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ABSTRACT

Effect of Enforcement Shock on Pushers' Activities: Evidence from an Asian Drug-Selling Gang*

We study a Singaporean drug-selling gang's dataset and empirically find that the gang's pushers purchased larger quantities of drugs during periods of enforcement shocks caused by enforcement activities targeting the gang's drug supply chain. This counter-intuitive finding can be explained by the pushers' profit targeting behavior. Given that enforcement shocks increased the pushers' cost of drugs, pushers must compensate by purchasing more drugs to sell in order to reach their profit targets.

JEL Classification: J46, K42

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1 Introduction

Drug gangs are the primary distributors of illegal drugs to end users in the United States, Europe and Asia. These gangs commit large numbers of violent crimes everywhere they operate.[1] Many countries have invested significant resources to combat these gangs. Yet, the effect of enforcement on such gangs remains an open question.

To answer this question, we use a dataset acquired from a transnational drug gang's books. The dataset traces the gang's operations in Singapore during the 1990s. The gang had a monopoly in crystal meth, more commonly known as "ice", and sold several other types of drugs such as ketamine, ecstasy and erimin. The boss of the gang supplied drugs to assistants who served a function similar to drug wholesalers, as these assistants later sold drugs to individual pushers. Pushers, in turn, sold drugs to end users. Our data covers every pusher's characteristics, all transaction details between assistants and pushers, as well as records of enforcement activities that specifically resulted in the arrest of its drug smugglers, hence disrupting the gang's supply chain. These enforcement activities first began in the third month after the gang's formation and lasted for nine weeks.[2] Henceforth, we refer to these enforcement activities as the "enforcement shock" and the nine-week period as the "enforcement shock period". We confirm that an enforcement shock actually occurred by matching the quantities confiscated by the authorities and the time period it occurred with official media announcements.

By using regression discontinuity design, we confirm that the enforcement shock was an exogenous supply shock to the gang. It pushed up the cost of drugs for assistants by 12-16%, and the price of drugs the assistants sold to the pushers by 5-10%. These increases in cost and price are consistently observed under different regression specifications and lasted for nine weeks. Owing to the gang's monopoly in the ice market, assistants passed through 87% of the cost increase of ice to pushers and this high pass-through rate remained unchanged throughout the enforcement shock period.[3] Despite the inflation in prices, donut RD and fixed effects regression together reveal that pushers exhibited abnormal demand responses. They did not decrease the demand for drugs, as predicted by the neoclassical demand theory. Instead, they demanded more of the drugs. This demand pattern is particularly pronounced for *early pushers*, the group of pushers who joined the gang before the enforcement shock hit. They responded by demanding 18% more of ice and ketamine, and 12% more of erimin.

[1] National Drug Intelligence Center [2009] states that gangs are the primary distributors of illegal drugs on the streets of America. Goldschein and McKenna [2012] note that the FBI says gangs commit 48% of violent crime, and are only becoming more dangerous. According to Lai [1982], the Singaporean drug gang "Ah Kong" was one of Europe's most notorious criminal organizations and controlled the European heroin trade in the 1970s. "It murdered and tortured in cold blood, annihilating all competition."

[2] This is not to say that enforcement shocks occurred every day and lasted for nine weeks. Rather, it means that the impact of the shocks lasted for nine weeks. In our dataset, the gang kept a blacklist of pushers who were unhappy about the price hike and who complained about the difficulties that they faced selling drugs during the time period.

[3] This high pass-through rate is estimated using the group of pushers who joined the gang before the enforcement shock occurred, the subsample of interest in this paper.

This counter-intuitive response can be explained by applying a theory of profit targeting. Our dataset indicates that 30% of the *early pushers* were heavy drug abusers. We verify whether pushers were profit targeting by comparing the drug purchasing behavior of pushers who were heavy drug addicts with pushers who were not. We find that pushers in the former group demanded 22% more of ice and 9% more of ketamine and erimin during the enforcement shock period compared with the latter group. As a robustness check, we further examine *early pushers*' demand behavior as the prices reverted back to the original level towards the end of the enforcement shock period. They consistently exhibited profit targeting behavior by demanding less drugs as the price of ice dropped. All reported results about the pushers' drug purchasing behavior are estimated using fixed effects regressions after controlling for market demand conditions, positive supply shocks, pushers' fixed effects and transaction details. They remain strong under different specifications. Qualitative interviews with ex-convicts also confirm the profit targeting behavior of pushers.

The end users' demand for drugs is largely fixed in the short run. With subdued profit margins, the only way for a pusher to meet his profit target is to sell drugs to more end users. One way the pusher could achieve this is via the substitution effect. That is, as some pushers exit the market due to enforcement shocks, each of the remaining pushers can acquire more market share. We find this scenario implausible for two reasons. First, 90% of pushers who were active before the enforcement shock continued trading during the enforcement shock period. The market share given up by the pushers who exited the market was not sufficient for the remaining active pushers to achieve their profit targets. More importantly, the total weekly quantity of ice sold by the gang did not stay the same but increased by 53% during the enforcement shock period.

A more likely explanation is that pushers acquired more buyers by venturing into the rival gangs' territories. This was a very costly action that pushers would not normally adopt because it could result in violent clashes, leading to the pushers' deaths or arrests. Pushers would only implement this strategy under extreme circumstances - when they face difficulties meeting their profit targets. This is because when a pusher who is a drug addict himself was desperate for drugs, he would do anything to attain his profit target to feed his addiction.

We observe that *early pushers* who had experienced the shock (i.e., had traded at least once during the enforcement shock period) are 47% more likely to exit the market due to arrest, as opposed to quitting or getting fired. This is a conservative estimate, because there may be cases where pushers exited the market due to arrest without the gang's knowledge. If a pusher was arrested because he clashed with a rival gang, he must have been arrested during the shock period or in the month following the shock period. It is similar to Dell [2015] whereby an effort by the authorities to clamp down on incumbent drug gangs resulted in violence because rivals wanted to usurp the weakened incumbents.

In rival territories, the gang's pushers mainly sold ice. Pushers continued to sell other drugs that the gang did not have monopoly power over, but did not purchase more of these drugs as they did for ice. That is because ice was still new to the market, and there was sizeable untapped potential in rival territories that these pushers could capture. In the case of other drug types, the market was very competitive and saturated, as the same drugs were sold across the island. Furthermore, because lower profit margins eroded the pushers' competitive edge, it would be challenging to sell non-monopoly drugs in rival territories.

Studying this drug gang has far-reaching implications from a policy-making perspective. Enforcement activities targeting the supply chain of a drug type that a gang holds monopoly over may have unexpected consequences, such as more violence. However, we may not observe this negative outcome if enforcement affects the supply chain of non-monopoly drugs in highly competitive and saturated markets.

Singaporean drug gangs have a long history of dominating the drug trade in many regions of the world.[4] According to market insiders, the drug gang we study was part of a transnational drug gang that operated in many Asian nations. Furthermore, many transnational drug gangs have operations similar to this gang. Hence, our findings about this gang are applicable to other transnational gangs that operate in Asia.[5]

We show that a conventional model of crime and punishment cannot capture the findings we have described in the previous paragraphs. We develop a benchmark model in which a pusher determines the quantity of drugs that he demands from an assistant to sell in the market, as well as the effort he devotes to developing his market territory. When enforcement activities cause an increase in the cost of drugs, thereby eroding the pusher's profit margins, the pusher reacts by demanding fewer units of drugs and shrinking his market territory. However, this result is not consistent with our empirical findings. We therefore extend this benchmark model by assuming that the pusher is subject to a profit target constraint. In reality, the presence of this profit target is because the pusher has to raise enough money to repay significant outstanding debt, or face severe penalties. In this case, when enforcement activities increase the cost of drugs, the pusher who has a binding profit target constraint will demand more drugs and expand his market territory. We find that this model's prediction fits our empirical findings more accurately.

The remainder of the paper is organized as follows. Section 2 provides the institutional background of the gang and the enforcement shock that the gang experienced. Section 3 gives an overview of the relevant literature. Section 4 describes the theoretical model providing explanations for why enforcement shocks could cause pushers to purchase more drugs, followed by data description in Section 5. Section 6 empirically identifies the enforcement shocks and sets up an estimation strategy for demand analysis. Section 7 presents an analysis of key results and Section 8 concludes the paper.

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[4]We share the information we found on one such publicly known Singaporean drug gang, "Ah Kong", that dominated the heroin trade across Europe in the 1970s. Refer to Supplementary Appendix Section 3.2.

[5]Refer to Supplementary Appendix Section 3.1 for corroborating evidence we have obtained from interviews that support the claims regarding the generalizability of our findings.

2 Background

Official data and sources on the Singaporean drug market that existed during the 1990s are scarce and limited. To supplement gaps in the available knowledge, we have spoken to government agencies, charities and over 100 ex-drug convicts who have information about this market during this particular time period.[6] This section is a summary of all the information we have collected.[7]

2.1 Drug-selling Gang

According to market insiders, a few gangs dominated the drug market in Singapore during the 1990s.[8] Collectively, these gangs held approximately 75% market share of the entire drug market. To maximize profit, the gangs divided Singapore into different locations and each gang only sold drugs in their respective areas of influence. Should a gang try to sell drugs in a rival gang's territory, turf wars would break out as each gang sought to protect its own territory. These turf wars were violent and could lead to death. For example, The Straits Times [2002] records the death of a pusher due to a turf war.

A report on drug raids, The Straits Times [2001], notes a multitude of drugs confiscated, indicating that each gang sold several types of drugs. This is because most drug users used a combination of drugs. For instance, the Central Narcotics Bureau [2018] in Singapore reports that ecstasy is often mixed with ice or ketamine. According to High Court Case [1997] and High Court Case [2000], ice, heroin, ecstasy and erimin were the most popular drugs in the 1990s. By market informants as well as media reports (e.g., Lee [2007], Tan [2018]), all the drugs sold in the Singaporean drug market were produced in countries outside of Singapore.

