in data I posit that these impacts can be observed through observation of the demand side, as represented by traffic flows to known drug market areas.

Here, I specify a difference-in-differences model to provide reduced form estimates of the impacts this initiative had on traffic into the target area. These traffic flows are an appropriate proxy for market demand if I am to adopt the assumption that drug users represent some *constant* proportion of the Safegraph population. This assumption is not possible to verify. However, Safegraph data is sourced from thousands of different popular mobile phone applications that had embedded the company's, now banned, software development kit.[14] There is no reason to suspect that drug users would become less likely to utilize any particular apps over time. Further, Li et al. (2023) documented relatively consistent sampling patterns for the Safegraph data across the time period in which I analyze before the COVID-

[14]See https://themarkup.org/privacy/2021/12/06/the-popular-family-safety-app-life360-is-selling-precise-location-data-on-its-tens-of-millions-of-user and https://www.cnet.com/tech/tech-industry/google-bars-apps-from-using-location-tracking-tool-that-sells-user-data/ for articles detailing controversy regarding the breadth of apps selling data to Safegraph.

19 lockdowns.[15] Adopting this assumption allows us to argue that changes in the underlying habits of drug consumers will be reflected in aggregate habits of all consumers (albeit with a large bias towards zero): a decrease in drug user traffic will result in an overall decrease in aggregate traffic of a smaller degree. If, as is likely, the policy impacts drug users and non-drug users differently, the bias towards zero will be even greater as *increased* traffic of non-drug users into the area potentially offset *decreased* traffic among drug users.

4.1.1 Data

Here, I utilize the "neighborhood patterns" data set formerly made available by Safegraph. This data supplanted their original mobility data that was employed in numerous COVID related papers (see Anderson et al. 2020; Bullinger et al. 2021; Dave et al. 2020; Courtemanche et al. 2021; and Dave et al. 2021 among others). Like that data, the neighborhood patterns data creates measures of mobility from individual cell phone location pings. Individuals with certain applications downloaded on their cell phones (which applications is largely proprietary knowledge to the company) unknowingly provide their location history to Safegraph. Kang et al. (2020) estimate that during my primary sample period, roughly 10% of the US population was represented in Safegraph's sample in any given week. The company then aggregates this location history to create monthly counts of the unique number of visitors to a given census block group. In the interests of anonymity and consumer privacy, the company reports visitor counts between two and four as four and does not report observations with less than two visitors.[16] This unique censoring and truncation regime in the data generating process does introduce some econometric issues that need to be addressed. However, here, as I solely examine overall traffic flows to CBGs (without further disaggregating by visitors' home CBGs) these issues do not impact us. Later in the appendix, when I examine more micro choice behavior for more granular disaggregated traffic data, more

[15] Throughout the paper, I include separate estimates on the limited sample in which Li et al. (2023) document consistent sampling.

[16] See `https://docs.safegraph.com/docs/monthly-patterns#section-privacy` for more details.

careful econometric methods are needed to account for these issues in the data generating process. All Safegraph data is available starting from January 2018. In the present study I employ data running through December 2021.

4.1.2 Estimating the Impact

I begin with a simple difference-in-differences model with a simultaneous treatment adoption corresponding to the official beginning of the initiative in August 2018. I observe census block group level traffic inflows monthly, taking the 47 census block groups that make up the initiative's target area as the treatment group. Tests of the parallel pre-treatment trends assumption, necessary for identification in difference-in-differences models, provide no evidence to suggest a violation of these trends. The results of these tests are included in the supplemental appendix.

Proceeding to the actual difference-in-differences specification, I specify the following negative binomial two-way fixed effects model:[17]

$$E[y_{it}] = exp\left(\tau \cdot KI\ \ Active_{it} + \mu_i + \delta_t\right) \tag{14}$$

Here, $KI\ \ Active$ is an indicator variable that is equal to one for dates in August 2018 and later for CBGs mapped to the official initiative target area. τ is my coefficient of interest; representing the average effect of the initiative on my outcome variables across all of the CBGs that make up the target area and across the entire window of observation after the initiative was begun. μ indexes census block group fixed effects aimed at capturing time-invariant unit-specific idiosyncrasies while δ indexes monthly fixed effects that aim to capture unit-invariant trends. I estimate this model with both total visits and unique visitors as outcome variables, on both the total sample and a sample restricted to the two-

[17] All of the regression models presented in the primary body of the paper are negative binomial regressions estimation by maximum likelihood. As such the variance of the outcome variable is specified as $Var[y_{it}] = E[y_{it}|x_{it}] + \omega(E[y_{it}|x_{it}]^2)$, where ω represents the dispersion parameter. Equivalent Poisson and OLS specifications are included in the supplemental appendix.

year period of March 2018 through February 2020 in which Li et al. (2023) demonstrate the most consistent Safegraph sampling.[18]

	Dependent variable:			
	Total Visits	Unique Visitors	Total Visits	Unique Visitors
Treatment Effect	-0.351***	-0.215***	-0.298***	-0.151***
	(0.034)	(0.036)	(0.028)	(0.033)
Month-Year Fixed Effects	✓	✓	✓	✓
CBG Fixed Effects	✓	✓	✓	✓
Sample	Full	Full	Reduced	Reduced
Observations	206,640	206,640	99,015	99,015
Dependent Variable Mean	7514	1668	8736	1977
IRR Treatment Effect	0.70	0.81	0.74	0.86
Overdispersion Parameter	16.0	13.15	25.9	17.23
Adjusted Pseudo R^2	0.13	0.16	0.14	0.16
BIC	3,611,747	2,978,223	1,746,066	1,463,900

Note: Standard errors are clustered at the census block group level. *p<0.1; **p<0.05; ***p<0.01

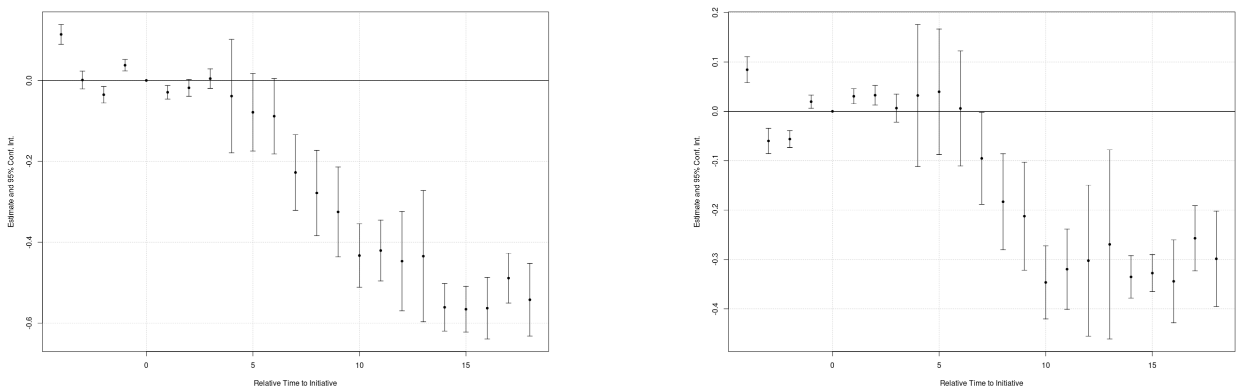
The initiative coincides with significantly lower visits to the target area relative to the remainder of the metropolitan area alongside corresponding reductions in the number of unique visitors. To further validate the statistical significance of the initiative's impact on total visits to the area, I employ a simple Monte Carlo simulation exercise. I randomly assign groups of 50 CBGs to be my placebo treatment group. CBGs in the real initiative's target area or in the likely alternative markets (detailed in a later section) are excluded entirely from this placebo analysis. The data is further restricted to my shortened time period in which Safegraph sampling is most consistent and the placebo treatment effect is estimated using the same two-way fixed effects negative binomial difference-in-differences model as above. The results of this simulation exercise show the empirical p-values of the absolute values of the t statistics on both my total visits estimate and my unique visitors specification are 0.00. This placebo exercise demonstrates that it is extremely unlikely that effects with the observed level of statistical significance of my estimated treatment effects could have arisen simply by chance. This test is similar to that employed in Funahashi et al. (2022) and discussed in Eggers et al. (2021). In the supplemental appendix I replicate

[18]It is also worth stating that the the limited sample avoids potential contamination from the bicycle patrol intervention evaluated in Lawrence (2023) that begun in January of 2021. Although, it should be stated that the areas covered by these two interventions are only partially overlapping.

the results of estimating this model with the exclusion of my likely alternative markets from the sample to address potential contamination bias and I further replicate my total visits result with a model with spatial lags of the dependant variable to address potential spatial autocorrelation.

4.1.3 Dynamic Effects on Market Traffic

To examine the dynamic effects of the initiative on market traffic I adopt a two pronged approach. First, I fit event study models to the data using an analogous two-way fixed effects negative binomial regression with the treatment effect disaggregated across relative treatment time. For clarity, as before, I restrict my sample to the period at which Safegraph sample sizes were most consistent.



(a) Total Visits

(b) Unique Visitors

Figure 2: Figures depicting estimates of the dynamic effect of the Kensington Initiative on total traffic flows (left) and unique visitors (right) into the target area.

The event studies demonstrate that at some point following the initiative's onset, the persistent decrease in both overall traffic and unique visitors to the Kensington Initiative's target area began. In the appendix, I explore the timing of the start of this decrease and demonstrate that it corresponds temporally to some of the larger sweeps that occurred as part of the initiative. It bears noting that there is a substantial amount of noise in the period before the initiative began, albeit without a clear direction of trend. In the supplemental appendix I demonstrate that a static test of the parallel trends assumption does not provide evidence of a violation and further document that my results are robust to a synthetic difference-in-differences specification (Arkhangelsky et al. 2021) that does not rely on any assumption of parallel pre-treatment trends.

4.2 Traffic to Alternative Drug Markets

A primary feature of my toy model is that individuals engaging in the markets for illegal drugs face a choice regarding whether to purchase in the larger Kensington agglomeration or to instead purchase in a more local market. In this section I test some of that model's implications. I identify five areas in the Philadelphia metropolitan area, outside of Kensington, that have a recent history of open-air drug dealing. I identify these locations from a combination of local news reports and press releases from state Attorney Generals, FBI DEA, DOJ, and local government sources. I map the locations mentioned in these sources to their constituent census block groups and define those areas as my alternative market CBGs.

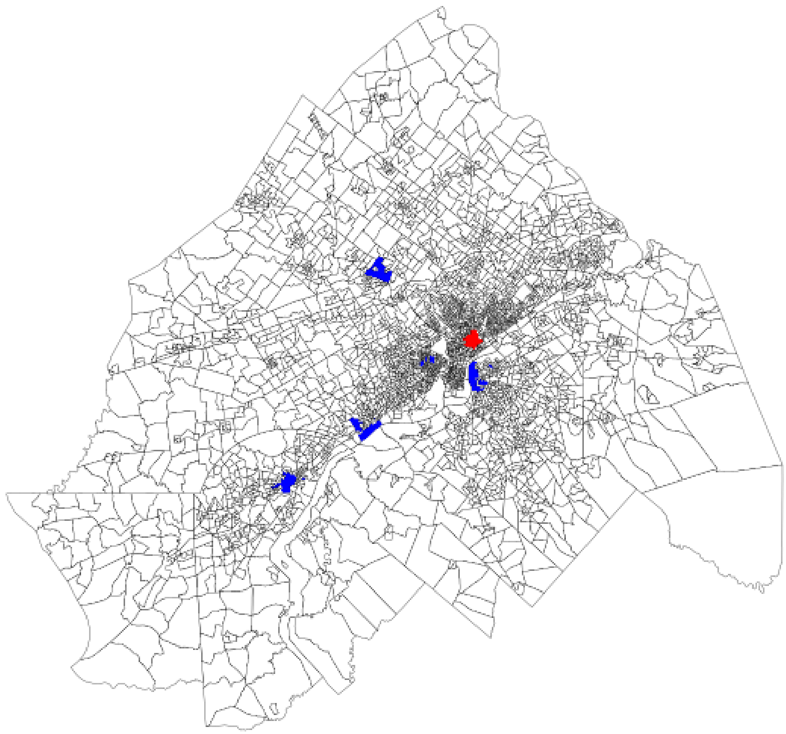


Figure 3: Figure depicting the location of the Kensington Initiative's focus area (in red) and my designated alternative market areas (in blue) within the broader 11 county Philadelphia metropolitan area examined in this study. The borders depicted are the census block group's that compose the region.

The derivation of my toy model demonstrated that different supply chain linkages between the agglomeration market and an alternative will result in the initiative having different impacts on demand. First, if there is no supply chain linkage between the two markets, the initiative will drive more customers to the alternative market. However, if the two markets are linked such that product flows from the agglomeration market to the alternative, there are two possibilities. In short, the alternative market could still see an increase in traffic, albeit less so than in the no linkage case, if the increased costs at the Kensington market are not entirely passed on down the supply chain or the alternative market could see a decrease in traffic if the increased costs in the larger market are amplified as the product moves down the supply chain.

My reduced form results in this section are intended to provide suggestive evidence regarding the direction of this market's supply chain. However, I first proceed by providing some empirical evidence that a linkage exists between these geographically disparate locations.

4.2.1 Co-movement of Kensington and Alternative Market Patterns

I argue that the set of geographies I am labeling as "alternative drug markets" are intrinsically linked to the Kensington area- either through facing the same regional demand for narcotics or through explicit supply chain linkages between these geographies. Here I provide evidence of this connection through various stylized facts regarding the time series of traffic to these geographies.

The correlation coefficient between the time series of monthly visitors to Kensington (averaged across CBGs) and the time series of monthly visitors to alternative markets (also averaged across CBGs) is 0.94 with a t statistic of 18.02. The correlation between traffic to Kensington and traffic to alternative markets is *highly* significant. Further, a Granger causality test, testing whether the time series of average Kensington target area CBGs' monthly traffic patterns Granger causes the time series of the average across my alternative markets, returns an F statistic of 2.48 with a p value equal to 0.048. A reverse of the same test fails to reject the null hypothesis that alternative market traffic does not Granger cause Kensington area traffic.[19] This is strong evidence that traffic to the Kensington area is predictive of traffic to alternative markets. This suggests the same conclusion that I will draw as I tie my reduced form causal results to my toy model: the drug supply in my alternative markets originates in Kensington (the central agglomeration) and moves outwards to these satellite alternative markets. Changes in Kensington spur changes in the smaller regional

[19] Both of these tests, along with the correlation test discussed above, were conducted on the entire 48 month sample to allow for selection of an optimal lag period. For the Granger causality tests, a lag of 10 periods was selected by minimizing AIC.

markets.[20]

The figure below plots the average time series of traffic flows to both the Kensington Initiative's focus area CBGs and my designated alternative market CBGs. The trajectories of both groups mirror each other closely. Increases and decreases in traffic occur simultaneously in both sets of locations.