The gang we study was a new entrant to the drug market in the 1990s but quickly established a monopoly over ice in Singapore. It also sold ketamine, ecstasy, erimin and small amounts of heroin to end users. The gang had its supply of ice, ketamine and erimin directly from overseas counterparts, because it was a franchise of a transnational drug gang that produced and trafficked these drugs across Asia. Supplies of ecstasy, however, were purchased from other players in the local Singaporean drug market.

The gang had three main layers in its hierarchical structure: the boss, assistants, and pushers. This structure was also common among other gangs. The boss of the gang was the mastermind behind the gang's drug business. He oversaw the entire gang's drug trade in Singapore, including securing the drug supply. Assistants acquired their drugs from the boss, and each assistant sold drugs to pushers. Pushers

[6]We have documented in detail the different channels we have exhausted in Supplementary Appendix Section 1.2.1. We also include the interview questions and responses we have received from the market insiders surveyed in Supplementary Appendix Section 1.2.2.

[7]Refer to Supplementary Appendix Section 1.2.3 for an overview of five empirical papers that have conducted interviews with vulnerable survey respondents. We discuss the methodology and ethical procedures these papers observed during the data collection process and compare our study's approach with these papers.

[8]Examples of these gangs and corresponding newspaper reports of their drug offences are provided in Supplementary Appendix Section 3.3, Table 1.

then sold drugs to individual end users. In the gang, each assistant recruited pushers independently and formed exclusive trading relations with pushers. However, pushers had the discretion to exit the gang without incurring any punishment.

Pushers entered the drug market mainly to earn as much money as possible. The ex-convicts we interviewed said that pushers had some profit targets to achieve because many of them were drug addicts who borrowed frequently from unlicensed moneylenders. These pushers were desperate for money and selling drugs was the most viable way for them to earn enough money to service their loans in a short period of time or feed their drug cravings.[9] This is consistent with media reports. For example, Hussain [2015] documents the case of a drug trafficker who trafficked drugs to pay off debts owed to unlicensed moneylenders.

Despite the severity of Singapore's drug laws, borrowers such as these pushers would rather sell drugs and try their luck with the authorities rather than default on debt with unlicensed moneylenders. This is because punishment is unavoidable if borrowers default on the illegal loans. Unlicensed moneylenders will force borrowers to repay the debts even if it means burning the borrower and the borrower's family members alive. For example, Loh [2015] writes that a group of four youths was arrested for involvement in "a series of island-wide loan shark harassment involving setting of fire and locking of gates." According to Asia One [2015], "For many, the long-term mental torture and harassment from unlicensed moneylenders is simply too much to bear." Thus, borrowers who reach a breaking point will often view pushing drugs as a preferable choice even though pushing drugs is punishable by death.

2.2 Enforcement

The Central Narcotics Bureau is the authority charged with executing the drug laws of Singapore, and its area of purview includes launching raids to crack down on drug trafficking and drug dealing.[10] Raids can be classified into either individual raids that happen at a specific location or island-wide raids that occur across several different locations over Singapore. An individual raid is normally conducted by 3 to 10 CNB officers, and typically results in the arrest of 1 to 20 individuals. For example, in an individual raid that happened in October 1999, 7 CNB officers were involved in arresting 5 suspects caught consuming heroin [Vasoo, 1999]. In a separate raid that occurred in December 1999, 8 CNB officers arrested 7 drug addicts [Chua, 1999]. Compared to individual raids, island-wide raids are much bigger in scale because they often involve dismantling a syndicate or arresting at least 50 drug offenders. For example, The Straits Times [1997] states that in an operation, more than 100 CNB officers worked to arrest 87 drug users. Similarly, Leong [1998] writes

[9] One ex-convict stated, "I was a drug addict and owed some loan sharks a lot of money. I begged my drug dealer to bring me into the market. I had no other choice."

[10] Singapore's drug laws are very strict. For example, Amnesty International [2004] states that the numbers of drug-convicts who faced death sentence in years 1997, 1998, and 1999 were 11, 24, and 35, respectively. We document the evolution of Singapore's drug laws during the 1990s in Supplementary Appendix Section 2.1, and provide some examples of sentences the courts meted out to drug traffickers in Supplementary Appendix Section 2.2.

that in September 1998, more than 100 CNB officers were involved in an island-wide operation where 165 people were arrested.

Raids can result in the arrest of three types of drug criminals: drug users, drug sellers and drug smugglers. Raids can also result in the confiscation of drugs, but not always. Some of the drugs may have been destroyed by the traffickers as the authorities are conducting the raids. For example, The Straits Times [1998] reports that a criminal tried to set fire to a packet of drugs when the authorities were breaking in to arrest him.

The enforcement shock we study in this paper refers to the arrest of a group of drug smugglers that supplied drugs to the drug-selling gang of our interest.[11] According to market insiders, the gang paid the drug smugglers in advance for several separate large shipments of different drugs. These shipments were smuggled into Singapore from overseas via different individuals. This was a form of risk diversification, as the loss to the gang would be minimized if any of the shipments were compromised.

In our gang's case, the authorities claimed to have received a tip-off that enabled them to take action against the suspected leader of the smugglers and to seize large amounts of drugs. The leader of the smuggling ring was arrested while he was in a cab, and forced to lead the authorities to his apartment where they confiscated large amounts of drugs. Because the leader could no longer oversee the fulfillment of all remaining shipments, the gang lost all the cash it paid and its drug supply. Furthermore, it took time before the gang could locate another trustworthy supplier. Thus, the gang had to raise the prices of the drugs on hand to recover losses.

However, many pushers were unhappy with the hike of prices even after the assistants explained it was due to enforcement raids. The gang's boss instructed all assistants to record the names and dates of the pushers making such complaints, thus forming a list equivalent to a blacklist. With this information, we know that when there were no complaints recorded, there was no longer an increase in prices, and the effects of the enforcement shock had subsided. Since the majority of the gang's pushers were saddled with debt, they had no choice but to continue selling drugs even with the price increases and heightened risk of arrest.[12]

3 Literature Review

Our paper contributes to the studies that investigate the various effects of enforcement on drug-related activities in three specific ways.

First, many empirical studies disagree when it comes to evaluating the effectiveness of supply-side enforcement that aims to reduce drug consumption by increasing drug prices. Using different data sources, some studies suggest that enforcement is less effective than expected (e.g., DiNardo [1993], Yuan and Caulkins [1998], Miron

[11] We verify that this enforcement activity did occur by matching newspaper articles with the records observed in the gang's dataset. See Section 5 for more details.

[12] According to Chu [2002], Johnny Koh, who served a 27-year jail sentence in the United States for running a crime network that stretched from Southeast Asia to South America, mentioned that the loss of heroin shipments due to raids did not discourage him from continuing the business. Rather, it only pushed him to sell more drugs to make up the losses.

[2003]). Other studies, such as Dobkin and Nicosia [2009], have produced contrarian views. Dobkin and Nicosia [2009] document a case where sudden government intervention in the U.S. to reduce the supply of methamphetamine precursors was effective, resulting in a sharp increase in the price and a drastic reduction in the purity of methamphetamine, as well as a significant decline in both the usage and felony arrests of methamphetamine. However, the impacts were largely temporary. Most of these studies mentioned have two main drawbacks. In addition to drawing information from different datasets, such studies also tend to rely only on proxies of drug demand and supply, and not actual variables. We contribute to this literature by using one comprehensive dataset that contains actual variables from an actual drug-selling gang. Thus, our study is not susceptible to potential errors that could arise from proxy selection or incompatible datasets.

Second, our paper is related to the studies that discuss the effects of enforcement on the behavior of drug market participants. Galenianos et al. [2012] build a search-theoretical model to study the roles that search frictions and moral hazard play in the drug market. They show that enforcement penalizing the drug sellers and reducing drug accessibility in the market may improve the quality/price ratio of drugs and strengthen the long-term relationship between sellers and buyers. Galenianos and Gavazza [2017] use a structural estimation model to quantify the findings in Galenianos et al. [2012]. They find that if drugs could be legalized and drug quality could be regulated, the average drug quality would improve significantly and the dispersion of drug quality would also reduce. Jacobi and Sovinsky [2016] also use a structural estimation model to highlight the role that limited accessibility to drugs plays in individuals' drug consumption decisions. They show that if marijuana is legalized in Australia resulting in open accessibility to all, marijuana use would increase by almost half on average. Counterfactual analysis also indicates that taxing marijuana would be effective in curbing the use of marijuana as well raising substantial tax revenue. Unlike these studies which deal with counterfactuals or structural estimation models, we use transaction-level data obtained directly from a gang to study a problem that other scholars have thus far not been able to study. By combining our dataset with data on enforcement activities, we can more accurately study how enforcement directly affected the behavior of the gang's drug-selling activities.

Third, we demonstrate unintended spillover effects from drug enforcement policies, contributing to an area that the literature has also focused on. For example, Adda et al. [2014] show that a policy experiment in a local area in London that decriminalized the possession of small amounts of marijuana enabled the police to redirect their efforts toward other crimes. The policy led to a reduction of all types of crimes overall and improved police effectiveness as measured by arrest and clear-up rates. However, the total welfare of the area likely fell as measured by house prices. Another study, Dell [2015], uses mayoral election outcomes in Mexico and a network model of drug trafficking to study the direct and spillover effects of policy efforts on drug-related violence. She finds that due to increased conflicts between rival traffickers and incumbent traffickers, drug-related violence increased substantially both in the places that directly experienced policy crackdowns, as well as along the alternative routes that policy crackdowns had diverted drug trafficking to.

Our study is similar to these papers in the sense that we are able to document the unintended policy consequences of enforcement on a drug-selling gang. Specifically, we show that if a drug-selling gang has a monopoly on a certain type of drug and if enforcement causes the monopoly gang's cost and price to increase, gang members will buy more drugs to sell and expand into rival gang's territories thereby causing violent turf wars to break out. To our knowledge, our finding has not yet been documented in the literature before.