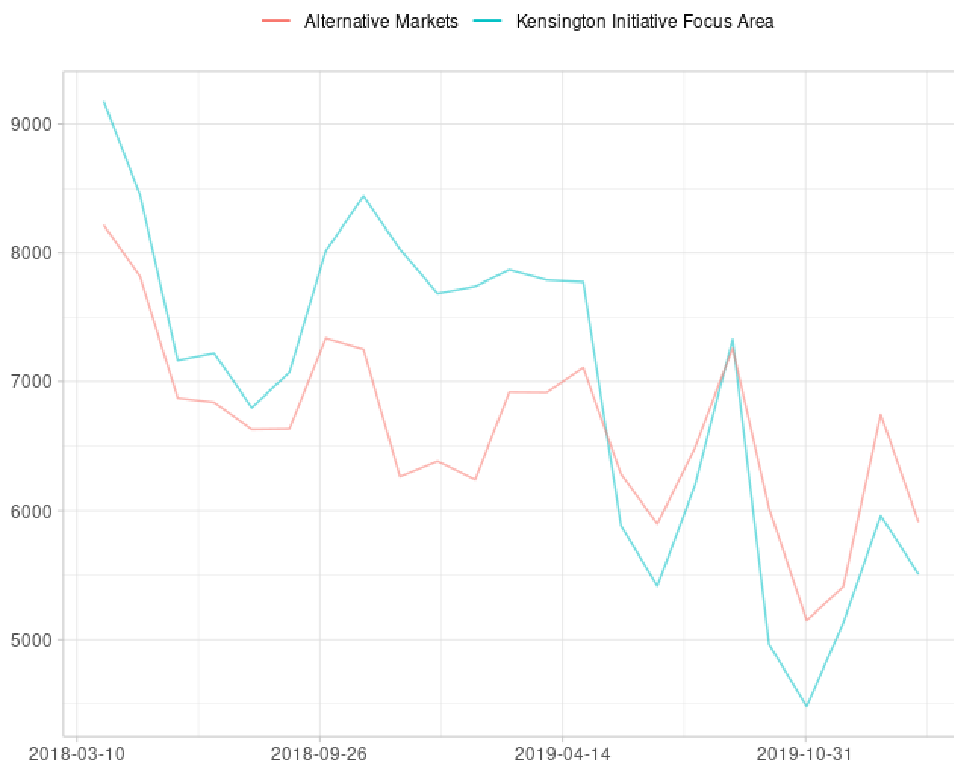


Figure 4: Figure depicting the average time trends of traffic flows to CBGs in the Kensington Initiative's focus area and those in my designated alternative markets.

In the context of my toy model presented earlier, these results suggest that the costs to sellers in alternative markets and by extension the demand in those alternative markets are impacted by enforcement effort in Kensington. This is evidence that narcotics flow from the agglomerative market outward into smaller regional distribution centers and that price signals are *amplified* as they move down through the supply chain.

[20]Analysis such as these simple Granger causality tests may be valuable tools for law enforcement analyzing cell phone location data with the intention of determining which market among a set of illegal drug markets is central, and by which their regional aims would be best served in focusing efforts at.

To further confirm the relationship between the traffic flows in alternative markets and those in the initiative's target area I employ the dynamic co-movement estimator of Croux et al. (2001). That estimator builds upon the decomposition of time series into the sums of waves at varying frequencies. Dynamic correlations at a given frequency are then defined analogously to more standard correlations, with spectral density replacing the variance of individual variables and cospectrum replacing their covariance (Croux et al. 2001). Following that paper, I first log-difference my series in order to render them stationary and proceed to construct a matrix of correlations across a given frequency band between each pair of CBGs in both my Kensington and alternative market sets, with constant weights given to each unit.[21] These correlations are defined as $\rho_{ij}(\Lambda_+)$. I then construct a new matrix of dissimilarities with each element defined as $1-\rho_{ij}(\Lambda_+)$. As in Croux et al. (2001), CBGs that strongly co-move have small dissimilarities. Lastly, following the example of the same paper, I apply metric multidimensional scaling to represent my dissimilarities on a two dimensional plane (Cox and Cox, 2001). CBGs that are closer to one another on the plane more closely co-move with one another. This two dimensional representation is plotted below.

[21] As in Croux et al. (2001) I compute these dynamic correlations with numerical integration methods. For this estimator, I make use of the reduced sample discussed earlier to ensure consistent sampling across the Safegraph data.

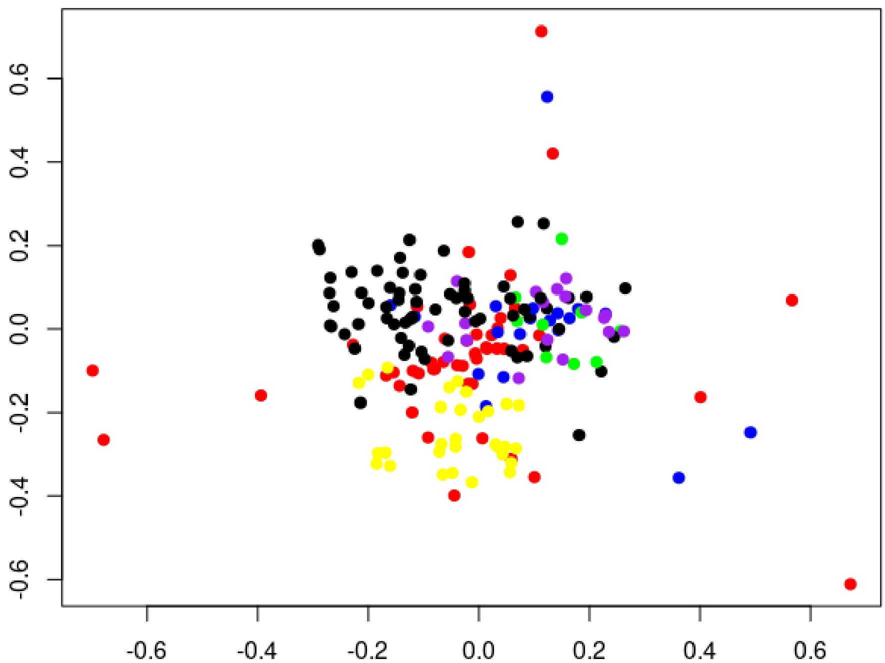


Figure 5: Figure representing the strength of co-movement between traffic flows to the initiative's target areas (in red) and those to my designated alternative market areas (in other colors). The Camden alternative market areas are in blue, Chester in green, Norristown in yellow, West Philadelphia in purple, and Wilmington in black.

The figure above demonstrates that each of the CBGs in my alternative market areas largely moves along with the others of that same market (shown by the clustering of individual colors). However, all of these clusters are overlapping one another and overlapping the red representing my initiative's target area. There is no clear pattern delineating units from the target area from those of the alternative markets. They are all interspersed among one another (with particular alternative markets clustering more tightly together). This suggests the existence of some persistent shock common to all of these alternative markets and the Kensington area, and intuitively, the existence of some within-market area persistent locally common shocks linking the trajectories of each geographically linked alternative market area.

The overall cohesion is 0.598. I block bootstrap[22] a variance around the cohesion statistic, following Berkowitz and Killian (1996) and Croux et al. (2001). There is no clear or specific benchmark for what null hypothesis to test regarding my estimated cohesion statistic, so I test whether my estimate of overall cohesion is statistically different from 0.50, the observed upper bound of cohesion estimates for the GDPs of eleven Economic and Monetary Union of the European Union nations from 1962 to 1997 (Croux et al. 2001). I am able to reject the null hypothesis that the true cohesion of my time series is equal to 0.50 with a p value of 0.025. This points somewhat in the direction of statistical significance for my estimate of cohesion: traffic patterns in the regional satellite drug markets co-move with trends in the Kensington market, suggesting some persistent common shock driving both. I posit that this shock is a supply chain linkage flowing from Kensington to the alternative markets. I proceed by estimating the causal impact of the initiative in Kensington on these geographically disparate alternative market geographies.

4.2.2 Estimating the Impact

My empirical strategy in this section is nearly identical to that employed in the previous section- but with a different "treatment" group and observations from the initiative's official target area removed to avoid contamination bias.

As was the case with my analysis of traffic to the Kensington Initiative's focus area, there is no evidence of a violation of the common trends assumption that identification relies upon for either dependent variable.[23] I will interpret (albeit cautiously) estimates from the following negative binomial difference-in-differences specification causally.

$$E[y_{it}] = exp\Bigg(\tau \cdot Alt\ \ Market,\ \ KI\ \ Active_{it} + \mu_i + \delta_t\Bigg) \tag{15}$$

As before, τ is my coefficient of interest and aims to capture the estimated impact on

[22]Blocks of length 3 are chosen to preserve some of the time dependent structure of the time series. I bootstap with 200 iterations.

[23]The results of these tests are presented in the supplemental appendix.

traffic flows to alternative markets caused by the initiative's onset.

	Dependent variable:			
	Total Visits	Unique Visitors	Total Visits	Unique Visitors
Alt Market, Treatment Effect	-0.237***	-0.186***	-0.215***	-0.147***
	(0.022)	(0.039)	(0.020)	(0.035)
Month-Year Fixed Effects	✓	✓	✓	✓
CBG Fixed Effects	✓	✓	✓	✓
Sample	Full	Full	Reduced	Reduced
Observations	204,384	204,384	97,934	97,934
Dependent Variable Mean	7539	1669	8756	1979
IRR Treatment Effect	0.79	0.83	0.81	0.86
Overdispersion Parameter	16.3	13.2	26.3	17.3
Adjusted Pseudo R^2	0.13	0.16	0.14	0.16
BIC	3,570,954	2,945,096	1,725,729	1,477,515

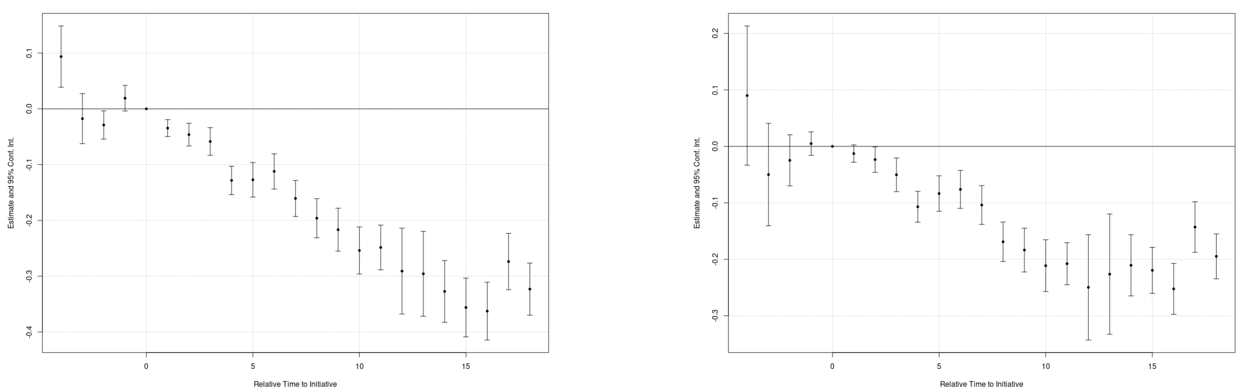
Note: Standard errors are clustered at the census block group level. *p<0.1; **p<0.05; ***p<0.01

It is notable here that the estimated effect on both total visits and unique visitors are comparable to that seen when examining the Kensington market, albeit to a smaller magnitude. This is indicative of what I should expect, the initiative is felt more accutely in the area that was directly targeted. The same placebo distribution used in my previous Monte Carlo exercise provides empirical p values of 0.00 for total visits and unique visitors respectively. It is highly unlikely that these estimates are arising by chance.

There are two potential biases in regards to my estimates here: I may be including in my set of alternative markets CBGs that in fact do not house significant markets for illegal drugs or I could be failing to include other relevant CBGs that do in fact house such markets. This second source of bias is more intuitive to address. To this point, the failure to include relevant CBGs would introduce a bias in my τ estimates towards zero, making it more difficult to detect a signal. If this is the case, then my estimate of impacts on traffic to alternative markets is merely an overly conservative estimate and the true effect is an order of magnitude more negative. To the other potential source of bias here, including incorrect CBGs in my alternative market set could introduce bias in either direction. However, when looking at effects on each CBG individually all but 7 of the 111 CBGs in my alternative market set have negative and statistically significant coefficients ($p < 0.05$) when estimated independently for unique visitors and all but 5 of that 111 have negative and statistically significant estimates for total visits. This is suggestive evidence that at the least the individual units of my alternative market set appear to be largely moving in the same direction and appear to be appropriately specified, aligning the individual estimates with their compound effect.[24]

4.2.3 Dynamic Effects on Market Traffic

Here, I briefly examine the dynamic effects of the initiative on traffic to alternative markets using event study specifications as before. The same caveats apply and are addressed in the supplemental appendix. The figures below plots dynamic estimates of the initiative's impact on total traffic and unique visitor to alternative markets. Interestingly, a more immediate impact is observed in these alternative markets than in the directly targeted area.



(a) Total Visits

(b) Unique Visitors

Figure 6: Figures depicting the synthetic difference-in-differences estimates of the dynamic effect of the Kensington Initiative on total traffic flows (left) and unique visitors (right) into alternative market areas.

[24]There is the further possibility that new markets are emerging in response to the crackdowns in the Kensington market. There is no way to directly test this possibility, and the potential use of machine learning to predict new drug market locations is outside the scope of the project at hand. However, the drug overdose results I present later at least provide evidence that if new markets were to emerge, their impacts are not offsetting the reductions in demand in known markets that I observe. I interpret all of my results as evidence of a genuine reduction in demand.

4.3 Between CBG Traffic Flows

I have argued that my counter-intuitive result, traffic flows in both the Kensington market and the alternative markets declining following an initiative targeted solely at the Kensington area, can be explained by the supply chain disruption mechanism discussed in my theory section. Here, I leverage a more granular version of the Safegraph patterns data (that I also utilize in the structural model presented in the supplemtental appendix) to empirically assess this mechanism. Using the patterns data unpacked as counts of the number of residents of CBG i visiting CBG j in month t, I estimate several models to demonstrate that the supply chain mechanism manifested itself as reductions in traffic flows between Kensington and the alternative markets.

I estimate the following negative binomial two-way fixed effects difference-in-differences model with several different treatment indicators aimed at capturing the impacts on different traffic flows throughout the metropolitan area.

$$E[y_{ijt}] = exp\Bigg(\tau \cdot Treatment\ \ Indicator_{ijt} + \mu_{ij} + \delta_t\Bigg) \tag{16}$$

The model is largely the same at those previously employed.[25] However, here, the μ terms are fixed effects representing pairs of census block groups. Treatment sets that I consider include traffic flows originating in the Kensington target area to alternative markets and from alternative markets to Kensington. I further replicate my primary results from before (flows to the Kensington target area and to the alternative markets[26]) with this richer disaggregated data. I employ the shorter pre-Covid sample to ensure more stable sampling. These results are presented in the table below:

[25] Unfortunately, due to the computational burden of computing all of the fixed effects for this estimation, I am unable to fit this model to a custom likelihood function that would account for Safegraph's unique censoring and truncation regime. These models are fit to a standard negative binomial distribution.

[26] As in the structural model in my appendix, individuals are only tied to their nearest alternative market to maintain consistency with my theoretical toy model. However, for my flows between Kensington and alternative markets all of these CBGs are considered.

	Dependent variable: Number of Visitors			
	Model 1	Model 2	Model 3	Model 4
Kensington Destination, Treatment Effect	-0.136*** (0.016)			
Alt Market Destination, Treatment Effect		-0.114*** (0.012)		
Kensington Origin- Alt Market Destination, Treatment Effect			-0.073*** (0.011)	
Alt Market Origin- Kensington Destination, Treatment Effect				-0.092*** (0.016)
Month-Year Fixed Effects	✓	✓	✓	✓
CBG Pair Fixed Effects	✓	✓	✓	✓
Observations	19,617,820			
Dependent Variable Mean for Treatment Group in Pre-Period	5.529	6.361	4.119	4.126
IRR Treatment Effect	0.87	0.89	0.93	0.91
Overdispersion Parameter	76.2	76.3	76.2	76.2
Adjusted Pseudo R^2	0.20	0.20	0.20	0.20
BIC	156,194,789	156,194,058	156,194,602	156,197,598

Note: Standard errors are clustered at the destination census block group level. *p<0.1; **p<0.05; ***p<0.01

The results in columns three and four provide evidence that the supply chain disruption precipitated by the initiative manifested itself as decreased traffic flows between the target area in Kensington and the alternative drug markets throughout the region. I interpret these results as providing evidence that once the initiative's impacts were felt in Kensington, dealers in satellite market areas that relied on the directly treated area as their source for product ceased their trips to that now more dangerous market (in terms of apprehension risk). Similarly, likely in response to more scarcity within the directly treated area, dealers from Kensington begin to travel less to alternative market areas in the region. This could plausibly be them ceasing deliveries to those areas. Altogether, this suggests that the initiative's successes in adversely impacting the narcotics trade outside of the target area could be driven primarily through its disruption of these regional between-market flows.

5 Second Order Impacts

5.1 Drug Overdoses

One of the Kensington Initiative's stated objectives is to reduce overdose deaths (Harding et al. 2021). Thus, assessing the initiative's impacts on overdoses is crucial to any assessment of its efficacy. Given that traffic to the area has been shown to be reduced with the initiative's onset, it would seem likely that overdoses throughout the area would be reduced. Here, I evaluate the program's impacts on overdose mortality across the Philadelphia metropolitan area.

I employ public use county level overdose mortality data provided by the CDC.[27] With this data I document the divergence in trends between the counties that make up the Philadelphia metropolitan area and other metropolitan counties across the United States.

Unfortunately, with the public use version of the data set I rely on, county-month observations with less than 10 overdose deaths are not shown in the data. As such, I fit my models here to a truncated Poisson distribution. I utilize two separate sets of comparison counties: all US metropolitan counties (counties labeled as being part of large or medium metro areas in the 2013 National Center of Health Statistics urban-rural classification scheme) and with the smaller subset of counties that were above average in overdose deaths (counties with mean monthly overdose death counts above 18). My samples cover 2018 through 2021, the same period as my Safegraph data.

Results from testing the common trends assumption are presented in the supplemental appendix. Two primary conclusions can be drawn from those results. First, the Philadelphia metropolitan area's trend in overdose mortality was not evolving along a different path than the bulk of US counties. However, when compared solely to the highest overdose counties there is a violation of the parallel trends assumption. Overdose mortality in the

[27] The unrestricted version of this data was unavailable for this project, as one of the authors is located outside of the United States.

Philadelphia metro area was already declining relative to the country's highest overdose mortality counties prior to the initiative's onset. This suggests a downward bias to my estimates of the initiative's impact, when compared to that highest mortality sample.

To estimate the initiative's impacts on overdose mortality the following model is specified.

$$E[overdose\ \ deaths_{it}] = exp\Big(\tau(KI\ *\ Phila\,metro)_{it} + \mu_i + \delta_t\Big) \tag{17}$$

The results from this estimation are presented below with the same two control groups discussed above. Further, I seek to control for the possible confounding influence of Naloxone availability- an increasingly prevalent opiate overdose reversing drug. I follow Doleac and Mukherjee (2022) in proxying for Naloxone availability and interest with Google Trends data. They show that increased Naloxone access correlates with increased internet searches for the drug. My trends variable is a composite of searches for "Narcan" (a trade name of the drug),"Naloxone" (the formal name of the drug), or "Buprenorphine" (a trade name for another common drug packaged with Naoloxone and prescribed for treating addiction). This data, available monthly at the designated marketing area level, was manually mapped to US counties and is included as a control variable with the intention of separating the potential impact of Naloxone in reducing opiate overdose mortality from the initiative's impact. The results from these regressions are presented below.

	Dependent variable: Count of Overdose Deaths			
	Sample			
	US Metro Counties	High Overdose Metro Counties	US Metro Counties	High Overdose Metro Counties
Philadelphia Metro County During Kensington Initiative	-0.231***	-0.228***	-0.223***	-0.222***
	(0.063)	(0.063)	(0.065)	(0.066)
Google Trends Narcan Searches	·	·	0.005***	0.005***
			(0.001)	(0.001)
County Fixed Effects	✓	✓	✓	✓
Month Fixed Effects	✓	✓	✓	✓
Observations	8,059	4,198	7,332	3,843
IRR Treatment	0.794	0.796	0.800	0.801
Dependent Variable Mean	24.62	30.51	24.62	30.51
Adjusted Pseudo R^2	0.66	0.48	0.49	0.48
BIC	47,985	28,194	42,139	25,756

Note: Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 1: Effect on overdose mortality in Philadelphia-metro counties

All estimates are negative and robust to the inclusion of Google searches for Naloxone. Relative to the rest of metropolitan America, the Philadelphia area sees a statistically significant decrease in overdose mortality of around 20%, evidence that the initiative did provide some relief to the area's opiate epidemic. Further, as shown in the supplemental appendix, when omitting Philadelphia County from the sample (the county which contains the initiative's focus area) the decline in overdose mortality is more pronounced. A nearly 27% decrease in overdose mortality is observed in the rest of the metro area. This suggests that, in contrast to my traffic results, the impacts of the initiative are felt more acutely in the surrounding region than they are in the area directly treated. Drug enforcement efforts have reverberating effects regionally.[28]

However, I must be cautious when interpreting the initiative's impacts relative to the country's highest overdose mortality counties causally given the downward bias present in the estimate due to the violation of the parallel trends assumption. Despite this, however, there seems to be clear evidence that, at the least, the initiative accelerated a downward trend in overdose mortality present in the region.

It is notable that these overdose results ostensibly contrast with those of Ray et al. (2023), who observed overdose mortality increasing in spatiotemporal clusters around drug seizures. However, their results are centered on tight windows of time in the immediate geographic vicinity of drug seizures, while I instead look at longer run impacts across the entirety of the large metropolitan region. Further, the market disruptions they leverage are likely street level dealers- pushing users to a costly and uncertain search with unfamiliar sources, as documented in Carroll et al. (2020). The disruptions I leverage, as a result of the law enforcement intelligence efforts driving them, are occurring at higher levels of the supply chain and are likely introducing scarcity into the market rather than inducing risky search behavior among users. This is in essence, they key feature of why I believe efficiently

[28] These observed reductions in overdoses regionally provide evidence that, at the least, any unobserved new markets that may be emerging in response to the initiative are not offsetting the reductions in demand observed in my known markets.

targeted interventions like the one I study here are able to work: they disrupt the entire supply chain leaving drug users with little avenue to search for a substitute. In the next section, I provide evidence that users may be "substituting" towards a legal drug prescribed as treatment for opiate use disorder.

5.2 Buprenorphine Dispensing

All of the results demonstrated thus far have pointed towards a genuine reduction in demand for narcotics brought upon by the Kensington Initiative. However, the question still remains as to what has happened to the individuals who were previously consuming drugs sourced in the disrupted illegal market. Here, I provide some preliminary evidence that these users may be attempting to switch towards a commonly prescribed "maintenance" drug in an effort to recover from addiction.

Buprenorphine, commonly sold under trade names Suboxone and Subutex, is a drug commonly prescribed to treat opioid use disorder (addiction). This drug is prescribed to reduce cravings for opiates and to mitigate withdrawal symptoms. Here, I utilize ARCOS data to compare quarterly Burprenorphine dispensing at pharmacies in counties in the "treated" Philadelphia metropolitan area to those in other metropolitan counties across the US. Specifically, I estimate a simple event study model with total doses of Burpenorphine dispensed in a county in a quarter as the outcome variable. The results are plotted in the figure below.[29] It is notable that the initiative's onset is associated with a marked increase in Burprenorphine dispensing across the metro. This increase corresponds to a 25% increase in dispensing relative to the metro's average dispensing levels in the period before the initiative. This result provides some evidence that users who are effectively being "priced out" of the market for illegal narcotics following the enforcement induced supply shock seem to be seeking a treatment based path for their opiate use disorder in an effort to entirely exit the market.

[29]The results of estimating a synthetic difference-in-differences model are presented in the supplemental appendix.

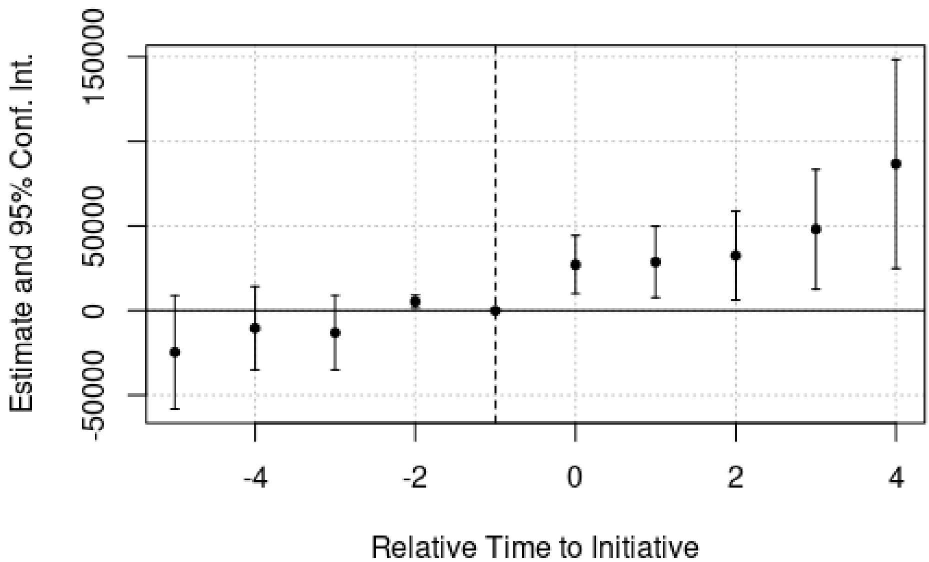


Figure 7: Figure depicting event study results showcasing the increase in Buprenorphine dispensing in the Philadelphia metropolitan area following the initiative's onset.

6 Conclusion

In this study I have demonstrated that locally specific interventions into the markets for illegal narcotics can have broad regional impacts. My empirical results provide suggestive evidence that, in my setting, narcotics flow from a central agglomerative market outwards towards local satellite markets. Locally specific supply side interventions, such as the Kensington Initiative that I evaluate here, can have persistent demand side impacts well outside of their target area. Law enforcement initiatives can reduce the demand for illegal narcotics beyond the area in which those efforts are employed through their influence on downstream narcotics costs. My results add to the growing literature on the downstream impacts of supply chain disruptions on illegal markets. Intelligence efforts and carefully targeted interventions can have real lasting regional impacts.

Making use of cell phone location data, I document a persistent decrease in traffic to the Kensington Initiative's target area, as well as to several other alternative markets for narcotics in the region identified by law enforcement sources. These empirical results are consistent with my toy general equilibrium model and theoretical framework and are robust to numerous alternative specifications including a structural approach that allows for heterogeneity among agents engaging in these markets for illegal narcotics and those that do not. I demonstrate that traffic flows to the Kensington Initiative's target area are tied to those of these regional alternative drug markets, and I further document that this initiative spurred a substantial decrease in overdose mortality throughout the metropolitan region, with the effect greater in the counties that the initiative did not directly target. This decrease in traffic to drug markets and decrease in overdose mortality was accompanied by an increase in the dispensing across the Philadelphia metro for a drug prescribed to treat opioid use disorder- suggesting that users being priced out of the market may be making effort to beat the addiction and exit the market entirely. All together, my results speak to the potential that carefully targeted law enforcement efforts can have in disrupting illegal markets.

Place-based policies can be used by law enforcement to beget desired impacts in non-directly targeted areas, given that they posses some prior knowledge of the relationship between those locations. This speaks to the generalizability of what I find in this study. For any centralized market for illegal drugs with a surrounding network of smaller satellite distribution markets, action taken solely at the central agglomeration can work to eliminate the regional satellite markets. Cell phone location data and some simple analyses of the time series of traffic flows can help to point law enforcement effort towards which is the central market so efforts can be efficiently employed to spur desired disruptive effects. I document such a disruption, unpack the mechanism through which it was able to be affected, and showcase it's impacts on a second order effect, overdose mortality. My findings suggest that law enforcement effort may be an underutilized resource in quelling the ongoing opiate epidemic in America.

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A Appendix

A.1 Police and Prosecutorial Activity

Here, I demonstrate that the official beginning of the Kensington Initiative saw with it an increase in police activity in the initiative's target area. To demonstrate this I utilize census tract level weekly arrest counts made available by the City of Philadelphia's District Attorney's Office, estimating the following equation on a sample of the data running from 2017 to 2019 to capture the initial impacts of the initiative.

$$E[Drug\ Arrests_{it}] = exp\Bigg(\tau \cdot KI\ \ Active_{it} + \mu_i + \delta_t\Bigg) \tag{18}$$

Here, i indexes census tracts, t indexes weeks, and $KI\ \ Active$ is a binary indicator equal to one if a census tract is part of the Kensington Initiative's target area and it is a week in August 2018 or later. The results from estimating this equation with a standard two-way fixed effects Poisson model are depicted below.

	Dependent variable:
	Number of arrests for drug sale or possession
KI Area Active	0.201*
	(0.106)
Census Tract Fixed Effects	✓
Week Fixed Effects	✓
Observations	36,676
IRR KI Active	1.22
Dependent Variable Mean	0.685
Adjusted Pseudo R^2	0.63
BIC	57,096
Note: Standard errors are clustered at the census tract level.	*p<0.1; **p<0.05; ***p<0.01

Table 2: Changes in police activity in the initiative's focus area.

As evidenced by this result, relative to the rest of the city, the initiative's target area saw an *increase* in arrests for drug possession and drug sales following the initiative's official start. This mirrors the result documented in Lawrence (2023), where an increase in narcotics arrests in a partially overlapping area was documented. While I am unable to assess this against any baseline level of real drug activity, I can at the least conclude that this is indicative of an increase in police attention to the area's drug activity and provides a basis for my argument that the initiative would make operating in the area more costly for drug sellers and traveling to the area more costly for drug users.

Next, I include results demonstrating that the onset of the initiative was not associated with any changes in the punitive nature of prosecution for crimes committed within the initiative area. I employ "future years of incarceration" and "future years of supervision" data provided by the Philadelphia District Attorney's Office Data Lab. This data captures the total penalties (in terms of incarceration or supervision) imposed for crimes committed in a given census tract in a given week. As with my arrest analysis, I limit my focus here to arrests for drug charges and construct a "years of supervision/incarceration per arrest" variable. This necessitates limiting my sample to observations in which a census tract observed at least one drug arrest in a given month. I cover the same 2017-2019 sample period as in my arrest analysis.

	Dependent variable:	
	Years of Incarceration per Arrest	Years of Supervision per Arrest
KI Area Active	-0.020	-0.226
	(0.020)	(0.157)
Census Tract Fixed Effects	✓	✓
Week Fixed Effects	✓	✓
Observations	7,724	7,829
Dependent Variable Mean	0.061	0.453
Adjusted R^2	0.03	0.09
RMSE	0.353	1.212
Note: Standard errors are clustered at the census tract level.		*p<0.1; **p<0.05; ***p<0.01

Table 3: Changes in police activity in the initiative's focus area.

There is no observable statistically significant impact on prosecutorial behavior relative to the rest of the city. To summarize, there is an increase in the likelihood of arrest for drug offences but no change in expected outcome of these charges. Thus, I can conclude that if individuals engaging in the market for narcotics are observing police and prosecution behavior, their expected cost of engaging in that market should be increasing. This would be in line with assumptions of the toy model elaborated on in the following section.

A.2 Compounding Effects of Sweeps

Next, I will examine the timeline of "kingpin sweeps", the targeted arrests of large scale Kensington drug dealers resulting from network based intelligence efforts.[30] These sweeps were a major focus and innovation of the initiative. I construct a timeline of these events from Attorney General press releases and court dockets and confirm my timeline with that found in Roman et al. (2022). I am unable to guarantee the *exact* dates of these sweeps. However, given that my data is at the monthly level this will not be a problem.[31] During the period of my study, there were five such sweeps. I further include two DEA sweeps that overlapped with the initiative and its intelligence efforts but were not explicitly a part of the initiative, for a total of seven sweeps.

[30] These are referred to as "jobs" in Roman et al. (2022)

[31] A table featuring the timeline and likely locations of these sweeps is found in the supplemental appendix.