More broadly, our paper is related to the literature studying the effect of enforcement on crime. These include studies that examine whether aspects such as the number of police officers [Levitt, 2002], police composition [McCrary 2007, Miller and Segal 2014] or high visibility patrolling [Di Tella et al. 2004, Klick and Tabarrok 2005, Evans and Owens 2007, Draca et al. 2011] are associated with a reduction in crimes. These previous works do not have information on crimes that are unknown to the authorities, whereas we have all the transactions conducted by a criminal organization. As far as we know, Levitt and Venkatesh [2000] is the only other paper that has a dataset collected directly from a drug-selling gang.

Our model is related to the literature on reference-dependent preference. In their seminal works, Kahneman and Tversky [2013] and Tversky and Kahneman [1991] suggest that an individual's preference responds not only to the absolute value of income but also to a reference point, and the preference features loss aversion such that the individual is more sensitive to losses (when income is below the reference point) than to gains (when income is above the reference point). Kőszegi and Rabin [2006] formalize the reference point as an individual's rational expectations and show that an individual's labor supply responds negatively to unanticipated income changes, but reacts positively to anticipated income changes. Using different datasets on the daily labor supply of New York City taxi drivers and different empirical methods, Camerer et al. [1997] and Crawford and Meng [2011] find evidence consistent with reference-dependent preference, while Farber [2005, 2008, 2015] show that reference-dependent preference is not an important factor in the labor supply decisions of the drivers. Other studies also disagree on the effects of income changes on labor supply decisions. In line with reference-dependent preference, Fehr and Goette [2007] show reduced effort by bicycle messengers in response to increased commissions. In a real-effort experiment, Abeler et al. [2011] show that an individual's behavior is driven by expectation-based reference-dependent preference. On the other hand, Oettinger [1999] finds increased labor participation by stadium vendors on days that wages are higher. Similarly, Stafford [2015] finds that fishermen work more when earnings are temporarily high. Our study contributes to this line of discussion by investigating how the reduction of drug-selling returns affects individuals' labor supply in drug-related activities.

4 Model

In this section we investigate the effects of enforcement shocks on the pushers' drug-demanding activities with two simple models. The benchmark model follows Becker [1968], in which we show that a pusher demands fewer units of drugs to sell in the market when there is an increase in enforcement activities. However, the results are not consistent with our empirical findings. We extend the benchmark model by introducing a profit target to the pusher's decision problem and show that if the profit target binds the pusher's drug-demanding decision, he demands more units of drugs when there is an increase in enforcement activities.

4.1 Benchmark Model

A pusher (referred to with the pronoun "he") determines the quantity of drugs q he purchases from an assistant to sell in the drug market as well as the effort level t he devotes to developing his market territory. The pusher's expected utility, denoted as $u(q,t)$, is given by

$$u(q,t) = p(q,t)q - c(e)q - d(t) - a(q)k$$

$p(q,t)$ is the price per unit of drugs sold in the end users market. e is the level of enforcement activities carried out by the authorities to prevent the gang from getting drugs, and $c(e)$ is the cost per unit of drugs purchased from the assistant. $d(t)$ is the cost of effort that the pusher incurs to expand his territory. Lastly, with probability $a(q)$ the pusher is arrested. After being arrested, the pusher receives a penalty, such as imprisonment, which generates disutility k to him.

We make the following assumptions to simplify the analysis. $p_t(q,t) > 0$ and $p_{tt}(q,t) < 0$, where here and in what follows we let subscripts denote partial derivatives. With a larger territory, the pusher can sell his drugs at a higher price. However, this increase of price diminishes as the territory enlarges. $p_q(q,t) < 0$ and $p_{qt}(q,t) \geq 0$. Hence, although the price decreases in the quantity of drugs for sale, this decrease of price is alleviated as the territory becomes larger. Functions $c(e)$, $d(t)$ and $a(q)$ are all differentiable and strictly increasing in their arguments. Moreover, both $d(t)$ and $a(q)$ are convex.

We also assume that $u(q,t)$ is strictly concave and reaches its maximum at a unique profile $(q^*,t^*) \in \mathbb{R}^2_+$, where $u(q^*,t^*) > 0$ so the pusher's participation is satisfied. In this case, the profile (q^*,t^*) is determined by the first-order conditions:

$$u_q(q^*,t^*) = p_q(q^*,t^*)q^* + p(q^*,t^*) - c(e) - a_q(q^*)k = 0$$

and

$$u_t(q^*,t^*) = p_t(q^*,t^*)q^* - d_t(t^*) = 0$$

The comparative statics $\partial q^*/\partial e$ and $\partial t^*/\partial e$ are then given as follows:

$$\frac{\partial q^*}{\partial e} = \frac{u_{tt}(q^*,t^*)c_e(e)}{u_{qq}(q^*,t^*)u_{tt}(q^*,t^*) - u_{qt}(q^*,t^*)u_{tq}(q^*,t^*)}$$

and

$$\frac{\partial t^*}{\partial e} = \frac{-u_{tq}(q^*,t^*)c_e(e)}{u_{qq}(q^*,t^*)u_{tt}(q^*,t^*) - u_{qt}(q^*,t^*)u_{tq}(q^*,t^*)}$$

Strict Concavity of $u(q,t)$ implies that the denominator of these equations are positive. Moreover,

$$u_{tt}(q^*,t^*) = p_{tt}(q^*,t^*)q^* - d_{tt}(t^*) \quad \text{and} \quad u_{tq}(q^*,t^*) = p_{tq}(q^*,t^*)q^* + p_t(q^*,t^*)$$

Given the assumptions made above, $u_{tt}(q^*, t^*) < 0$ and $u_{tq}(q^*, t^*) > 0$. Therefore,

$$\frac{\partial q^*}{\partial e} < 0 \quad \text{and} \quad \frac{\partial t^*}{\partial e} < 0$$

The reasoning of these results is intuitive. By demanding one additional unit of drugs to sell in the market, the pusher's profit increases by $p_q(q,t)q + p(q,t) - c(e)$. However, his probability of being arrested increases by $a_q(q)$, in which case he suffers the penalty k. The optimal quantity of drugs q^* to demand from the assistant is obtained when these two effects offset each other. Similarly, by expanding his market territory slightly, the pusher's revenue increases by $p_t(q,t)q$, while the additional cost of effort he incurs is $d_t(t)$. The optimal level of effort is reached when these countervailing forces cancel out. An increase in enforcement activities has a direct effect of reducing the profit margin of selling drugs, hence it is optimal for the pusher to demand fewer units of drugs to lower the risk of being arrested. Indirectly, demanding fewer units of drugs leads the pusher to optimally shrink his market territory to reduce the cost of effort. We summarize the results in the following proposition.

Proposition 1. *The pusher demands fewer units of drugs from the assistant and shrinks his territory when there is an increase in enforcement activities.*

4.2 Profit Targeting Model

In our dataset, more than half the pushers were borrowers who were saddled with debt. Without sufficient profits from selling drugs, these pushers may fail to repay their debts and suffer large disutilities. Following the literature on reference-dependent preference, we modify the benchmark model to incorporate the idea of profit targeting.

Denote $m^T > 0$ as the pusher's profit target. The pusher's expected utility is now given by

$$u(q,t) = \left\{ \begin{array}{cl} p(q,t)q - c(e)q - d(t) - a(q)k & \text{if} \quad p(q,t)q - c(e)q - d(t) \geq m^T \\ -l - a(q)k & \text{if} \quad p(q,t)q - c(e)q - d(t) < m^T \end{array} \right\}$$

Therefore, if the pusher's profit falls short of the target, he suffers a disutility l.[13] Everything else in the benchmark model remains unchanged.

Let $(q^{**}, t^{**}) \in \mathbb{R}^2_+$ denote the quantity of drugs and effort level that maximize the pusher's expected utility in the presence of a profit target.[14] Notice that if the

[13]We take the cost of effort $d(t)$ as pecuniary, so it is deducted in the calculation of profits. It could be the case that the pusher has to bribe managers of entertainment venues for having access to these venues, or has to pay market informants for the referrals of new drug users in order to expand his market territory. The qualitative results are unchanged if this cost is non-pecuniary, such as the cost of fights against rivals.

[14]Here we implicitly assume that there exists a profile (q^{**}, t^{**}) such that

$$p(q^{**}, t^{**})q^{**} - c(e)q^{**} - d(t^{**}) - a(q^{**})k \geq -l$$

Thus, the profit target is reachable and participation in the market is profitable. If such a profile does not exist, the pusher will optimally opt out of the market.

profile (q^*, t^*) in the benchmark model satisfies $p(q^*, t^*)q^* - c(e)q^* - d(t^*) \geq m^T$, then $(q^{**}, t^{**}) = (q^*, t^*)$. In this case, the profit target imposes no restriction on the pusher's optimal drug-demanding activities, and the effects of enforcement shocks described in Proposition 1 still hold. However, if $p(q^*, t^*)q^* - c(e)q^* - d(t^*) < m^T$, the profile (q^*, t^*) does not generate enough profit for the pusher, and therefore is no longer optimal. Instead, in this case the optimal profile (q^{**}, t^{**}) is determined by

$$p(q^{**}, t^{**})q^{**} - c(e)q^{**} - d(t^{**}) = m^T$$

and

$$p_t(q^{**}, t^{**})q^{**} - d_t(t^{**}) = 0$$

The profit target constraint should be binding. If the left hand side of this constraint is strictly larger, then the pusher can reduce the quantity of drugs slightly to lower the risk of being arrested without violating the profit target. Besides, the first-order condition regarding the market territory should also hold, otherwise the pusher can adjust his territory size to increase his profit.