I anticipate the sweeps having a compounding effect, with each additional sweep adding on to the impacts of the previous sweeps. As such, I specify the following model:

$$E[visits_{it}] = exp\Bigg(\tau_1(S_1) + (\tau_1 + \tau_2)(S_2) + ... + (\tau_1 + ... + \tau_7)(S_7) + \mu_i + \delta_t\Bigg) \tag{19}$$

The model is estimated to fit a negative binomial distribution with standard errors clustered at the CBG level. Each of the τ coefficients is intended to capture the *additional* impact of that sweep on traffic to the market area, so that the sum of τ/sweep estimates represents the cumulative impact of the initiative up to that point.

	Dependent variable:
	Total Visits
Sweep 1	0.075***
	(0.011)
Sweep 2	-0.069***
	(0.024)
Sweep 3	-0.066***
	(0.014)
Sweep 4	-0.152**
	(0.067)
Sweep 5	-0.023
	(0.058)
Sweep 6	0.023
	(0.035)
Sweep 7	0.212
	(0.041)
CBG Flow Fixed Effects	✓
Month by Year Fixed Effects	✓
Observations	206,640
Dependent Variable Mean	7514
Overdispersion Parameter	16.2
Adjusted Pseudo R^2	0.13
BIC	3,609,826
Note: Standard errors are clustered at the census block group level.	*p<0.1; **p<0.05; ***p<0.01

Individually, most of these sweeps did not have strong perceptible effects on traffic to the area. However, it is notable that sweeps two, three, and four have strong negative and statistically significant effects. These sweeps occurred in October of 2018, and January and February of 2019 respectively. The largest impact occurs with the sweep in February 2019. This result largely coincides with the dynamic results shown early. It was in early 2019 that the trajectory of traffic flows into the initiative's focus area began to drastically decrease. These were three of the largest sweeps of the period. The first of this particular set of sweeps that occurred in October of 2018 resulted in the arrest of 57 suspects and the dismantling of an organization believed to do over $5 million annually.[32]The sweep conducted in January 2019 was conducted by the DEA and resulted in a purported drug boss eventually receiving an almost 20 year prison sentence for distributing a narcotic under the brand name "funeral".[33]. The third of this set of sweeps occurred in February 2019 and was a direct component of the Kensington Initiative. It appears to have been the most impactful of the entire time period. This sweep dismantled a drug organization estimated to do over $7.7 million in sales each year and was highlighted by the seizure of nearly five kilograms of heroin and a kilogram of crack cocaine.[34]

SA Supplemental Appendix: Online Only

SUPPLEMENTAL APPENDIX. ONLINE ONLY. NOT INTENDED FOR PUBLICATION

SA.1 Parallel Trends Testing

Here, I document my tests of the common trends assumption for my three primary difference-in-differences specifications

[32]Source: `https://www.cbsnews.com/philadelphia/news/da-more-than-50-suspects-arrested-in-kensington-drug-bust/`

[33]Source `https://www.justice.gov/usao-edpa/pr/kensington-drug-boss-sentenced-almost-twenty-years-prison-supplying-narcotics`

[34]Source `https://www.attorneygeneral.gov/taking-action/attorney-general-shapiro-announces-results-of-major-drug-operation-in-kensington/`

SA.1.1 Primary Specification, Equation (14)

I specify the following model to validate the necessary identifying assumption of parallel pre-treatment trends.

$$
\begin{aligned}
E[outcome] = exp\Big(&\alpha_1 + \alpha_2(treated) + \alpha_3(time\ trend) + \alpha_4(treated \cdot time\ trend) + \\
&\alpha_5(time\ trend \cdot post) + \alpha_6(time\ trend \cdot post \cdot treated)\Big)
\end{aligned}
\tag{20}
$$

In this specification, α_4 is the coefficient of interest. A statistically significant coefficient different than zero would imply that in the pre-treatment period treatment and control group observations were evolving along separate trajectories, violating the parallel trends assumption needed for identification. The model is fit to a negative binomial distribution with standard errors clustered at the census block group level. Both total visits to a CBG and the number of unique visitors to that CBG are utilized as separate outcome variables.

	Dependent variable:	
	Total Visits	Unique Visitors
Intercept	9.073***	7.585***
	(0.017)	(0.023)
Treatment Group	-0.066	-0.083
	(0.141)	(0.242)
Time Trend	-0.031***	-0.014***
	(0.001)	(0.002)
Time Trend · Treatment Group	0.001	-0.011
	(0.018)	(0.036)
Time Trend · Post Period	0.026***	0.007***
	(0.001)	(0.002)
Time Trend · Post Period · Treatment Group	-0.014	0.012
	(0.015)	(0.032)
Observations	206,640	206,640
Overdispersion Parameter	1.55	1.16
Adjusted Pseudo R^2	0.0004	0.0005
BIC	4,079,166	3,475,429

Note: Standard errors are clustered at the census block group level. *p<0.1; **p<0.05; ***p<0.01

These results indicate that the parallel pre-trends assumption is not violated and a simple difference-in-differences framework should be able to causally identify the impacts of the initiative on both the total visitors to treated CBGs and the number of unique visitors to those CBGs.

SA.1.2 Primary Specification- Alternative Markets. Equation (15)

To justify my identification here, I employ the same model as above to test for commonality in pre-treatment trends between my treatment and control groups. As before, the significance on the "time trend by treatment group" coefficient would imply a violation of this common trends assumption.

	Dependent variable:	
	Total Visits	Unique Visitors
Intercept	9.077***	7.590***
	(0.017)	(0.024)
Treatment Group	-0.124	-0.192
	(0.111)	(0.119)
Time Trend	-0.032***	-0.014***
	(0.001)	(0.002)
Time Trend · Treatment Group	0.001	0.009
	(0.005)	(0.010)
Time Trend · Post Period	0.026***	0.008***
	(0.001)	(0.002)
Time Trend · Post Period · Treatment Group	-0.015***	-0.018*
	(0.004)	(0.010)
Observations	204,384	204,384
Overdispersion Parameter	1.56	1.17
Adjusted Pseudo R^2	0.0006	0.0007
BIC	4,034,839	3,436,832

Note: Standard errors are clustered at the census block group level. *p<0.1; **p<0.05; ***p<0.01

SA.1.3 Overdose Mortality Specification. Equation (17)

Since I employ a standard difference-in-differences framework, I first test the parallel trends assumption using the same model I used earlier. The results from this estimation are presented in the table below.

	Dependent variable: Count of Overdose Deaths	
	Sample	
	US Metro Counties	High Overdose Metro Counties
Intercept	3.017***	3.056***
	(0.060)	(0.047)
Treatment Group	0.189	0.150
	(0.262)	(0.261)
Time Trend	0.010***	0.033***
	(0.004)	(0.004)
Time Trend · Treatment Group	-0.002	-0.024***
	(0.007)	(0.007)
Time Trend · Post Period	-0.003	-0.018***
	(0.003)	(0.003)
Time Trend · Post Period · Treatment Group	-0.002	0.013*
	(0.007)	(0.007)
Observations	8,059	4,198
Dependent Variable Mean	26.62	30.51
Adjusted Pseudo R^2	0.012	0.079
BIC	133,019	49,461

Note: Standard errors are clustered at the census block group level. *p<0.1; **p<0.05; ***p<0.01

There are two primary conclusions from this table. First, the Philadelphia metropolitan area's trend in overdose mortality was not evolving along a different path than the bulk of US counties. However, when compared solely to the highest overdose counties there is a violation of the parallel trends assumption. Overdose mortality in the Philadelphia metro area was already declining relative to the country's highest overdose mortality counties prior to the initiative's onset. This suggests a downward bias to my estimates of the initiative's impact, when compared to that highest mortality sample.

SA.2 Contamination Bias in Primary Results

My primary results estimated the impacts of the initiative on traffic into the initiative's target area on a sample which in its control group includes units that I later consider as treated when looking at my spillover effects. This could potentially bias my estimates due the contamination from the other treatments (de Chaisemartin and Haultfoeuille 2020).

To address this concern, and to demonstrate the robustness of my primary results, here I replicate those results in a sample with units receiving my "spill over treatment" purged from the analysis. As demonstrated below, my results do not change.

	Dependent variable:			
	Total Visits	Unique Visitors	Total Visits	Unique Visitors
Treatment Effect	-0.357***	-0.220***	-0.303***	-0.155***
	(0.034)	(0.036)	(0.028)	(0.032)
Month-Year Fixed Effects	✓	✓	✓	✓
CBG Fixed Effects	✓	✓	✓	✓
Sample	Full	Full	Reduced	Reduced
Observations	201,312	201,312	96,462	96,462
Dependent Variable Mean	7579.6	1681.5	8791.7	1990.0
IRR Treatment Effect	0.70	0.80	0.76	0.86
Overdispersion Parameter	16.05	13.10	25.93	17.12
Adjusted Pseudo R^2	0.13	0.16	0.14	0.16
BIC	3,522,353	2,905,110	1,702,045	1,427,579

Note: Standard errors are clustered at the census block group level. *p<0.1; **p<0.05; ***p<0.01

SA.3 Spatial Autocorrelation

To address potential spatial autocorrelation in my specification's dependant variable I estimate a simple simultaneous adoption difference-in-differences model using the two-way fixed effects maximum likelihood estimator for spatially lagged counts described in Andersson et al. (2009) and Glaeser (2017).

Following that model, I model my outcome variable (total visits) as following a Poisson count distribution. However, now I model the Poisson distribution's λ expected value parameter as:

$$E[y_{it}] = exp\left(\rho \sum_{j \neq i}^{N} w_{ij} E[y_{jt}] + \tau \cdot Treatment\ Active_{it} + \mu_i + \delta_t\right) \tag{21}$$

In this formulation, the τ parameter is my estimate of the causal impact of the initiative on traffic flows to the Kensington area or the Alternative Market areas and ρ captures the impacts of neighbor traffic flows (Gibbons and Overman 2012). My spatial weights matrix, W, is constructed as a queen matrix in that all adjacent CBGs have an equal spatial dependence on one another. As in my other specifications, μ and δ are vectors of unit and time fixed effects respectively.

The results from this specification are displayed in the table below:

	Dependent variable:	
	Total Visits	
ρ	-0.006***	-0.006***
	(0.001)	(0.001)
Kensington Treatment Effect	-0.262***	
	(0.083)	
Alternative Market Treatment Effect		-0.237***
		(0.030)
Month-Year Fixed Effects	✓	✓
CBG Fixed Effects	✓	✓
Observations	204,240	
Dependent Variable Mean	7415.5	
IRR Treatment Effect	0.77	0.79
Adjusted Pseudo R^2	0.94	0.94
BIC	73,337,688	73,247,986
Note: Standard errors are clustered at the census block group level.	*p<0.1; **p<0.05; ***p<0.01	

As is evident from the results above, the results of my primary specifications are robust to the inclusion of a spatial lag of the dependent variable, a correction for biases introduced due to spatial autocorrelation.

SA.4 Micro Behavior and Heterogeneous Responses

All of my previous analysis has relied on the assumption that some unknown proportion of cell phone users in my data are traveling for drug related activity. While, this assumption is in some ways intuitive, here I adopt a more structured econometric approach to directly address this assumption. I specify a simple model of discrete choice to serve as the core of my approximation of the data generating process behind a more granular version of the same Safegraph patterns dataset. My model separates the utility functions (and associated parameters) of those traveling to engage in the market for illegal drugs from those traveling for other purposes. The parameters I estimate have direct analogues to the parameters of the toy model I presented earlier. This modeling strategy allows us to make claims regarding average changes in behavior at the *individual* level from the aggregated data that I utilize. This strategy further allows us to examine geographically heterogeneous responses to the initiative by individuals not involved in these markets.

My model is fully derived in the supplemental appendix SA.4. In short I fit my data to a negative binomial distribution with a μ parameter equal to the expected number of visitors to location j, originating in location i, in time period t. The expectation is modeled as:

$$E[y_{ijt}] = N_{it} \cdot \tau_{it} \cdot \left((\phi_1 \cdot \frac{exp(\bar{x}^1_{ij\tau k}\bar{\alpha}_k)}{1 + \sum_j exp(\bar{x}^1_{ij\tau k}\bar{\alpha}_k)}) + (\phi_2 \cdot \frac{exp(\bar{x}^2_{ij\tau k}\bar{\alpha}_k)}{1 + \sum_j exp(\bar{x}^2_{ij\tau k}\bar{\alpha}_k)}) \right) \tag{22}$$

Here, N_{it} is the number of residents of location i present in the Safegraph data at time t. τ_{it} is the average number of travel opportunities faced by an individual residing in location i in a month t, for each location i. I observe in the data a lower bound of this τ_{it} as the average number of locations, j, visited by each resident of i that appears in my Safegraph sample in month t. This however fails to account for repeat visits, especially individuals choosing to stay at home in multiple travel opportunities. As such, I model the true τ_{it} as $\tau_{it} = \tilde{\tau}_{it} + \Delta\tau_{it}$, where $\tilde{\tau}_{it}$ is the observed lower bound, the delta term represents an additive component to be estimated as a function of the observed lower bound and geographic specific covariates. While the true τ_{it} is a natural number, my estimate, $\hat{\tau}_{it}$, which is not necessarily a natural number, represents the *average* τ across the individuals resident in that geography in that time period. I model the predicted value of my true τ_{it} as:

$$\hat{\tau}_{it} = \tilde{\tau}_{it} + exp(\beta_0 + \beta X_i) \tag{23}$$

The new predicted $\hat{\tau}_{it}$ represents the estimated average number of choice opportunities afforded to an individual originating in CBG i traveling in month t. The vector of geographic covariates, x_i includes the walkability index for location i, from the EPA's Smart Location

Database[35], and the logs of per capita income and population density for location i from the 2014-2018 5 year ACS.

ϕ_1 and ϕ_2 represent the probabilities attached to class membership in the drug involved or non-drug involved classes of agents. since I do not observe individuals and posterior estimation would be infeasible due to computational limitations, I will exogenously assign a base probability that an agent falls into either class and estimate parameters that shift these probabilities based on demographic characteristics of individual n's home geography, i. I assume a base probability common across all geographies that an agent falls into my drug travel class. This base probability represents an lower bound to membership in that class. Here, I use a base probability, ϕ_0, of 0.01. This is chosen to mirror the 1.3% of US adults reporting to have misused opioids in the past month in the 2017 National Survey on Drug Use and Health conducted by the Substance Abuse and Mental Health Administration. [36]. I model heterogeneity across locations as a logisitic function that shifts his probability based on some covariates. In my context, I introduce a proxy for for the rate of illegal drug usage in a census block group as the shifter covariate.

$$\phi_1 = \phi_0 + (1 - \phi_0) \cdot \left(\frac{1}{1 + exp(-(\beta_0 + \beta_1 x_i)} \right) \quad and \quad \phi_2 = 1 - \phi_1 \tag{24}$$

Here, my shifter covariate, x_i, is the per capita rate of Burpenorphine (Suboxone) dispensed to pharmacies in the zip code that census block group i is mapped to. I utilize data provided by ARCOS for a base year 2017 (before out sample begins) divided by the 2013-2017 ACS 5 year total population estimate for each zip code and crosswalk this from zip code to census block group with the HUD-USPS Zip Code Crosswalk. This shifting allows geographies with greater rates of Burphenorphine (a drug prescribed for "maintenance" treatment of opiate substance abuse disorder) dispensing to have larger populations

[35]This walkability index is meant to capture the ease within a community of walking to "stores, jobs, and other places" (Thomas and Reyes 2021). Higher values are associated with more walkable communities.

[36]Source:https://www.samhsa.gov/data/release/2017-national-survey-drug-use-and-health-nsduh-releases

of individuals engaging in travel for drug markets. In estimating this, to ensure this class membership shifting function has the desired properties, I restrict $\beta_1 > 0$[37]. This ensures that the proportion of individuals assigned to my "drug traveling" class is increasing in geographies with larger amounts of Burpenorphine dispensing. Further, I make the simplifying assumption that these probabilities are constant throughout the life of my model and only vary across geographies through the geographic specific covariate that shifts this baseline probability.

The exponential terms in both fractions of the expected visitor counts represent the utility functions (and associated parameters) agents in either class. These utility functions for each class are essentially gravity models and are the same (albeit with different parameter values) across classes. They are specified as follows, with c indexing the two classes of agents:

$$\begin{aligned} U^c_{ijt\tau} =& \alpha^c_0 + \alpha^c_1 Dist_{ij} + \alpha^c_2 Highway_j + \alpha^c_3 Rail_j + \alpha^c_4 KI_j + \alpha^c_5 Alt_j \\ &+ \alpha^c_6 Post_t + \alpha^c_7 KI\ Post_{jt} + \alpha^c_8 Alt\ Post_{jt} + \epsilon_{nij\tau} \end{aligned} \tag{25}$$

Each of these α parameters is analogous to one of the parameters in my toy model. These relationships are discussed in my appendix. The α_7 and α_8 parameters are aimed at capturing changes to the attraction of agents of class c to the Kensington or alternative market areas[38] following the initiative's onset.

I estimate these parameters by maximizing a custom likelihood function that accounts for the censoring and truncation pattern present in the Safegraph data. In short, I optimize a smoothed approximation of a piecewise likelihood function, explicitly modeling the conditional expectation of the negative binomial distribution as described and an approximation of the overdispersion parameter, ω, based on a simple method of moments, relying on the $Var[y|\mu, \omega] = \mu + \omega\mu^2$ identity provided in Cameron and Trivedi (2005). As such, I specify

[37]To ease estimation, I force this parameter restriction using a penalty function- exponentially increasing the negative log likelihood objective of my minimization problem when the condition is violated.

[38]For consistency with my toy model, individuals are only tied to their *nearest* alternative market.

my overdispersion parameter as: $\hat{\omega} = \frac{s^2 - \bar{y}}{\bar{y}^2}$, where s^2 is the sample variance and $\bar{y}$ is the sample mean.

$$\mathcal{L}_n(\beta, \alpha, y_{ijt}, x_{ijt}) = \begin{cases} \frac{PDF^{NegBin}(E[y_{ijt}], y_{ijt})}{1 - CDF^{NegBin}(E[y_{ijt}], 1)} & \text{if } y_{ijt} > 4 \\ \frac{PDF^{NegBin}(E[y_{ijt}], 4) + PDF^{NegBin}(E[y_{ijt}], 3) + PDF^{NegBin}(E[y_{ijt}], 2)}{1 - CDF^{NegBin}(E[y_{ijt}], 1)} & \text{if } y_{ijt} = 4 \end{cases} \tag{26}$$

More explicit descriptions of my estimation and optimization strategy are detailed in supplemental appendix SA.4, along with the entire results of this estimation. The geographic heterogeneity introduced in my ϕ_i and τ_{it} parameters allow us to estimate location specific marginal effects of the initiative on traffic flows. These marginal effects are the difference in observed post-initiative traffic flows and computed counterfactuals of those same observations based on estimated parameters.

$$ME_{i,j \in KI, t \in post} = E[y_{i,j \in KI, t \in post} | D = 1] - E[y_{i,j \in KI, t \in post} | D = 0] \tag{27}$$

The average marginal effect for each CBG is the mean of those marginal effects for flows initiating there. I then scale this marginal effect by the mean flow

$$\hat{ME}_i = \frac{1}{N_{i,j \in KI, t \in post}} \sum_{j \in KI} \sum_{t \in post} ME_{i,j \in KI, t \in post} \tag{28}$$

Here, I briefly present my results my results graphically. The figure below plots a heat map showcasing geographic heterogeneity in reductions in traffic flows to Kensington following the initiative's onset, relative to imputed counterfactuals had the initiative not occurred.

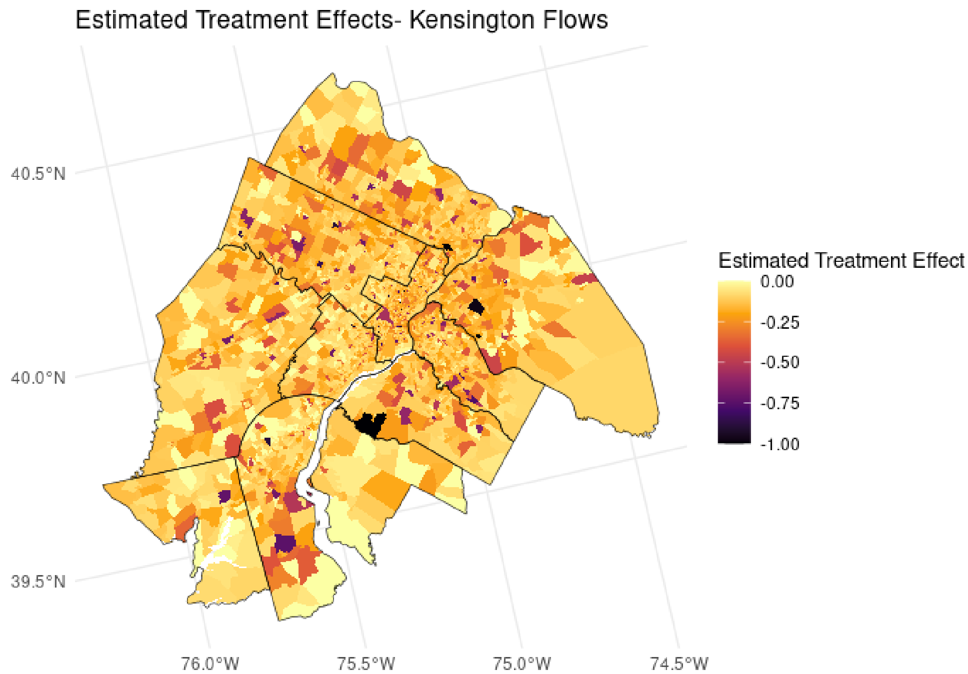


Figure 8: Figure depicting the geographic heterogeneity in marginal responses to the initiative for flows to the targeted area.

It is noteworthy that the initiative's impacts are felt most acutely in the metro area's suburbs in which connections to the city and the Kensington area are more marginal. It is as if a ring surrounding the Kensington area cuts through the suburban counties highlighting the areas most impacted by the initiative. The outer stretches of the metro are largely unimpacted, and the city of Philadelphia itself, and the closest inner ring suburbs are only effected to a lesser degree. This may because for the areas closest to Kensington, costs to travel to the market are substantially lower, leaving less room for the initiative's increased costs to drive consumers away.

The same overall pattern, depicted below, is observed when examining marginal effects for flows to the alternative market areas. However, here, the effect is stronger in throughout the city and inner ring suburbs. Individuals seem to be pushed away from the alternative markets even in farther flung corners of the metro area.

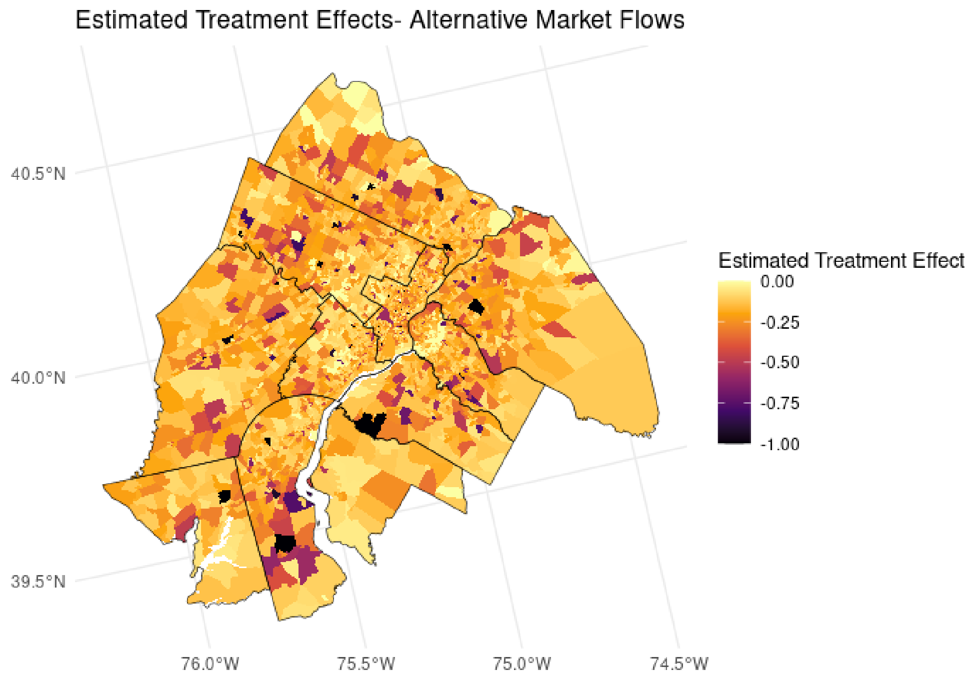


Figure 9: Figure depicting the geographic heterogeneity in marginal responses to the initiative for flows to alternative market areas.

Full tables of parameter estimates are included in a seperate section of the supplemental appendix. Heat maps of estimated treatment effects when looking at counterfactual settings in which only the drug using class is impacted by the initiative are included later in the supplemental appendix as well. They largely exhibit the same patterns.

SA.5 Modeling Heterogeneity Among Agents

SA.5.1 Derivation of My Model of Discrete Location Choice

To begin, I assume that each month is divided into τ travel opportunities in which a destination is chosen from a mutually exclusive set of all possible travel destinations. There is a specific τ_{it}, the average number of travel opportunities faced by an individual residing in location i in a month t, for each location i. I observe in the data a lower bound of this τ_{it} as the average number of locations, j, visited by each resident of i that appears in my Safegraph sample in month t. This however fails to account for repeat visits, especially individuals choosing to stay at home in multiple travel opportunities. As such, I model the true τ_{it} as $\tau_{it} = \tilde{\tau}_{it} + \Delta\tau_{it}$, where $\tilde{\tau}_{it}$ is the observed lower bound, the delta term represents an additive component to be estimated as a function of the observed lower bound and geographic specific covariates. While the true τ_{it} is a natural number, my estimate, $\hat{\tau}_{it}$, which is not necessarily a natural number, represents the *average* τ across the individuals resident in that geography in that time period. I model the predicted value of my true τ_{it} as:

$$\hat{\tau}_{it} = \tilde{\tau}_{it} + exp(\beta_0 + \beta X_i) \tag{29}$$

The new predicted $\hat{\tau}_{it}$ represents the estimated average number of choice opportunities afforded to an individual originating in CBG i traveling in month t. The vector of geographic covariates, x_i includes the walkability index for location i, from the EPA's Smart Location Database[39], and the logs of per capita income and population density for location i from the 2014-2018 5 year ACS.

I proceed with the assumption that individuals residing in each location i are homogeneous (this will subsequently be relaxed). In each of these choice opportunities, an individual selects one location to travel to. The utility of an individual n residing in location i electing to travel to location j in time τ is equal to:

$$U_{nij\tau} = x_{ij\tau k}\alpha + \epsilon_{nij\tau} \tag{30}$$

Here, the error term, $\epsilon_{nij\tau}$, captures heterogeneity specific to the nth individual based upon their location choice at travel opportunity, τ. As demonstrated in McFadden (1978), if the ϵ terms are independent and identically distributed with type 1 extreme value distributions, they will integrate away when deriving the multinomial logit choice probabilities. α represents a vector of covariates entering the utility function.

[39]This walkability index is meant to capture the ease within a community of walking to "stores, jobs, and other places" (Thomas and Reyes 2021). Higher values are associated with more walkable communities.

Their outside option is to select to remain within their home CBG, which would yield a utility: $U_{ni(j=i)\tau} = 0$.

Individual n selects to travel to location $j = \tilde{j}$ if the following condition is met:

$$U_{ni\tilde{j}\tau} = max\{U_{nij\tau}\} \tag{31}$$

The covariates entering these utility functions are choice specific attributes, since I do not have individual information. Thus, the probability that individual n elects to travel to location j in time τ can be represented with the conditional logit formulation of McFadden (1973) and is equal to:

$$P_{nij\tau} = \frac{exp(x_{ij\tau k}\alpha)}{1 + \sum_j exp(x_{ij\tau k}\alpha)} \tag{32}$$

Here, I introduce an additional assumption: that there are two types of agents in this model- those involved in the market for illegal drugs and those who are not. The framework I adopt here is similar in flavor to that of the latent class model for discrete choice described in Greene and Hensher (2003). However, since I do not observe individuals and posterior estimation would be infeasible due to computational limitations, I will exogenously assign a base probability that an agent falls into either class and estimate parameters that shift these probabilities based on demographic characteristics of individual n's home geography, i. I assume a base probability common across all geographies that an agent falls into my drug travel class. This base probability represents an lower bound to membership in that class. I model heterogeneity across locations as a logisitic function that shifts his probability based on some covariates. In my context, I introduce a proxy for for the rate of illegal drug usage in a census block group as the shifter covariate.

$$\phi_1 = \phi_0 + (1 - \phi_0) \cdot \left(\frac{1}{1 + exp(-(\beta_0 + \beta_1 x_i)} \right) \quad and \quad \phi_2 = 1 - \phi_1 \tag{33}$$

Here, my shifter covariate, x_i, is the per capita rate of Burpenorphine (Suboxone) dispensed to pharmacies in the zip code that census block group i is mapped to. I utilize data provided by ARCOS for a base year 2017 (before out sample begins) divided by the 2013-2017 ACS 5 year total population estimate for each zip code and crosswalk this from zip code to census block group with the HUD-USPS Zip Code Crosswalk. This shifting allows geographies with greater rates of Burphenorphine (a drug prescribed for "maintenance" treatment of opiate substance abuse disorder) dispensing to have larger populations of individuals engaging in travel for drug markets. During my estimation procedure, I will vary this base probability, ϕ_0, to test the robustness of my model's estimation. In estimating this, to ensure this class membership shifting function has the desired properties, I restrict $\beta_1 > 0$[40]. This ensures that the proportion of individuals assigned to my "drug traveling" class is increasing in geographies with larger amounts of Burpenorphine dispensing. Further, I make the simplifying assumption that these probabilities are constant throughout the life of my model and only vary across geographies through the geographic specific covariate that shifts this baseline probability.

Now, the probability that individual n residing in location i travels to location j in choice opportunity τ can be represented as:

$$P_{nij\tau} = (\phi_1 \cdot \frac{exp(x^1_{ij\tau k}\alpha^1)}{1 + \sum_j exp(x^1_{ij\tau k}\alpha^1)}) + (\phi_2 \cdot \frac{exp(x^2_{ij\tau k}\alpha^2)}{1 + \sum_j exp(x^2_{ij\tau k}\alpha^2)}) \tag{34}$$

Here, the ϕ_c parameters represent the probabilities of being in either class. Each class has it's own utility function (detailed in this models' estimation section) with its own parameter values that are analogous to those from the demand equations derived in my toy model.

The expected number of individuals residing in location i electing to travel to location j at choice opportunity τ is equal to:

$$E[y_{ij\tau}] = N_{i\tau} \cdot P_{nij\tau} \tag{35}$$

[40]To ease estimation, I force this parameter restriction using a penalty function- exponentially increasing the negative log likelihood objective of my minimization problem when the condition is violated.

Where, $N_{i\tau}$ is the population of location i at time τ. For my estimation, I utilize "home summary" data provided by Safegraph, which includes the total population of users for each home CBG in their sample, as my N_{it} parameter.