The comparative statics $\partial q^{**}/\partial e$ and $\partial t^{**}/\partial e$ are now given as follows:

$$\frac{\partial q^{**}}{\partial e} = \frac{c_e(e)q^{**}}{p_q(q^{**}, t^{**})q^{**} + p(q^{**}, t^{**}) - c(e)}$$

and

$$\frac{\partial t^{**}}{\partial e} = \frac{\partial q^{**}}{\partial e} \cdot \frac{p_{tq}(q^{**}, t^{**})q^{**} + p_t(q^{**}, t^{**})}{d_{tt}(t^{**}) - p_{tt}(q^{**}, t^{**})q^{**}}$$

In these equations, $p_q(q^{**}, t^{**})q^{**} + p(q^{**}, t^{**}) - c(e)$ should be positive, otherwise the pusher can simultaneously increase his profit and reduce the probability of being arrested by selling fewer units of drugs in the market. Therefore,

$$\frac{\partial q^{**}}{\partial e} > 0 \quad \text{and} \quad \frac{\partial t^{**}}{\partial e} > 0$$

That is, with an increase in enforcement activities, the pusher expands his market territory and demands more units of drugs to sell in the market. Intuitively, when there are more enforcement activities, a pusher who wants to hit a profit target needs to sell more drugs to counteract the rise of the cost of drugs, even though this decision also increases the pusher's risk of being arrested. Meanwhile, to alleviate the negative impact of the increased quantity on the price, the pusher chooses to expand his territory accordingly. We summarize these results in the following proposition.

Proposition 2. *If the pusher has a binding profit target, he demands more units of drugs from the assistant and expands his territory when there is an increase in enforcement activities.*

5 Data Description

Our data covers one year of the gang's transactions in its formative year in the 1990s.[15] The dataset is holistic and self-contained in a single book. The first part

[15] Refer to Supplementary Appendix Section 1.1.1 for a description about how we obtained this dataset and how others have also managed to obtain datasets about other drug-selling gangs.

of the dataset covers detailed information about every pusher as well as all transactions between pushers and assistants within the gang. The pushers' information were collected for screening purposes. Keeping transaction records was especially important for the gang because it was in its formative year, and needed data for demand estimation, inventory management and other decision-making purposes. The second part describes how and why the gang recorded information that are relevant to the market conditions, such as enforcement shocks or high demand periods.

The data contains the trading details between 352 pushers and their respective assistants. Assistants were wholesalers who sold drugs to pushers, whereas pushers sold directly to drug users in the retail market. Hence, we only observe drug trades at wholesale level and have no knowledge about the pushers' interactions with end users in the retail market. We can identify each pusher but cannot identify assistants. Trades between pushers and assistants occurred on a weekly basis. We observe a total of 2,767 such trades. 90% of pushers traded with assistants at least 5 times during the data period. A single trade can consist of multiple orders involving the purchases of drugs including ice, ketamine, ecstasy and erimin. We define an order to have occurred when a drug type of a particular quality is purchased in a trade. For example, if a pusher purchased (good quality) ice and (good quality) ketamine in a single trade, we consider two orders to have been made in this trade. If the pusher purchased both (good quality) ice and (very good quality) ice, we would also consider two orders made in this trade. By this accounting rule, there are 8,424 orders made in the data period.[16] The dataset is representative in the sense that it traces every pusher's transaction with assistants since his first drug trade with the gang within the data period. Owing to different entry and exit points, the dataset has an unbalanced panel structure.[17]

Pushers' Characteristics

The pushers' personal characteristics were gathered by the gang at the time of recruitment for screening purposes. The key statistics on pushers are summarized in Table A1. Pushers were mostly ethnic Chinese males and only a handful were Indian males. Their age ranges from 19 to 52, with a mean of 32. Only half of the pushers held full time jobs, and they made an average of S$1,488 a month.[18] Around 66% of the pushers were gang members and about 60% of the pushers had been arrested prior to becoming pushers.

Pushers also exhibited certain behavioral patterns. 69% of pushers were addicted to drugs before becoming pushers and half of these addicts had previously undergone drug rehabilitation. Of those who had undergone drug rehabilitation, 90% had spent

[16] There are 9,133 orders recorded in the book. We exclude 5% of orders relating to some less popular and unidentifiable drug types. Moreover, we exclude a handful of trades that occurred in the year after the specific calendar year we mentioned above because we only have this limited information about the gang in this year.

[17] In Supplementary Appendix Section 1.1.2, we provide an explanation of how we obtained permission from the different agencies required before we could use the data.

[18] The average monthly wages in Singapore ranged from S$1500-S$3000 during the 1990s. (Source: TradingEconomics.com). SGD/USD during the 1990s was 0.55-0.70. (Source: http://www.canadianforex.ca/forex-tools/historical-rate-tools/yearly-average-rates).

at least one year in rehabilitation. A substantial number of pushers were heavy borrowers who were saddled with debt. Over half of the pushers had gambling habits. A market insider we interviewed shared that these are main reasons why one would want to become a pusher. Assistants made remarks on the pushers' exit from the gang, if any. Over a third of the pushers exited because they were caught by the authorities, whereas 57% quitted of their own volition. The reported arrest rate is a conservative estimate that is likely to represent the lower bound of actual arrests, because assistants may not have observed all arrests. Only 7% were fired by assistants. The average trading tenure of the pushers within the gang was five months.

Order-Level Characteristics

Table 1 summarizes the key information we observe on transactions related to four types of drugs. Ice sales comprised 42% of all orders, followed by ketamine (23%), ecstasy (21%) and erimin (15%). During the 1990s, ice was a new synthetic drug in Singapore and was most expensive in terms of both cost and price. One gram of ice cost assistants about S$84, and it was sold to pushers for about S$156. Cost refers to the price at which assistants bought drugs from the boss. Pushers have no knowledge about the assistant's cost. However, when we mention price, we specifically refer to the price that assistants sell drugs to pushers. Therefore, the price we study in this paper is the wholesale price of the drug because we do not observe the retail price of the drugs. The cost and price of ice were roughly 4 to 5 times higher than other drugs. The average quantity of ice sold in an order was 11 grams, which was also about four times smaller than the quantities of other drugs. Despite the relatively smaller quantity sold, ice was the staple of the gang. Assistants added a markup of about 50% to 90% on the drugs, and made about S$400-S$700 profit from each order. Because of the high storage cost of drugs, assistants received piecemeal supplies every few days. Hence, the costs and prices of drugs we observe reflect the most recent drug market conditions.

The drugs sold by the gang were all addictive, but they differed in potency and effect. We do not have the exact measure of purity, but the gang recorded whether the quality of each drug was average, good or very good. The majority of ecstasy and erimin was of good quality. There was no ice or ketamine of average quality. There were no prevalent modes of delivery for drugs. Pushers collected the drugs in person half of the time, while assistants delivered them to pushers the other half of the time.

Drugs can be broadly classified into three main categories: stimulant, depressant and hallucinogen. Ice and ecstasy are stimulants, while ketamine and erimin are depressants.[19] It was common for drug users to use a combination of drugs. Pushers purchased at least two types of drugs in 70% of trades, and purchased all four types of drugs in nearly one third of trades. In trades where only one type of drug was bought, ice was most often the drug of choice. Mixing drugs creates an addictive effect which provides users both the dissociative sedation of a depressant and the energy of a stimulant. The tendency of drug users to mix drugs was reflected in the pushers' trades.

[19]Ketamine is often classified as a hallucinogen as well.

Gang's Records on Events

It is well documented that it is common for gangs to keep detailed records. For example, apart from business transactions, gangs kept information about gang members, assassination targets, the payments made to corrupt officials, recipes for manufacturing drugs and personal recollections of running a gang.[20] The gang we study is no exception. Apart from recording business-related and pusher-related details, it also recorded the feedback from the pushers and whether pushers complained about price hikes. Leveraging these records, we are able to identify the periods when the gang experienced a positive supply shock and high demand. By consolidating the records with newspaper articles, we can also identify the occurrence of enforcement shocks.

Demand Surge

In the gang's records, there are two periods during which the gang recorded major demand surges. These dates are in the middle of January until the end of February, and December of the same year. These time periods coincide with major holiday seasons in Singapore. For example, New Year's and Christmas occurred in late December to early January, while the Lunar New Year fell in January or February. During these festive periods, end users were more likely to have extra funds from festive bonuses, and extra leisure time to use drugs due to public holidays. We learn about the demand surge during these periods by reading the assistants' remarks in the books. An example of a typical remark would be an assistant writing about a pusher's feedback about which nightclub was hosting a big Christmas party and which drugs were popular. These remarks helped the gang learn more about market demand and to improve inventory management for future demand surges. Whenever we observed such remarks, we translated them into data and refer to them using the binary variable *DemandSurge*. Note that these records about demand surges were not random isolated events, but reflect an increase in market demand. We prove this quantitatively in detail in the next section.

Enforcement Shock

We learn about the police's enforcement activities through two types of gang records. On one hand, the gang placed marks on days where drugs were not delivered to the gang on time and whether the delay was related to enforcement activities. As the gang was still in its formative years, it did not have sophisticated intelligence-gathering tools such as undercover agents or special technological equipment to verify these enforcement shocks. Instead, the gang relied on a much more traditional method of verifying and understanding what caused delays in their drug supply chain - newspapers and official media. The reason the gang went through the meticulous effort of scanning through newspaper articles is because there were only two possibilities that could have disrupted the gang's drug shipments. First, it could be due to a tip-off from someone within the gang that led the authorities

[20] We provide further examples of such records in Supplementary Appendix Section 3.6.

to launch a successful drug raid that resulted in the arrest of the gang's smugglers. Second, it could be that the gang's smugglers had absconded with the gang's drugs. If the supply disruption was due to a tip-off, the gang could use this information to cleanse the gang of any traitors that provided the information to the authorities. Conversely, if the smugglers stole the goods, the gang could hunt them down and recover the drugs.

One the other hand, the gang also made marks where pushers complained about the price increase of drugs during the trade. The gang did this to keep track of pushers that were likely to cause problems or potentially rebel due to unhappiness over the higher drug prices. If too many pushers complained about the price, then the big boss would have to take action to remedy the situation and pacify the pushers.

We scoured through newspaper articles from the 1990s and found that the articles corroborated with the time periods marked in the dataset. We also found a newspaper article detailing how the authorities arrested a group of drug smugglers, which exactly matches what we observe in the gang's book records. This particular raid happened in April, five weeks after the end of the first demand surge in the records. Other than one day of public holiday (Good Friday), there were no other major holidays in Singapore during that time in April that would have caused a demand surge for drugs. Neither did we find any news reporting police raids that took place in response to the increased demand during this period.