Since, each month (indexed by t) is divided into some number of choice opportunities indexed by τ the expected count of individuals from i traveling to j in month t is equal to:

$$E[y_{ijt}] = \sum_{\tau} E[y_{ij\tau}] = \sum_{\tau} N_{i\tau} \cdot P_{nij\tau} \tag{36}$$

Subdividing the observed time period into unobserved choice opportunities to more easily model high dimensional choice environments is similar in flavor to the strategy employed in Koulayev et al. (2016), who model individual payment opportunities as choice opportunities for payment instrument selection aggregating up to the individuals total payment instrument choice bundle. Here, I introduce the assumption that in each month t, the population of residents of i is consistent across all τ. Following from this, the expected count simplifies to:

$$E[y_{ijt}] = N_{it} \sum_{\tau} P_{nij\tau} \tag{37}$$

The $\sum_{\tau} P_{nij\tau}$ term can be replaced as follows:

$$\sum_{\tau} P_{nij\tau} = \tau_{it} \cdot E[P_{nij\tau}] = \tau_{it} \cdot \hat{P}_{nij\tau} \tag{38}$$

$\hat{\tau}_{it}$ represents the number of choice opportunities an individual from location i faces in period t. It is defined and estimated as discussed above. Now, assuming that my error terms are normally distributed across τ:

$$\hat{P}_{nij\tau} = E[(\phi_1 \cdot \frac{exp(x^1_{ij\tau k}\alpha^1)}{1+\sum_j exp(x^1_{ij\tau k}\alpha^1)}) + (\phi_2 \cdot \frac{exp(x^2_{ij\tau k}\alpha^2)}{1+\sum_j exp(x^2_{ij\tau k}\alpha^2)})]$$

$$= (\phi_1 \cdot \frac{exp(\bar{x}^1_{ij\tau k}\bar{\alpha}^1)}{1+\sum_j exp(\bar{x}^1_{ij\tau k}\bar{\alpha}^1)}) + (\phi_2 \cdot \frac{exp(\bar{x}^2_{ij\tau k}\bar{\alpha}^2)}{1+\sum_j exp(\bar{x}^2_{ij\tau k}\bar{\alpha}^2)}) \tag{39}$$

Where, the bar terms represent the averages of the parameter or variable in question across all τ within a given t.

Putting this all together, I can state:

$$E[y_{ijt}] = N_{it} \cdot \hat{\tau}_{it} \cdot \left((\phi_1 \cdot \frac{exp(\bar{x}^1_{ij\tau k}\bar{\alpha}^1)}{1+\sum_j exp(\bar{x}^1_{ij\tau k}\bar{\alpha}^1)}) + (\phi_2 \cdot \frac{exp(\bar{x}^2_{ij\tau k}\bar{\alpha}^2)}{1+\sum_j exp(\bar{x}^2_{ij\tau k}\bar{\alpha}^2)})\right) \tag{40}$$

This equation represents the expected number of visits from individuals residing in location i to location j in period t. This expectation will be used as the μ parameter of a negative binomial count distribution. I estimate the overdispersion parameter, ω, using a simple method of moments, relying on the $Var[y|\mu,\omega] = \mu + \omega\mu^2$ identity provided in Cameron and Trivedi (2005). As such, I specify my overdispersion parameter as: $\hat{\omega} = \frac{s^2-\bar{y}}{\bar{y}^2}$, where s^2 is the sample variance and $\bar{y}$ is the sample mean. To fit this model to the negative binomial distribution, I rely upon the parameterization of the distribution provided in Hilbe (2011). The other parameters of this distribution can then be estimated with maximum likelihood methods accounting for the truncation and censoring patterns of the Safegraph data discussed previously.

SA.5.2 Estimation

I estimate this model utilizing the Safegraph Neighborhood Patterns data previously discussed. However, now I disaggregate the visitors to each CBG based on their home CBGs.

Effectively, I have counts of the number of residents of CBG i that choose to visit CBG j in a given month. Since these disaggregated visitor counts are much lower than those for total visitors, Safegraph's censoring and truncation becomes more problematic in this setting. As such, I maximize a piece-wise log-likelihood function that nests Safegraph's data privacy rules alongside my previously specified model into my data generating process. The log-likelihood of the nth observation is equal to:

$$\mathcal{L}_n(\beta, \alpha, y_{ijt}, x_{ijt}) = \begin{cases} \frac{PDF^{NegBin}(E[y_{ijt}], y_{ijt})}{1 - CDF^{NegBin}(E[y_{ijt}], 1)} & \text{if } y_{ijt} > 4 \\ \frac{PDF^{NegBin}(E[y_{ijt}], 4) + PDF^{NegBin}(E[y_{ijt}], 3) + PDF^{NegBin}(E[y_{ijt}], 2)}{1 - CDF^{NegBin}(E[y_{ijt}], 1)} & \text{if } y_{ijt} = 4 \end{cases} \tag{41}$$

Observations with values of 4 (the lower bound reported in the data) have a likelihood equivalent to the probability density function of observing a 2, 3, or 4 in a negative binomial distribution with a μ parameter equal to $E[y_{ijt}]$ as described in the above section. Observations with values above 4 have likelihoods equivalent to the same PDF being evaluated at the y_{ijt} value. To account for the truncation present in the data generating process, the PDF's of observed data are scaled by the cumulative distribution function of the negative binomial distribution with a μ parameter equal to $E[y_{ijt}]$ evaluated at the lower truncation bound of 1. This piecewise formulation accounts for the censoring and truncation observed in Safegraph's data generating process.

Given that this likelihood function is non-differentiable, typical numerical optimization algorithms can be quite slow in converging to a solution. However, as demonstrated in Bertsekas (1975), Kreimer and Rubenstein (1992), and Elhedli et al. (2000), the "simple kinks" in the non-continuous likelihood function can be approximated by some continuous and differentiable function through the inclusion of additional parameters- leading to form an entirely differentiable problem that is less costly for optimization algorithms. This approximation technique is similar to the strategy employed in Tishler and Zang (1981) for maximum likelihood estimation of peicewise linear regressions.

To introduce smoothness at the break point, I approximate the indicator function with a sigmoid function of the form: $\sigma(x) = \frac{1}{1+e^{-x}}$. Now, my approximation of the nth observation's likelihood function is:

$$\mathcal{L}_n(\beta, \alpha, y_{ijt}, x_{ijt}) = \frac{PDF^{NegBin}(E[y_{ijt}], y_{ijt}) + \sigma(\epsilon(y_{ijt} - 4)) \cdot (PDF^{NegBin}(E[y_{ijt}], 4) + PDF^{NegBin}(E[y_{ijt}], 3) + PDF^{NegBin}(E[y_{ijt}], 2))}{1 - CDF^{NegBin}(E[y_{ijt}], 1)} \tag{42}$$

The inclusion of the sigmoid function approximates the piecewise nature of the true likelihood function as a smooth and differentiable function.[41] This approximation is common in machine learning applications (see Zhang et al. 1996; Amin et al. 1997; Martrinelli et al. 2023) as it can significantly ease the computational burden of the optimization algorithm. Further, employing this differentiable approximation allows for us to efficiently calculate the gradient of my approximated likelihood function, which at the optimum can be used to construct the empirical Fisher Information Matrix, which in turn is functionally equivalent to the negative expected Hessian matrix of the log likelihood function (Greene 2018; Martens 2020). The inverse of the outer product of the gradient/score is a valid estimator of the asymptotic variance-covariance matrix for maximum likelihood estimates (Berndt et al. 1974; Wooldridge 2010).

The gradient based limited-memory BFGS algorithm (Nocedal 1980; Liu & Nocedal 1989) is utilized to recover the model's parameters. The entire log-likelihood to be maximized is[42]:

$$\mathcal{L}(\beta, \alpha, y, x) = \sum_n \left(log(\mathcal{L}_n(\beta, \alpha, y_{ijt}, x_{ijt})) \right) \tag{43}$$

As discussed in the previous section estimating the actual probability distribution of the latent classes is not computationally feasible in my setting.

Lastly, the utility functions for each class are the same (albeit with different parameter

[41] I use 0.5 as my ϵ parameter value.

[42] Computationally, I instead minimize the negative log likelihood.

values) and specified as follows, with c indexing the two classes of agents:

$$\begin{aligned}U^c_{ijt\tau} =& \alpha^c_0 + \alpha^c_1 Dist_{ij} + \alpha^c_2 Highway_j + \alpha^c_3 Rail_j + \alpha^c_4 KI_j + \alpha^c_5 Alt_j \\ &+ \alpha^c_6 Post_t + \alpha^c_7 KI\ Post_{jt} + \alpha^c_8 Alt\ Post_{jt} + \epsilon_{nij\tau}\end{aligned} \tag{44}$$

Each of these α parameters is analogous to one of the parameters in my toy model. The α_1, α_2, and α_3 parameters are related to that model's ψ_i parameters, representing costs of transportation. The α_4 and α_5 parameters are analogous to the ϕ_i parameters of the toy model: representing the probability of individual consumer knowledge of Kensington and alternative drug markets. To relate more directly to my toy model, individual CBGs are assigned to their nearest alternative drug market. These parameters represent an intrinsic draw to the locations. The α_6, α_7, and α_8 parameters represent the changes in that attraction to either market that occur with the initiative's onset, which I argue to be a positive change in enforcement effort in the Kensington market ($\Delta e_k > 0$ in the context of my toy model). Thus, the α_7 parameter is directly analogous to the $\frac{\partial D_k()}{\partial e_k}$ comparative static from my toy model, it should capture changes in Kensington market demand resulting from changes in Kensington enforcement effort. Similarly, the α_7 parameter relates to the $\frac{\partial D_a()}{\partial e_k}$ comparative static from my toy model: changes in alternative market demand resulting from changes in Kensington enforcement effort. These same parameters, when pertaining to the non-drug using class of agents are able to provide insight into the visitors/visits question discussed earlier. They are able to capture the return of non-drug using agents to these drug market areas as drug activity is reduced.

I limit my analysis here to the period before COVID-19 (both to allow for a more consistent sample and to limit my sample size to ease the computational burden) and eliminate observations in which the origin and destination CBG are the same. Altogether this results in 24 parameters to be estimated across 19,617,820 observations; a costly albeit feasible problem with computational optimization routines.

SA.5.3 Full Results

The table below displays the results from estimating this model. Unfortunately, I am unable to replicate the sandwhich estimator for robust standard errors for maximum likelihood estimates discussed in Greene (2018). The formula provided there simplifies to my standard estimator when the gradient/score construction of the Fisher Information Matrix replaces the actual negative Hessian matrix, resulting in the loss of the sandwhich structure and its associated robustness. As such, standard errors displayed here should be interpreted cautiously. In the table below, “Class 1” refers to agents engaging in the market for illegal drugs and “Class 2” refers to those agents traveling for more typical reasons.

	Class Membership Probabilities:		
	0.01/0.99		
	Dependent variable: Number of Visitors		
	Class:		
	Class 1	Class 2	
Utility Function Parameters			
Intercept	$2.088e^{-6}$	$1.593e^{-7}$	
	(0.00)	(0.00)	
Distance	-0.0062	0.0538	
	($3.22e^{-6}$)	($4.23e^{-5}$)	
Highway Destination	0.0002	0.0005	
	($5.47e^{-5}$)	($2.38e^{-8}$)	
Rail Destination	0.0065	-0.0658	
	(0.0001)	($4.85e^{-7}$)	
Kensington Destination	-0.1333	-0.0022	
	($5.71e^{-6}$)	($1.54e^{-8}$)	
Alt Market Destination	0.0126	-0.0003	
	($1.35e^{-5}$)	(1.96^{-8})	
Post Period	0.0153	0.0177	
	($3.88e^{-5}$)	(3.05^{-7})	
Kensington Destination, Post Period	0.0203	-0.0036	
	($5.55e^{-5}$)	(1.22^{-8})	
Alt Market Destination, Post Period	-0.051	0.0017	
	($7.45e^{-5}$)	(1.48^{-8})	
Class Membership Function Parameters			
Intercept			2.858
			(6.61^{-5})
Buprenorphie Per Capita			0.9916
			(1.92^{-5})
Choice Opportunity Function Parameters			
Intercept			15.589
			(7.01^{-6})
Walkability			0.0139
			(6.64^{-5})
Income			-0.0296
			(0.0001)
Density			0.0439
			(4.78^{-5})
Observations	19,617,820		
BIC	45,632,107		

Note: Standard errors are in parentheses and are calculated as the square root of the main diagonal of the inverse of the outer product of the score, as discussed in Wooldridge (2010).

First, it bares reminding that due to my inability to calculate a robust estimator of standard errors, any claims to statistical significance are tenuous at best. Given this fact, and the difficulty in contextualizing these parameter values given the complex form of the function they are defined for, I will limit ourselves to discussion of the sign and direction of these effects. Further, it is evident that I am able to explain very little about the travel behavior of the non-drug involved class of agents My model does little to explain the intricacies of the typical individual's travel behavior. However, for the class specified to travel to engage in the markets for illegal drugs, I am able to pull estimates from the data that are consistent with the predictions of my toy model.

SA.5.4 Marginal effect heat maps for alternative counterfactuals

Here, I present heat maps for estimated marginal effects based upon counterfactuals generated to simulate settings in which only the drug using class of individuals is impacted by the initiative. The patterns seen in previous maps are largely replicated here.

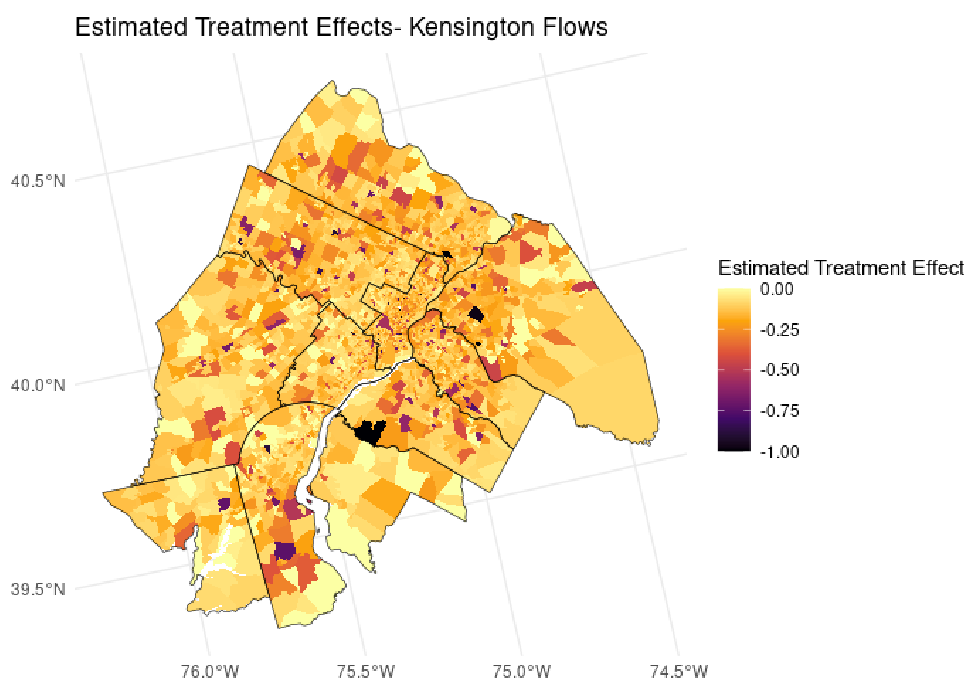


Figure 10: Figure depicting the geographic heterogeneity in marginal responses to the initiative for flows to alternative market areas.

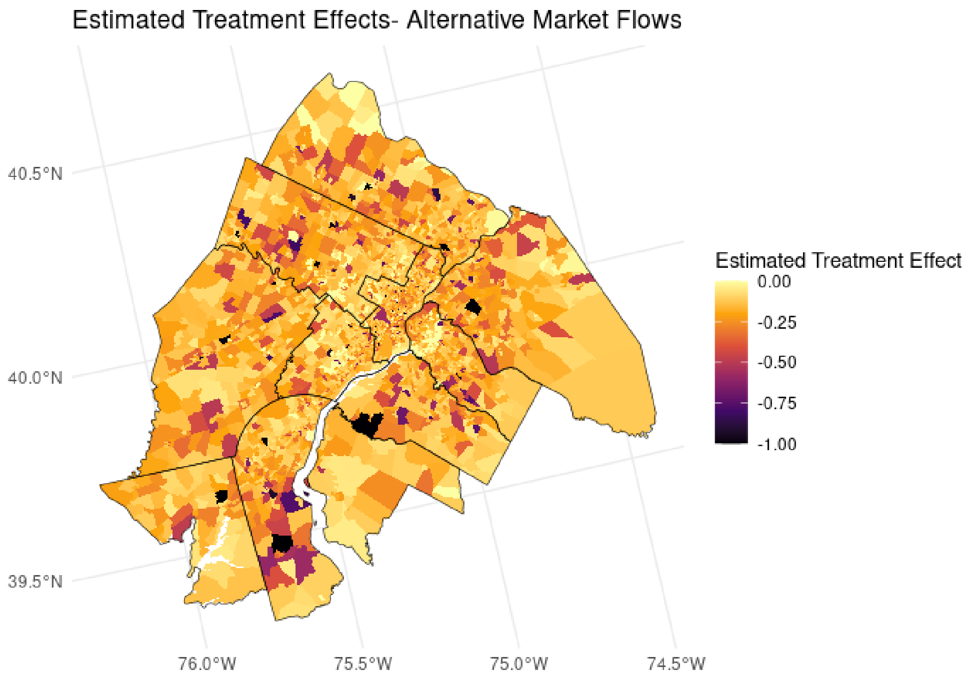


Figure 11: Figure depicting the geographic heterogeneity in marginal responses to the initiative for flows to alternative market areas.

SA.6 Overdose Mortality Results Omitting Philadelphia

My primary traffic results suggest that the impacts of the initiative are felt more intensely in areas not directly treated. While the limitations of my data, and the nature of drug users locational choices, prevent us from being able to replicate a similar strategy in identifying these spillovers on overdose outcomes, here I present results omitting Philadelphia county from my data. Doing so allows us to limit my analysis of "treated areas" solely to the non-directly treated regions of the Philadelphia metropolitan area. However, while the entirety of the initiative's focus area is in Philadlephia county, the vast majority of that county's area was not a part of the target area. As such, other viable "spillover" areas are now removed from my sample. The results from this analysis are shown below:

	Dependent variable: Count of Overdose Deaths			
	Sample			
	US Metro Counties	High Overdose Metro Counties	US Metro Counties	High Overdose Metro Counties
Philadelphia Metro Counties During Kensington Initiative	-0.310***	-0.307***	-0.308***	-0.307***
	(0.058)	(0.058)	(0.059)	(0.060)
Google Trends Narcan Searches	·	·	0.005***	0.005***
			(0.001)	(0.001)
County Fixed Effects	✓	✓	✓	✓
Month Fixed Effects	✓	✓	✓	✓
Observations	8,011	4,150	7,288	3,799
IRR Treatment	0.733	0.736	0.735	0.736
Dependent Variable Mean	24.24	29.84	24.24	29.84
Adjusted Pseudo R^2	0.65	0.45	0.65	0.45
BIC	48,229	43,667	43,968	25,382

Note: Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 4: Effect on overdose mortality in Philadelphia-metro counties

It is evident that the impact of the initiative on reducing overdose mortality was even greater outside of Philadelphia county. I view this result as being in line with the my findings on traffic to illegal drug markets. The impacts of the initiative are felt more acutely in areas connected but downstream from the directly targeted area.

SA.7 Timeline of Kensington Initiative

Below is a general timeline of the initiative and the various block-level "kingpin" sweeps that it entailed. The locations and dates listed are drawn from news reports, press releases from the attorney general's office, information provided by Caterina Roman and her team in their policy briefs, and locations and dates listed on criminal dockets filed for these cases. I am unfortunately unable to guarantee the specific dates and locations.

08/16/2018- AG Shapiro publicly launches Kensington Initiative

Date	Location	CBG
08-30-2018	H and Potter St	421010177012
10-04-2018*	Kip and Cambria	421010176022
01-01-2019*	3100 Weymouth St	421010177011
02-14-2019	3300 Argyle St	421010192004
07-09-2019	600 E Clementine St	421010177011
08-12-2020	4100 G St	421010383001
06-02-2021	800 E Madison St	421010177012

Table 5: Timeline of block sweeps, * denotes, arrest was part of seperate overlapping DEA initiative, not directly KI.

SA.8 Block Level Sweeps

Initially it was my intention to estimate the effects of the individual block level sweeps *within* the treated area at a more granular level. Since these sweeps happen within the initiative's target area, I built a secondary data set at the individual business by week level, looking exclusively at convenience stores (bodegas) located within the target area. These were then mapped to their constituent blocks, and event studies were estimated to see if the aggregate number of weekly visitors to stores on "swept" blocks were (presumably negatively) impacted by these sweeps relative to those on other blocks within the area. Estimated results were precisely estimated zeros, with no divergence in trends observable either before or after these sweeps. This may be due to noise present in the data as I begin to look at levels even more granular than that of the census block group. Further, as discussed in the previous appendix section, I cannot be entirely certain of the locations or dates of these sweeps. As such, it is possible that treated and untreated groups contaminate one another. Or, further, it may well be possible that as soon as a block is swept and "kingpins" are removed someone else is there to take their place. I cannot say for sure (regarding any of these possibilities) and as such leave these null results out of the paper and instead proceed by treating these sweeps as having a cumulative impact on one another for the entire treatment area. Some further discussion about these kingpin sweeps and what was recovered in them can be found in Roman et al. (2021).

SA.9 A More in Depth Derivation of My Toy Model

To motivate this paper's primarily analyses, I specified a stylized toy model aimed at capturing the primary features of a regional agglomeration market for illegal narcotics. Here I present a more in-depth derivation of that same model.

To begin, I assume a linear city of length 1 with a drug market located at either end. There are consumers located uniformly across the city's length. Consumers can only purchase from one of the two markets. One of the markets is denoted k and represents the Kensington drug market agglomeration. The other market is denoted a and represents a smaller alternative drug market. This is a simple Hotelling model in which full information demand for each market can be determined by equating the cost to the marginal consumer for purchasing from either market. Consumers are price takers and a monopolistic seller in either market seeks to maximize their own profit through price competition, selecting an optimal p_k or p_a that consumers purchasing in either market will face.[43] Each market has a separate marginal cost. Since market k represents the Kensington agglomeration, I will assume that $c_k < c_a$. I can assume that $c_a = c_k + \omega$, where ω is some additional fixed cost entailed for operating outside of Kensington.

To derive the demand side, I assume examine a marginal consumer located at some point in the linear city, x. I include transit costs as a function of other exogenous factors:

$$t_k = \frac{1}{\psi_k}x \quad and \quad t_a = \frac{1}{\psi_a}(1-x) \tag{45}$$

The ψ_i variables represent the ease of transportation between locations. These variables in themselves could be functions of other exogenous variables, such that the ψ_i variable's value increases as more transit infrastructure is introduced, effectively lower the cost of movement to location i.

[43]Much of the "supply side" of this model's framework is similar to that found in Poret (2002), where a monopolist is seen as distributing narcotics wholesale to oligopolistically competing distributors. My framework is quite similar with the influence of the monopolist wholesaler modeled as an exogenous input into the retailers' cost functions.

Bare in mind that $x : \{x|0 \leq x \leq 1\}$ and $\psi_i : \{\psi_i|0 < \psi_i \leq 1\} \ \forall \ i$.

Prices selected by monopolist sellers in each market are functions of some cost faced by sellers that is a function of enforcement effort in that market and a constant parameter, b_i such that $b_k > b_a$. Thus, $c_i = c(e_i, b_i)$ such that:

$$\frac{\partial \ c_i(e_i, b_i)}{\partial e_i} > 0 \tag{46}$$

Since the b_i component is fixed I neglect this notation from further derivations for readability. Increases in police effort in either market, e_i, increase the marginal cost of operating in that market.

Now, solving the Hotelling model for demand under full information can be solved by considering the case of the marginal consumer located at some point in which she is indifferent between purchasing at either market:

$$p_k + \frac{1}{\psi_k}x = p_a + \frac{1}{\psi_a}(1 - x) \tag{47}$$

This yields the following demand equations:

$$D_k(p_k, p_a, \psi_k, \psi_a) = -\frac{((p_k - p_a)\psi_a - 1)\psi_k}{\psi_k + \psi_a} \tag{48}$$

And:

$$D_a(p_k, p_a, \psi_k, \psi_a) = \frac{((p_k - p_a)\psi_a - 1)\psi_k + \psi_k + \psi_a}{\psi_k + \psi_a} \tag{49}$$

Both of these are strictly positive for $\frac{1}{\psi_a} > p_k - p_a > \frac{-1}{\psi_k}$.

Introducing an information dynamic, there is an exogenous probability ϕ_k that an agent is aware of the Kensington market and a probability ϕ_a that an agent is aware of the alternative market. For simplicity, all agents have a uniform probability of being aware of either market. Some proportion of the agents are aware of both markets. Thus, using the solutions from the full information setting:

$$D_k() = \phi_k[(1-\phi_a) + \phi_a(-\frac{((p_k - p_a)\psi_a - 1)\psi_k}{\psi_k + \psi_a})] \tag{50}$$

And:

$$D_a() = \phi_a[(1-\phi_k) + \phi_k(\frac{((p_k - p_a)\psi_a - 1)\psi_k + \psi_k + \psi_a}{\psi_k + \psi_a})] \tag{51}$$

Now, the maximization problem of the monopolist seller in market k can be represented as:

$$\max_{p_k \geq 0}\{\phi_k[(1-\phi_a) + \phi_a(-\frac{((p_k - p_a)\psi_a - 1)\psi_k}{\psi_k + \psi_a})] \cdot (p_k - c_k(e_k))\} \tag{52}$$

The seller in market a faces a symmetric optimization problem which when solved yields optimum price vectors.

$$p_k^* = \frac{((c_k(e_k) + p_a)\phi_a\psi_a + 1)\psi_k + (1-\phi_a)\psi_a}{2\phi_a\psi_a\psi_k} \quad and \quad p_a^* = \frac{((c_a(e_a) + p_k)\phi_k\psi_a - \phi_k + 1)\psi_k + \phi_a}{2\phi_k\psi_k\psi_a} \tag{53}$$

Now, I can solve for the equilibrium prices as functions of solely exogenous parameters:

$$p_k^* = \frac{((c_a(e_a) + 2c_k(e_k))\phi_a\phi_k\psi_a + (2-\phi_a)\phi_k + \phi_a)\psi_k + ((2-2\phi_a)\phi_k + \phi_a)\psi_a}{3\phi_a\phi_k\psi_a\psi_k} \tag{54}$$

And:

$$p_a^* = \frac{((2c_a(e_a) + c_k(e_k))\phi_a\phi_k\psi_a + (1-2\phi_a)\phi_k + 2\phi_a)\psi_k + ((1-\phi_a)\phi_k + 2\phi_a)\psi_a}{3\phi_a\phi_k\psi_a\psi_k} \tag{55}$$

Lastly, these equilibrium prices are used to express demand in both markets as functions of exogenous parameters.

$$D_k()^* = \frac{((c_a(e_a) - c_k(e_k))\phi_a\phi_k\psi_a + (2\phi_a - 1)\phi_k\phi_a)\psi_k + ((\phi_a - 1)\phi_k + \phi_a)\psi_a}{3\phi_a\phi_k\psi_a + 3\phi_a\phi_k\psi_k} \tag{56}$$

And

$$D_a()^* = -\frac{((c_a(e_a) - c_k(e_k))\phi_a\phi_k\psi_a + (-\phi_a - 1)\phi_k + \phi_a)\psi_k + ((-2\phi_a - 1)\phi_k + \phi_a)\psi_a}{3\phi_a\phi_k\psi_a + 3\phi_a\phi_k\psi_k} \tag{57}$$

While these demand functions are not quite tractable, I am able to compute a few comparative statics that are important for motivating my analysis:

$$\frac{\partial D_k()}{\partial e_k} = -\frac{\psi_a\psi_k}{3\psi_a + 3\psi_k} \cdot \frac{\partial c_k()}{\partial e_k} \quad and \quad \frac{\partial D_k()}{\partial e_a} = \frac{\psi_a\psi_k}{3\psi_a + 3\psi_k} \cdot \frac{\partial c_a()}{\partial e_a} \tag{58}$$

$$\frac{\partial D_a()}{\partial e_k} = \frac{\psi_a\psi_k}{3\psi_a + 3\psi_k} \cdot \frac{\partial c_k()}{\partial e_k} \quad and \quad \frac{\partial D_a()}{\partial e_a} = -\frac{\psi_a\psi_k}{3\psi_a + 3\psi_k} \cdot \frac{\partial c_a()}{\partial e_a} \tag{59}$$

Unsurprisingly, demand in each market moves negatively with levels of police effort in that market through impacts on marginal costs in that market. If, as I have assumed, cost in each market is merely a function of police effort in *that* market, an increase in effort in either market will predictably drive demand to the alternative market. However, if instead the two markets are linked such that the product in one market is sourced from the other, costs in the subordinate market will also be function of effort in the chief market. For example, if the product in the alternative market is sourced from the Kensington market (such that $\frac{\partial c_a(e_a,e_k)}{\partial e_k} > 0$), demand in the alternative can be expressed as:

$$D_a()^* = -\frac{((c_a(e_a, e_a) - c_k(e_k))\phi_a\phi_k\psi_a + (-\phi_a - 1)\phi_k + \phi_a)\psi_k + ((-2\phi_a - 1)\phi_k + \phi_a)\psi_a}{3\phi_a\phi_k\psi_a + 3\phi_a\phi_k\psi_k} \tag{60}$$

I represent alternative market costs here as a function of police effort in the directly targeted market rather than as a function of prices in that market intentionally, to keep the model more generalizable. In this set up, I am able to capture the essence of a market in which product in the alternative markets are directly sourced from retailers in Kensington as well as the possibility that the exogenous supplier to both markets is physically operating in that market at some level above retail (as suggested by DEA reports describing Kensington as a major transit point for Mexican cartels). The marginal effects of changes in enforcement effort in the alternative market on alternative market demand remains unchanged while the marginal effect of changes in enforcement effort in the Kensington market on alternative market demand can be expressed as:

$$\frac{\partial D_a()}{\partial e_k} = (\frac{\partial c_k()}{\partial e_k} - \frac{\partial c_a()}{\partial e_k}) \cdot \frac{\psi_a\psi_k}{3\psi_a + 3\psi_k} \tag{61}$$

The direction of this effect is determined by differentials in price transmission. If the price pass through rate in the alternative market is less than that in the source market, demand will still increase in the alternative, but to a lesser extent than if the two markets were not linked. If instead the impact on costs is amplified through the supply chain, and the pass through rate in the alternative exceeds that of its source, the alternative market would see a *decrease* in demand. Thus, given that my Kensington Initiative treatment only directly impacts the targeted Kensington area, an estimated decrease in demand in alternative markets would provide empirical evidence of a supply chain linkage in which illicit narcotics flow from Kensington outwards to alternative markets, with a pass through rate greater in these satellites than in their source market.

SA.10 Visual Representation of Model's Logic

First, I visually represent the logic of the model for the case in which costs to sellers in either market are functions of police in only that market. The last partial derivatives displayed under those nodes imply that increases in effort in that market will lead to increases in demand in the opposing market.