Using these set of marks, we create a binary variable *Enforcement* to indicate an enforcement shock. *Enforcement* captures the incidences where pushers complained about the price hike following the gang's drug supply chain disruption.

Supply Shock

The gang also made similar records during a (positive) supply shock in August. During that time period, the gang's cost of drugs decreased because it found a cheaper supplier, but assistants did not pass on the cost savings to pushers. Many pushers received news that the gang was withholding cost savings from them, and made complaints. Thus, the gang recorded the pushers who made complaints. The rationale was that if only a handful of pushers complained, the gang would have the option of being able to identify these pushers and take the necessary pre-emptive actions. During that time period, there was indeed a small surge in the number of pushers who exited the gang, leading the gang to become concerned about retention rates. We create binary variable *SupplyShock* to indicate the incidences of complains.

Incidence of Events on the Timeline

Variable *Enforcement*, *DemandSurge* and *SupplyShock* are drawn from the records next to each transaction record (i.e., price, quantity sold), and they vary at trade level. We compute the likelihood of the occurrence of these events in each week and plot the patterns in Figure 1. The demand increase occurs over the same months in a year (see the blue triangle on the both side of the timeline). The positive supply shock (see blue dots) takes place in Week 30. As we will soon discuss in Figure 3, the structural impact of the positive supply shock was more long-term and kept the cost of ice low up until the next demand surge in the year.

As for the enforcement shock (represented by orange diamonds), it broke out in Week 13 but its impact lasted for about 8 weeks. The shock impact in fact lasted for about 8 weeks, and was substantiated by the sustained high cost and price level after the shock. We will elaborate more about this in the next section. For convenience, we refer to Week 13-21 as the "enforcement shock period".

6 Identification of Enforcement Shock and Its Impact

6.1 Stylized Facts

An Exogenous Enforcement Shock

By reconciling public news reports and market insiders, we know the gang lost a large incoming shipment of drugs due to the "enforcement shock" in Week 13. To understand whether this event is an exogenous shock, we use regression discontinuity plots to examine the fluctuation in cost and price when the shock occurred. Time of the week is the forcing variable in this context, and we set the cutoff at Week 13 as indicated in the gang's records. Figure 3 depicts RD plots for cost, with each subplot representing one drug type. A common feature of these cost RD plots is that the cost of drug exhibited a discontinuous jump at the cutoff for all drugs, except for ecstasy.[21] The elevated costs remained high for 8 weeks before reverting to pre-shock levels. This 8-week time window perfectly coincides with the "enforcement shock period" indicated by the gang's records. In addition, similar pattern of jumps are observed in the prices of ice and ketamine, as depicted in Figure 4.[22] These pronounced sudden jumps in drug cost and price strongly suggest that the enforcement shock is an exogenous shock to the gang's business. We will discuss in detail why no price jump is observed in ecstasy and erimin later.

Pushers' Abnormal Demand Response

The pushers' demand followed an increasing trend over time. To learn about the pushers' demand response to price changes, we present the movement of de-trended

[21] As explained in Section 2, the gang we study had its own overseas supply of ice, ketamine and erimin, but purchased ecstasy from a supplier in the local market. We observe a sudden drop in the cost of ecstasy when the enforcement shock impacted the gang. This drop is because the gang purchased more ecstasy from the local supplier as a reaction to the enforcement shock. We will discuss more about ecstasy in Section 7.

[22] A uniform kernel and polynomial degree of 3 were chosen as they fit the data better. We have experimented with various bandwidths and bin sizes using methods suggested by Calonico et al. [2014], Hirth et al. [2016] and Calonico et al. [2017]. The family of Mean Square Error (MSE) - optimal bandwidth selection methods yield similar suggestions and RD plot are produced using the suggested optimal bandwidths. RD plots look similar when using bin size suggested by different selection methods. The RD plots presented in this paper use the bin size that is selected based on an evenly spaced mimicking variance number of bins using spacing estimators

demand against price in Figure 5. Few interesting observations emerged: Overall, there is a moderate negative relationship between the price and quantity demanded. This could be due to be addictive nature of drugs as a consumption good. Sometimes, the pushers' demand responded to noticeable price changes occurred after a week. Facing enforcement-induced price hikes, pushers exhibited abnormal demand patterns. Very intriguingly, pushers increased demand for ice as the price hiked, and this demand remained at the same level for 4 weeks before dropping back below pre-shock levels. The pushers' demand for ketamine also increased slightly, although this increase was not as pronounced and stable as for ice. The enforcement shock pushed up the price for erimin slightly, but it did not interrupt the increasing trend of the pushers' demand for erimin. Moreover, pushers had a very dramatic increase in demand for ecstasy after the enforcement shock hit. Even though increased demand was expected given the sliding price of ecstasy, this exaggerated demand increase was never observed again in later weeks when similar price slides occurred. In a neoclassical model, one would expect a drop in the pushers' demand when faced with a price surge. Nevertheless, we have just documented a set of counter examples to this theory. These observations suggest that conventional demand may not always work, and some behavior models may be more appropriate in explaining the pushers' behavior.

6.2 Identification of Enforcement Shock

The objective of this paper is to examine the true magnitude of the impact of enforcement shock on the pushers' demand, and to investigate whether the pushers' abnormal demand behavior was affected by their profit targets. However, prior to this, we will first confirm the nature of the enforcement shock and to what extent it affected the assistants' cost of drugs, and the price at which assistants sold drugs to pushers.

The Regression Discontinuity Design

Based on observed regression discontinuity jumps in cost and price at the time of the enforcement shock, we continue to adopt regression discontinuity to analyze the cost and price. The validity of RD design hinges on the assumption that neither assistants nor pushers had precise control of the treatment (i.e., enforcement). The density of forcing variable in Figure 2 shows no discontinuity at cutoff validating this assumption. To implement RD design, we use a non-parametric way to consistently estimate the treatment effect of the enforcement shock. We denote X as the forcing variable - the day of the drug trade. We use days instead of weeks as the forcing variable to fully utilize the day-to-day trading information we have in the data. The gang's records suggest that the enforcement shock occurred in Week 13. Thus, we set the cutoff, c, as the first observed trading day in Week 13, which is the 72nd day based on the trading data. We let D denote the receipt of treatment as a function of trading day X. It is a dummy variable with value of 1 if $X \geq c$ and with value of 0 if $X < c$. As suggested by Imbens and Lemieux [2008], executing non-parametric estimation with a rectangular kernel amounts to estimate a local linear regression of the following form over a window of width h:

$$Y = \alpha_l + \tau_1 D + \beta_l T + (\beta_r - \beta_l) D \times T + \epsilon \tag{1}$$

, where $c - h \leq X \leq c + h$ and T equals to $X - c$, which is a transformed X.

Y is the dependent variable, which can be cost or price. τ_1 is the parameter of interest, which captures the treatment effect of enforcement.

Consistent with the RD plot, RD estimates suggest that the enforcement shock caused the drug costs and prices to leap. The choice of kernel has little impact in practice [Lee and Lemieux, 2010]. Nevertheless, we experimented with various kernel and optimal bandwidth selection methods. The estimated sizes of cost and price jumps remain robust. Panel A of Table 2 and Table 3 present RD estimates of the treatment effect. The enforcement shock caused drug cost to surge by 10% for ice, by 10-12% for ketamine and by 9-10% for erimin. It then led to a 10% price jump in ice and 10-14% price jump in ketamine. We detect that there is no significant change in the price of erimin. The RD estimates are obtained using h that are MSERD optimal bandwidth or CERRD optimal bandwidth. The MSERD optimal bandwidth is around 30 days and CERRD optimal bandwidth is short at around 20 days, depending on the drug type. Hence, the RD estimates present the local average changes in cost and price over a period of a month before and after the cutoff. To see how cost and price responded on the day the enforcement shock hit (again, we assume it occurred on the first observed trading day of Week 13), we perform estimation in Equation 1 but with the pushers' fixed effects. Both cost and price responded strongly to the enforcement shock spontaneously. We observe an 18-20% instantaneous cost jump for ice, ketamine and erimin. The price jump is even more exaggerated when the ice price went up by 26%, ketamine price increased by 17% and erimin price shot up by 9%.

The abrupt surge in the costs of drugs in RD estimates is strong evidence to support the claim that the enforcement shock was a random shock to the drug gang. The enforcement shock broke out at Week 13, but its impact on the assistants' cost of drugs and selling prices of drugs to pushers lasted for at least a month.

Nature of the Enforcement Shock

News reports reveal that the enforcement activities caused the arrests of drug traffickers and resulted in the loss of incoming shipments of ice, ketamine and erimin. The timing of the reported enforcement activities corroborates the gang's records. If the enforcement shock indicated in the gang's records is the one reported by the news, then we should also observe that the perceived enforcement shock had equal impact on every assistant's cost and selling price. To validate this, we estimate cost and price in Equation 2 and 3. By comparing and contrasting results using different definitions of enforcement shocks, we pin down the nature of the perceived enforcement shock.

$$C_{ito} = \alpha_1 + \beta_1 Enforcement_{it} + \delta_1 Supply_{it} + \phi_1 Demand_{it} + \gamma_1 G_{ito} + \rho_1 T_{it} + \epsilon_{ito} \tag{2}$$

$$\begin{aligned} P_{ito} = {} & \alpha_2 + \beta_2 Enforcement_{it} + \delta_2 Supply_{it} + \phi_2 Demand_{it} \\ & + \eta_2 C_{ito} + \gamma_2 G_{ito} + \eta_2 Q_{ito} + \psi_2 DrugNum_{it} + \Phi_2 X_i + \rho_2 T_{it} + \varsigma_{ito} \end{aligned} \tag{3}$$

, where C_{ito} is the cost (in natural log terms) to the assistant from whom pusher i purchased drugs in order o of trade t, and P_{ito} is the price at which the assistant sold the drug to pusher i.

We use the pushers' fixed effects to estimate both cost and price equations. $Enforcement_{it}$ is the key variable in this equation, representing the existence of an enforcement shock. The parameters of interest are β_1 and β_2. They capture the impact of the enforcement shock on cost and price, respectively. We create two measures to represent $Shock_{it}$: $TradeShock_{it}$ and $Shockwave_{it}$. $TradeShock_{it}$ is drawn straight from the data, hence it is the most crude measure of the shock. It is a binary variable with value of one if a pusher i complained about the drug price when trading with the assistant in trade t, and zero otherwise.

As shown in Figure 1, about 40% of the pushers complained about increased price in the 8 weeks following Week 13. To check if the enforcement shock we study is a shock that impacted all the pushers' trades with the gang, we create $Shockwave_{it}$, which is a binary variable with value one if the trading date falls within Week 13-21 and with value zero otherwise. If the estimates are not statistically different when using $TradeShock_{it}$ and $Shockwave_{it}$, then we can confirm that the enforcement shock had impacted the trades of all pushers within this gang.

Drug cost and price may be directly affected by supply and demand conditions. We control for these market conditions using $Supply_{it}$ and $Demand_{it}$. $Supply_{it}$ is a binary variable that captures the period where the positive supply shock occurred, which falls within Week 30-34. $Demand_{it}$ is a binary variable that indicates the period where demand surge occurred, which falls within Week 0-8 and Week 47-51. Both cost and price vary with the quality of drugs and also exhibit time trends. We further control for these factors using G_{ito} and T_{it}. While the former measures the quality of drugs, the latter indicates the week of the trade. $DrugNum_{it}$ is the number of drugs sold in trade t. We add this variable to reflect the pushers' budget constraints. X_i is the pushers' fixed effects.

Panel C-D of Table 2 display the estimation using $TradeShock_{it}$ and $ShockWave_{it}$, respectively. The estimated effects of the enforcement shock on cost are almost identical under these two measures across drug types. This implies that assistants who were trading with pushers (regardless of whether pushers complained about the price hike) during Week 13-21 all experienced cost increases.

The effect on price using $TradeShock_{it}$ is shown in Panel C of Table 3. The estimates confirm that pushers who complained about the price during Week 13-21 did face higher asking price from the assistants (except for ketamine). However, they were not the only ones who received higher asking price during this period. In fact, assistants raised the wholesale prices of ice, ketamine and erimin to all pushers who traded with them during this period (see estimates when using $ShockWave_{it}$ in Panel D of Table 3).[23] Therefore, $ShockWave$ is the best proxy of an enforcement shock.

In addition, the magnitude of the enforcement effect on cost is largely consistent across different models, RD regression or the pushers' fixed effects, for all drug types. The positive effect on price are also observed under these models for ice, ketamine

[23]When we re-define $ShockWave_{it}$ to be Week 13-20, the estimated effect is almost identical to that under $TradeShock_{it}$.

and erimin. In comparison, fixed effects regression with $ShockWave_{it}$ estimates slightly larger cost (price) effects than RD regression. Therefore, the enforcement shock had triggered a cost and price response in the wholesale market which lasted for about 8 weeks.

Furthermore, the impact of the enforcement shock on the gang's business can also be revealed by the pushers' participation patterns and their trading intensity. On one hand, there were 44 pushers who traded at least once before Week 13. The enforcement shock discouraged pushers from joining the drug trades (please refer to the green lines in Figure A.1), but did not deter the existing pushers from continuing to trade. A total of 59 pushers traded at least once during the entire enforcement shock period (see yellow line in Figure A.1). On the other hand, the trading intensity of existing pushers stopped growing (see dashed lines in Figure 1). There was a growing trend in the number of transactions that occurred each week before Week 13, and such growth was stunted after the enforcement shock.

Collectively, these findings enabled us to affirm that the enforcement shock occurred on Week 13 and had impacted all pushers who traded with the gang during Week 13-21, not only those who complained about the price hike. This conclusion in turn brings back the question as to why we continued to observe pushers exhibiting non-decreasing demand for drugs despite the price increase in the wholesale market.

7 Demand Response to Enforcement Shock

We examine the pushers' demand response to the enforcement shock using the following equation:

$$\begin{aligned} Q_{ito} = \alpha_3 + \beta_3 Enforcement_{ito} + \delta_3 Supply_{it} + \phi_3 Demand_{it} \\ + \eta_3 P_{ito} + \psi_3 G_{ito} + \Lambda_3 W_{it} + \Phi_3 X_i + \rho_3 T_{it} + \nu_{ito} \end{aligned} \tag{4}$$

The dependent variable Q_{ito} is the quantity of drugs (in natural log terms) that pusher i purchased in order o of trade t. W_{it} includes the trading intensity (denoted as $Intensity_{it}$) and the total number of types of drugs sold (denoted as $DrugNum_{it}$ as shown in the price equation above). $Intensity_{it}$ is measured by the days between trade t and trade $t+1$ for pusher i. A pusher may demand larger quantities in a trade if he expects to return for the next purchase after a longer period of time. Controlling for trading intensity helps us to purge the effect of higher demand due to the pushers' stock up. We consider the number of drug types sold in a trade to reflect the effect of a pusher's budget constraint on his demand for a particular drug.

We continue to use $ShockWave$, our most preferred proxy, to represent the enforcement shock in the demand analysis. Since the enforcement shock was exogenous, coefficient β_3 captures the causal response of the pushers' demand in response to the enforcement shock. We use both donut RD and fixed effects regression to understand the pushers' abnormal demand response. Since the gang had monopoly power on ice and over 40% of the transactions were ice-related, we focus our analysis on ice.

7.1 Increased Demand Response

Donut RD

While the impact of the enforcement shock immediately manifested in the cost and price of the drugs, we do not observe any jumps in the pushers' demand during the week the enforcement shock hit. Unlike costs and prices, the pushers' demand is also driven by their selling ability and a set of demand factors in the end users market. Transaction data shows that the average trading interval between a pusher and an assistant is 8 days. Hence, there is no reason to expect a simultaneous demand response from pushers. The demand pattern shown in Figure 5 also demonstrates that pushers often responded to price changes with a one-week delay, and such a pattern is particularly pronounced in the demand for ice. As such, we adopt donut RD analysis dropping the transactions that occurred within one week before and after the shock. Namely, we drop the trading data for Week 12, 13 and 14.

We perform donut RD using different kernels and with/without covariates.[24] The RD estimates are presented in Panel A of Table 4. Very intriguingly, pushers reacted to the sudden inflation of prices by purchasing more of ice and by keeping demand for other drugs unchanged. The estimated increase in the demand of ice ranges from 13%-254%. Donut RD estimates, except for 254%, are less accurately estimated due to the small sample around the cutoff. Similar results are obtained when we drop transactions that occurred 7 days before and after the first observed trading day in Week 13 (namely, Week 12 and 13).

One may be concerned about the distributional effect. More desperate pushers may choose to join the trade at the cutoff, contributing to the positive demand response. To detect the occurrence of such manipulation, McCrary [2008] suggests testing the continuity in the density of the assignment variable at the cutoff. Most of the baseline variables are the pushers' characteristics, which are determined prior to the treatment cutoff. Figure A.6 shows these covariates are 'locally" balanced on both sides of the cutoff. In addition, Figure A.7 shows the continuity of time varying baseline characteristics, which are also smooth at the cutoff. Regression tests, as suggested in Lee and Lemieux [2010], are performed and support no selection at the cutoff. Moreover, the density plots of the forcing variable are smooth at the cutoff for both *early pushers* and *new comers* (see Figure A.4 and A.5).

Fixed Effects Regression

Donut RD is informative in highlighting the immediate demand response from the pushers, but it represents the "local" jumps in demand. To understand whether the pushers' positive demand response lasted throughout the enforcement shock period where prices persistently stayed high, we perform fixed effects regression controlling for pusher's fixed effects. Output is shown in Panel B of Table 4. Compared with normal trading days, pushers demanded 5% more of ice and did not decrease demand for ketamine and erimin during the enforcement shock period, after controlling for a set of trade-level characteristics. These estimates are much smaller than

[24] The covariates controlled are log price, days to the next trading day. Quality is further controlled for ice and ketamine.

those estimated under pooled OLS regressions (results not shown), suggesting the possibility of heterogeneous response from the pushers.

Hence, we further examine the demand behavior of the pushers who joined before the enforcement shock hit (namely *early pushers*) and those who joined after (namely *new comers*), separately using fixed effects. Interestingly, we find very strong demand responses from the group of early pushers on all drug types. The enforcement shock caused them to demand 18% more of ice and ketamine, and 12% more of erimin (Panel C of Table 4). On the other hand, we observe a less drastic response from the group of new comers. The new comers' demand during this enforcement shock period is not statistically different from the demand during the normal days. This is expected because they just joined the gang and were focused on building up a customer base. Over the data period, the standard deviation of price was S$4 for ketamine/ecstasy and S$7 for erimin, whereas the standard deviation of price for ice was S$36 during the same period. That is why we observe less exaggerated price increases than cost increases (in percentage terms) for ketamine and erimin. Assistants continued to sell ketamine and erimin despite the lower profitability because these products were complementary to ice. It was common for pushers to purchase ketamine, erimin and ice in the same bundle. Since assistants could make more profit for each unit of ice sold, they were inclined to sell ketamine and erimin together with ice. It helps us to understand why the group of early pushers had a pronounced increased in demand for ketamine and erimin as well.

In addition, 30% of early pushers were heavy drug addicts. This type of pushers was often in need of a constant inflow of money to feed personal drug addictions. Panel C of Table 4 shows that they exhibited an even more dramatic response, with a noticeable 22% increase in demand for ice during the enforcement shock period. Their demand increases for ketamine and erimin were 9% and 10% respectively, but these estimates were less precisely estimated due to the small sample.