Consumer

$$D_i = f(p_i, p_{-i}, \psi_i, \psi_{-i}, x_i, x_{-i})$$

A ——————————— K

$$p_a = f(D_a, c_a(e_a))$$

$$\frac{\partial c_a}{\partial e_a} > 0; \quad \frac{\partial p_a}{\partial e_a} > 0; \quad \frac{\partial D_a}{\partial e_a} < 0; \quad \frac{\partial D_a}{\partial e_k} > 0$$

$$p_k = f(D_k, c_k(e_k))$$

$$\frac{\partial c_k}{\partial e_k} > 0; \quad \frac{\partial p_k}{\partial e_k} > 0; \quad \frac{\partial D_k}{\partial e_k} < 0; \quad \frac{\partial D_k}{\partial e_a} > 0$$

Now, I represent the setting in which costs to sellers in the alternative market are also a function of effort in the Kensington market, i.e. a supply chain linkage between the two markets. Now, increases in effort in Kensington market are transmitted to the alternative in increases prices there. The impact on demand in the alternative market is ambiguous and depends on the relative responsiveness in pricing between the two markets. However, there is a case in which demand in the alternative can decrease with increases in effort in Kensington.

Consumer

$$D_i = f(p_i, p_{-i}, \psi_i, \psi_{-i}, x_i, x_{-i})$$

A ——————————— K

$$p_a = f(D_a, c_a(e_a, e_k))$$

$$\frac{\partial c_a}{\partial e_a} > 0; \quad \frac{\partial p_a}{\partial e_a} > 0; \quad \frac{\partial D_a}{\partial e_a} < 0$$

$$\frac{\partial c_a}{\partial e_k} > 0; \quad \frac{\partial p_a}{\partial e_k} > 0; \quad \frac{\partial D_a}{\partial e_k} \gtreqless 0$$

$$p_k = f(D_k, c_k(e_k))$$

$$\frac{\partial c_k}{\partial e_k} > 0; \quad \frac{\partial p_k}{\partial e_k} > 0; \quad \frac{\partial D_k}{\partial e_k} < 0; \quad \frac{\partial D_k}{\partial e_a} > 0$$

SA.11 OLS and Poisson Replication of Primary Results

Here I present the OLS and Poisson results replicating my primary specifications. First, OLS results for the initiative's impact in the directly targeted area.

	Dependent variable:			
	Total Visits	Unique Visitors	Total Visits	Unique Visitors
Treatment Effect	-1737.8***	158.0	-2064.6***	64.1
	(610.6)	(368.4)	(563.4)	(307.1)
Month-Year Fixed Effects	✓	✓	✓	✓
CBG Fixed Effects	✓	✓	✓	✓
Sample	Full	Full	Reduced	Reduced
Observations	206,640	206,640	99,015	99,015
Dependent Variable Mean	7514	1668	8736	1977
Adjusted R^2	0.83	0.70	0.87	0.73
Note: Standard errors are clustered at the census block group level.				*p<0.1; **p<0.05; ***p<0.01

Next, is the same results estimated with a Poisson fixed effects models.

	Dependent variable:			
	Total Visits	Unique Visitors	Total Visits	Unique Visitors
Treatment Effect	-0.275**	0.106	-0.266***	0.033
	(0.118)	(0.233)	(0.083)	(0.170)
Month-Year Fixed Effects	✓	✓	✓	✓
CBG Fixed Effects	✓	✓	✓	✓
Sample	Full	Full	Reduced	Reduced
Observations	206,640	206,640	99,015	99,015
Dependent Variable Mean	7514	1668	8736	1977
Adjusted Pseudo R^2	0.91	0.88	0.93	0.89
Note: Standard errors are clustered at the census block group level.				*p<0.1; **p<0.05; ***p<0.01

Now, I turn my attention towards the alternative market area impacts. First, the results with OLS estimation.

	Dependent variable:			
	Total Visits	Unique Visitors	Total Visits	Unique Visitors
Alt Market, Treatment Effect	-1868.6***	-316.7***	-1820.4***	-319.4**
	(225.2)	(106.7)	(218.0)	(137.3)
Month-Year Fixed Effects	✓	✓	✓	✓
CBG Fixed Effects	✓	✓	✓	✓
Sample	Full	Full	Reduced	Reduced
Observations	204,384	204,384	97,934	97,934
Dependent Variable Mean	7539	1669	8756	1979
Adjusted R^2	0.83	0.70	0.88	0.73
Note: Standard errors are clustered at the census block group level.				*p<0.1; **p<0.05; ***p<0.01

Lastly, I present the replication of my alternative market results fit with a Poisson fixed effects model.

	Dependent variable:			
	Total Visits	Unique Visitors	Total Visits	Unique Visitors
Alt Market, Treatment Effect	-0.302***	-0.249***	-0.240***	-0.205**
	(0.038)	(0.076)	(0.032)	(0.078)
Month-Year Fixed Effects	✓	✓	✓	✓
CBG Fixed Effects	✓	✓	✓	✓
Sample	Full	Full	Reduced	Reduced
Observations	204,384	204,384	97,934	97,934
Dependent Variable Mean	7539	1669	8756	1979
Adjusted Pseudo R^2	0.91	0.88	0.93	0.089

Note: Standard errors are clustered at the census block group level. *p<0.1; **p<0.05; ***p<0.01

SA.12 Overdose Mortality Results Omitting Baltimore

A particular concern for the results in this paper is that I am merely observing drug users substituting spatially to drug markets further away- outside of the scope of analysis. In particular, south of the Philadelphia area metro is Baltimore, Maryland, a city well known for its own markets for illegal narcotics. If drug users were simply responding to the initiative by migrating to a completely different metropolitan area, I would still be observing the same reductions in overdose mortality and traffic flows to drug markets across the Philadelphia metro. However, the conclusions I draw regarding the supply chain disruption generating a genuine reduction in demand across the Philadelphia region would be negated. It does bare noting, however, that along with the results I present here, the increase in Buprenorphine dispensing across the Philadelphia metro seems to cut against the possibility of this hypothetical far flung geographic substitution story holding true.

None the less, I address this concern in two ways. First, I present my primary overdose results replicated with the omission of the counties within the Baltimore metropolitan area. Second, I change the focus and estimate the impacts on overdose mortality *within* the Baltimore metropolitan area (omitting Philadelphia area counties). I do not spend much time arguing this, but I do believe that this result in particular adds extra strength to my story and suggests that the supply chain disruption induced by the Initiative may be even broader than I have previously argued.

First, the results from the primary overdose results are displayed below, with Baltimore metro counties omitted. Notably, there is little change in the estimated effect. There is still a statistically significant reduction in overdose mortality observed in the Philadelphia metro.

	Dependent variable: Count of Overdose Deaths
	Sample
	US Metro Counties
Philadelphia Metro County During Kensington Initiative	-0.243***
	(0.062)
County Fixed Effects	✓
Month Fixed Effects	✓
Observations	7,895
IRR Treatment	0.78
Dependent Variable Mean	24.36
Adjusted Pseudo R^2	0.66
BIC	47,333
Note: Standard errors are clustered at the county level.	*p<0.1; **p<0.05; ***p<0.01

Table 6: Effect on overdose mortality in Philadelphia-metro counties, omitting Baltimore-metro counties.

Now, estimates of the Initiative's impacts on overdose mortality in the Baltimore metropolitan area are presented in the table below. I estimate a *reduction* in overdose mortality across the Baltimore metro corresponding with the Kensington Initiative's onset. This suggests that the supply chain disruption precipitated by the initiative may have broader impacts than I previously argued. Baltimore is only about 100 miles south of Kensington, Philadelphia. The two are connected by a singly direct highway connection. If DEA and other law enforcement reports are to be believed as accurate, and Kensington is truly a broad regional distribution center for narcotics beyond its own metropolitan area, then the same mechanism I am arguing is at work across the Philadelphia metro could be at work across the broader northeastern United States. Evaluating this in detail is beyond the scope of the study at hand. However, this does provide some optimistic evidence that truly effectively targeted law enforcement interventions can reap widespread reverberating impacts nationwide.

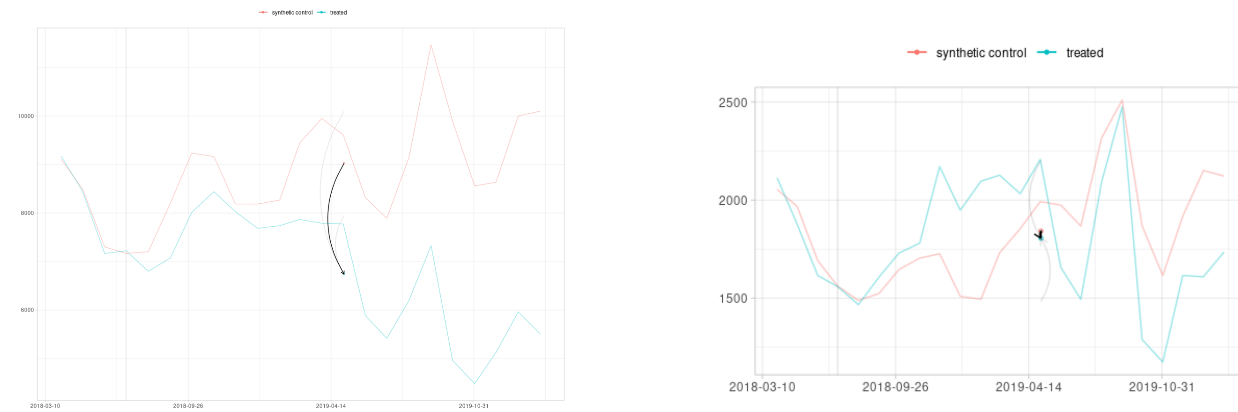
	Dependent variable: Count of Overdose Deaths
	Sample
	US Metro Counties
Baltimore Metro County During Kensington Initiative	-0.288***
	(0.062)
County Fixed Effects	✓
Month Fixed Effects	✓
Observations	7,653
IRR Treatment	0.75
Dependent Variable Mean	24.36
Adjusted Pseudo R^2	0.66
BIC	45,789
Note: Standard errors are clustered at the county level.	*p<0.1; **p<0.05; ***p<0.01

Table 7: Effect on overdose mortality in Baltimore-metro counties during the initiative in Kensington, omitting Philadelphia metro-counties.

SA.13 Synthetic Difference-in-Difference Results of Primary Specification

In case there is concern regarding the validity of the parallel trends assumption that identification in my difference-in-differences models has relied upon, here I present results from estimating using the synthetic difference-in-differences model of Arkhangelsky et al. (2021). This model creates a synthetic counterfactual that by design in parallel in pre-treatment trends to the treatment group, allowing identification in settings in which the assumption may be violated. It bares noting, however, that this model treats my outcome variable as continuous (in the same way that OLS does) ignoring the discrete nature of the variables evaluated here.

First, I present the results for total stops and for unique visitors to the Kensington Initiative's target area.

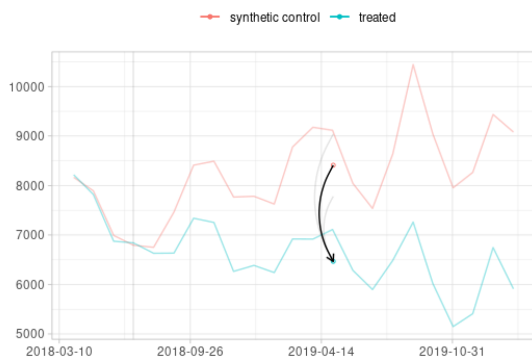


(a) Total Visits

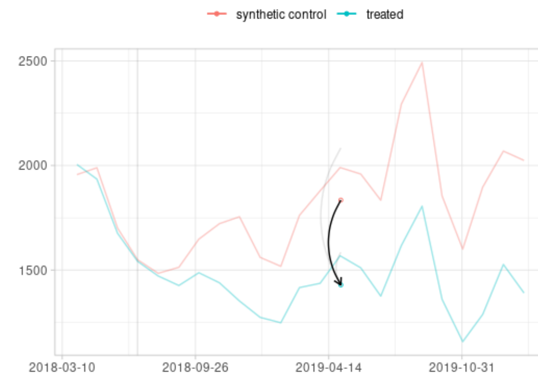
(b) Unique Visitors

Figure 12: Figures depicting estimates of the dynamic effect of the Kensington Initiative on total traffic flows (left) and unique visitors (right) into the target area.

For the total visits to the targeted area, the synth DiD model returns an overall estimated effect of -2284.19 with a standard error of 552.89. The results for unique visitors (as demonstrated in the above figure) are much messier. The estimated effect is statistically insignificant. The estimated effect is -37.13 with a standard error of 375.2. Next I proceed to the same models, but examining traffic and visitors to the alternative market areas. These estimates are depicted below. The estimated effect on total traffic to the alternative markets is -1944.47 with a standard error of 284.9. The estimated effect on unique visitors to the alternative markets is -406.07 with a standard error of 99.6.



(a) Total Visits



(b) Unique Visitors

Figure 13: Figures depicting estimates of the dynamic effect of the Kensington Initiative on total traffic flows (left) and unique visitors (right) into the alternative market areas.

SA.14 Alternative Specifications for Buprenorphine Dispensing

SA.14.1 OLS Regression Results

Here, I present the overall OLS results for estimating the initiative's impact on Buprenorphine prescribing in counties of the Philadelphia metro following the Kensington Initiative's impact. The results are presented in the table below. Overall, the estimated effect corresponds to about a 25% increase in Buprenorphine dispensing in the metro compared to other metro counties throughout the country.

	Dependent variable:
	Doses
Philadelphia Metro, Post Initiative	75965.4**
	(35591)
County Fixed Effects	✓
Quarterly Fixed Effects	✓
Observations	34,120
DV Mean, Treatment Group, Pre Period	305003.7
Adjusted R^2	0.968961
Note: Standard errors are clustered at the county level.	*p<0.1; **p<0.05; ***p<0.01

SA.14.2 Synthetic Difference-in-Difference Results

Here, I present the results of a synthetic difference-in-differences estimation of the initiative's impact on Buprenorphine dispensing. The overall estimated effect is 16012.89 with a p-value of 0.0094. This result is displayed graphically in the figure below.

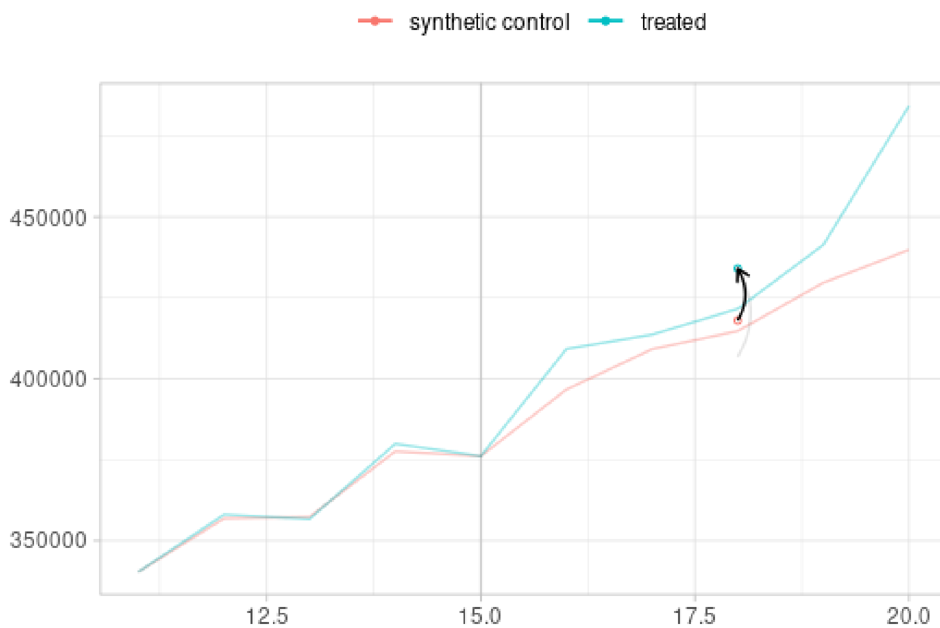


Figure 14: Figure depicting synthetic difference-in-difference results (overlayed for clarity) showcasing the initiative's estimate impact on increasing Buprenorphine dispensing in the Philadelphia metro.