Thus far, we have excluded the discussion on ecstasy because the supply of ecstasy was not affected by the enforcement activities. However, the pushers' demand pattern for ecstasy during the enforcement shock period was highly coherent with their abnormal demand behavior for the drug types discussed. The price elasticity of demand for ecstasy is -1.76 during shock period, which is 0.70 more than the -1.06 during the off shock period. This difference is statistically significant. While facing the same price drop in ecstasy, pushers responded much more drastically during the enforcement shock period, as compared to normal days. This piece of evidence further highlights the pushers' absurd demand responses to the enforcement shock.

Lastly, one may argue that pushers responded positively to the shock because they stocked up for the future in fear of a prolonged supply shortage. We contest this challenge by controlling for the trading intensity $Intensity_{it}$ in the regression, and find our results remain strong. Generally speaking, pushers who returned to assistants for the next purchase after a longer time period tended to be the ones who bought more. However, pushers on average did not trade less often during the enforcement shock period. The average trading interval was 7.74 days during normal periods, and the trading interval during the enforcement shock period was 8.17 days.

7.2 Pushers' Profit Targeting and Adoption of Costly Technology

Following Becker [1968], pushers would reduce their drug-selling activities or temporarily exit the market when their marginal return from selling drugs is reduced. It is clear by now that the observed pushers' demand response to the enforcement shock is highly inconsistent with the neoclassical predictions. We believe that a profit targeting model we adopted is better suited to explain our findings. That is, pushers demanded more drugs during the enforcement shock period because they had their profit targets to reach. In this section, we argue why this is a plausible explanation with suggestive evidence. Hereafter, we focus our discussion on the subsample of early pushers, as the observed trading behavior of pushers who joined the trade after the enforcement shock was likely to be confounded by non-shock related factors. We will also mainly emphasize trades of ice, as ice represents the largest trading volume.

The key cause of the early pushers' increased demand response is that the enforcement shock had subdued the pushers' profit margins. The enforcement shock pushed up the assistants' cost of drugs and assistants passed the cost burden directly to pushers. Using pooled samples of all drug types, fixed effects estimates show that the average pass-through of cost is high at 67% during the normal days and increased by 5% (statistically significant) during the enforcement shock period.[25] The cost pass-through of ice was high at 87% during the normal days and assistants kept the same pass-through rate during the enforcement shock period. Assistants were able to do so because of the gang's monopoly power on ice. The markets for ketamine, ecstasy and erimin were more established, and hence more saturated. The cost pass-through on these drugs were also substantial. We observe some drop in the pass-through during the enforcement shock period, but the estimated decrease was not statistically significant.[26] Pushers always bought these drugs in a bundle together with ice, which allowed the gang to extend its monopoly power on ice to other drugs they sell. On the other hand, when faced with the hikes in the purchasing cost of drugs, pushers had limited power to fully pass through the cost to the end users because of the higher competition they faced in the end users market. Taken together, pushers were the ones who absorbed the majority of the cost burden induced by the enforcement shock.

When pushers are profit targeting, the optimal response to decreased profit margins is to buy more and sell more. It is easy to understand that pushers who are heavy drug addicts are profit targeting individuals. For any individual, if they are truly profit targeting, we should consistently observe this behavioral pattern. In ad-

[25] This pattern of cost pass-through hold true for both early pushers and new comers.

[26] We are not elaborating on the cost pass-through in detail here, because the pass-through rates were quite different for the group of early pushers and the group of new comers. The early pushers were mostly trading at early months after the formation of the gang, and hence received a higher rate of cost-pass through on ice as compared to the group of new comers who were active in the later months of the data period. They receive a lower cost pass-through possibly because the gang started to face competition in the ice market or the gang started to gradually gain economies of scale and shared cost reductions with the new comers. We present the cost pass-through for early pushers and the full sample in Table A5.

dition to examining the early pushers' demand response after the enforcement shock hit, we further investigate their demand response as the price hike induced by the enforcement shock died down. Figure 4 shows that the enforcement shock caused the price to remain high during Week 13-20, and the price returned to pre-shock level during Week 21-29. We repeat the fixed effects regression performed in Panel B of Table 3, but focus on the changes of price before and after the cutoff of the first observed trading day in Week 21. We find that the price of ice the early pushers transacted at dropped by 13% in Week 21 (see Panel A of Table 5). To study the average price change between the two periods, we create a variable $PostShock$, which equals to 1 if drug trades occurred during Week 21-29 and equals to 0 if drug trades occurred during Week 13-20. The average (ice) price difference decreased by 5% (see Panel B of Table 5). This reversion of price served as a perfect natural setting for us to conduct a robustness check. In this scenario, the sudden price reduction made it easier for pushers to reach their profit targets. As profit targeting individuals, they should have bought less and sold less drugs accordingly. This is exactly we observe. Panel B of Table 5 shows that early pushers decreased their demand for drugs by 22%. This piece of evidence strongly supports our postulation that pushers were profit targeting.

With a fixed demand pool of end users in the short run, who were the pushers selling their extra inventory to? One potential explanation is that the total market demand from the gang remained unchanged, but some pushers became inactive because of the price increase, allowing the active pushers to sell more. However, note that 90% of the pushers remained active during the enforcement shock period. For the counterargument to be true, the market share held by the remaining 10% of the pushers who were inactive must be substantial, which is not plausible. Panel B of Table A6 shows that the total weekly quantity sold by the gang during the enforcement shock period increased by 73%, which further confirms there was no substitution effect.

The next question that arises is: how did pushers gain access to an expanded end users market? We believe that pushers adopted a costly strategy to sell more drugs. That is, pushers were driven to seek new customers in rival gangs' territories. Recall that the gang we study was the first to introduce large quantities of ice into the market. On normal days, pushers were only selling drugs on the gang's turf. Stressed by the decreased profit margins and the need to hit their profit targets, pushers had no choice but to break into rival gang's territories to sell to more customers. These were territories in which pushers had no protection and where they risked violent clashes with rival gangs that could lead to death or arrest. This is a type of technology pushers would not employ during the time when drug price was only marginally higher, because it is too costly.

This explanation is highly plausible, because our data shows an increased exit and arrest rate after the enforcement shock period. As exhibited in Figure A.1, the likelihood of pushers exiting the market increased right after the enforcement shock period (note the surge in Month 5). This figure is drawn using the full sample of pushers. We re-calculate the exit patterns for those pushers who had ever traded during the enforcement shock period (i.e., under column "Had Shock") in Table A2 and the results reinforce our hypothesis. Pushers among this group experienced a surge in exits after the enforcement shock period ended, as compared to those who did not trade during the enforcement shock period.[27]

Pushers exited the market for different reasons. 54% of the early pushers exited out of their own volition and 39% of them exited because they were arrested, whereas the remainder were fired by assistants. The statistics are similar for the full sample of pushers, except their rate of arrest is slightly lower at 35%. To study the impact the enforcement shock had on each pusher's probability of arrest, we create a dummy variable *Arrested* to indicate pushers who exited because they were arrested, and define *HadShock* to indicate pushers who traded during the enforcement shock period at least once. We regress *Arrested* on *HadShock* using the sample of early pushers. The results show that pushers who traded at least once during the enforcement shock period were 47% (estimated with robust error and p-value is 0.001) more likely to be arrested compared to those had not traded during the enforcement shock period. Notice that Figure A.1 reveals that the probability a pusher exited because of arrest increases with his tenure. To show that the increase in arrest rate is not caused by the pushers' tenure in the gang, we further control for the month of exit in the regression and continue to find a slightly lower but similar estimate of 44%. Collectively, these pieces of evidence support the hypothesis that pushers may have employed aggressive methods to expand their market during the enforcement shock period, which resulted in their arrests right after the enforcement shock period. This estimate is the lower bound, because there may have been pushers who exited the market due to arrest without the assistants' knowledge.

One a side note, assistants sold 54% more of ice and enjoyed 4% increase in profit margin during the enforcement shock period, but suffered from 14-17% decrease in profit margin for ketamine and erimin sales (see Table A6).

8 Conclusion

Using a dataset from a Singaporean drug-selling gang, we show that when an enforcement shock increased the assistants' costs of supplying drugs to pushers, assistants passed through most of the cost increase to pushers. Lowered profit margin did not effectively reduce the number of pushers who continued to sell drugs during the enforcement shock period. Moreover, pushers who remained active in the market actually sold more drugs than they did when there was no enforcement shock. The reason for this counter-intuitive phenomenon is because many pushers had specific profit targets. They sold more because they adopted a costly technology to expand their customer pool. If the market structure is perfectly competitive rather than a monopoly, then it would be too costly for pushers to break into rival gangs' territories and may not lead pushers to demand more drugs. Thus, how successful an enforcement policy on the drug market also hinges on the market structure of the particular drug type.

To our knowledge, this is the first paper that can quantitatively document how

[27]Notice that the exit month is imputed using a pusher's tenure and date of the first trade. The estimated exit month may be later than the actual exit month, but would not be earlier than the actual exit time, because assistants may not know if a pusher exited the market due to arrest.

enforcement activities cause pushers within a drug-selling gang to buy more drugs to sell to end users in the short run. It would be very interesting to understand the long-run effects of enforcement activities. Due to short time span of our data, we are unable to do this in the current paper. This would be a very important direction for future research.

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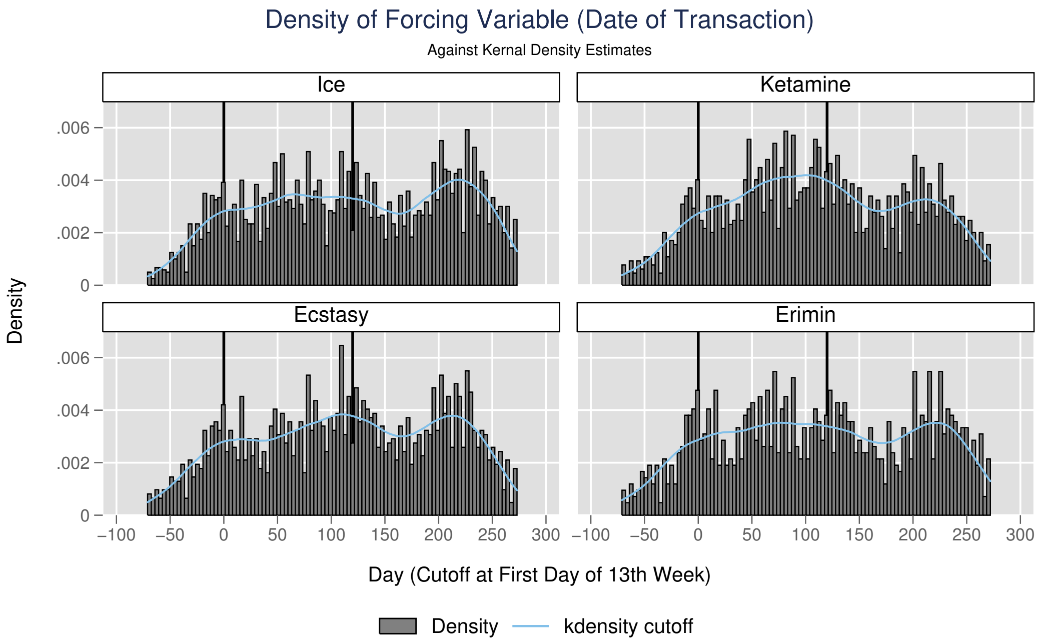
Table 1: **Statistics on Drug Type (Order Level)**

	Ice	**Ketamine**	**Ecstasy**	**Erimin**
Unit Cost (S$/gram)	83.98	17.45	15.66	20.20
Unit Price (S$/gram)	156.40	25.88	24.05	34.18
Unit Profit(S$/gram)	71.91	8.39	8.35	14.00
Quantity (gram)	10.59	51.42	65.39	41.80
Quality				
Average	0.06	0.00	0.28	0.04
Good	0.48	0.40	0.97	0.95
Very Good	0.52	0.60	0.03	0.01
No. of Orders	3508	1900	1784	1231

Figure 1: Likelihood of A Shock and Trading Intensity

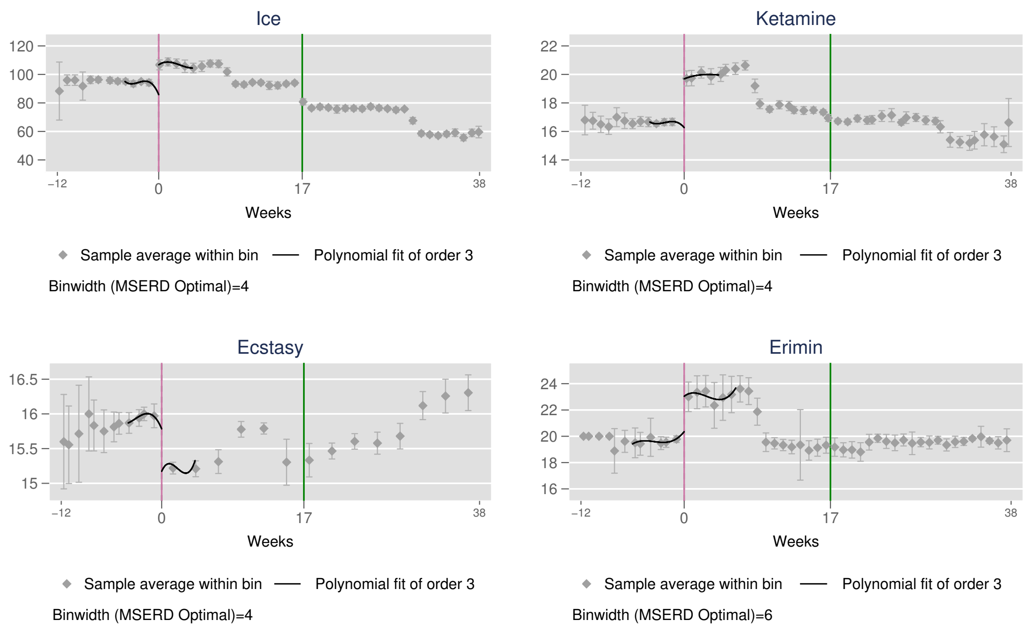
Note: Red refence line at week 13.

Figure 2: Density of Forcing Variable



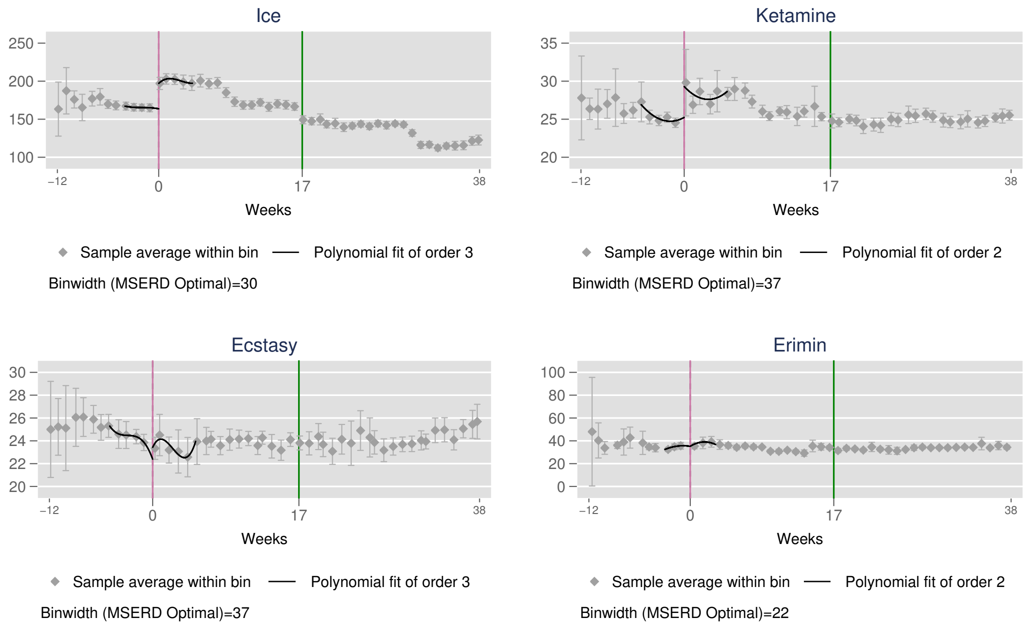
Note: Bin Num=100

Figure 3: Cost Hike After the Shocks



Note:
Red refence line indicate the cutoff (at week 13).
Green reference line indicate the week 30.

Figure 4: Price Hike After the Shocks



Note:
Red refence line indicate the cutoff (at week 13).
Green reference line indicate the week 30.

Figure 5: Quantity v.s Price

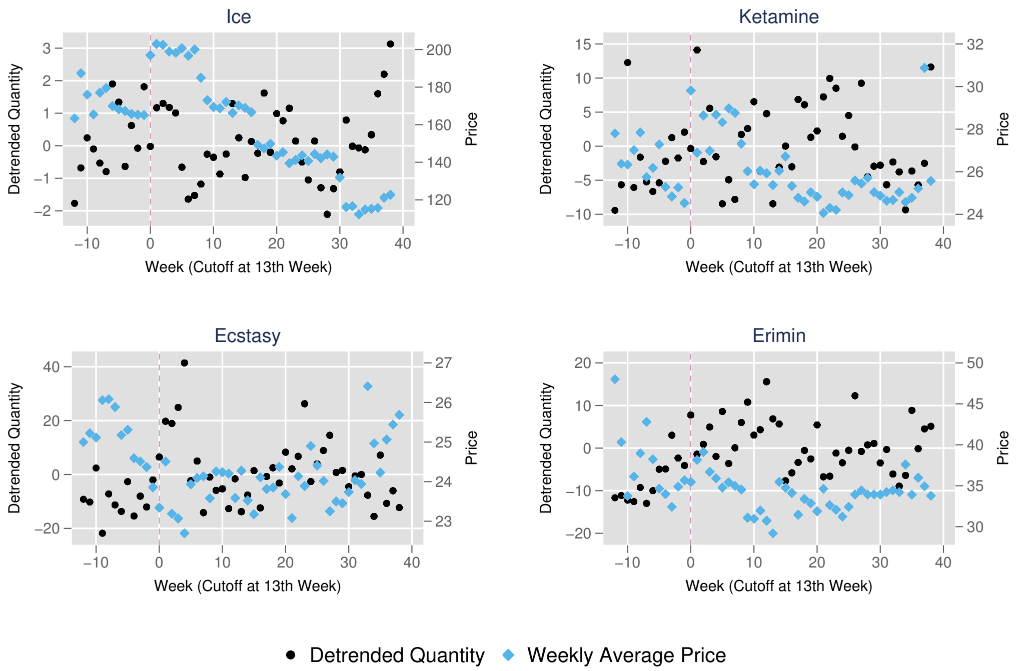


Table 2: **Impact of Shock on Cost**

	(1) Ice	(2) Ketamine	(3) Esctasy	(4) Ermin
Panel A: RDD Cutoff=First Trading day of Week 13				
RD Estimate (Kernel=Uniform, MSERD Optimal BW)	0.099***	0.120***	-0.021	0.102**
	(0.034)	(0.024)	(0.014)	(0.043)
RD Estimate (Kernel=Triangular, MSERD Optimal BW)	0.095***	0.108***	-0.022	0.101**
	(0.036)	(0.024)	(0.015)	(0.044)
RD Estimate (Kernel=Uniform, CERRD Optimal BW)	0.096**	0.096***	-0.023	0.087*
	(0.045)	(0.026)	(0.017)	(0.049)
RD Estimate (Kernel=Triangular, CERRD Optimal BW)	0.088*	0.080***	-0.017	0.087*
	(0.047)	(0.027)	(0.019)	(0.050)
Observations	3485	1888	1798	1225
Panel B: Local Linear Regression (FE=Pusher)				
Dummy(Cutoff>=0)=1	0.198***	0.207***	-0.062***	0.187***
	(0.008)	(0.013)	(0.007)	(0.018)
Cutoff	-0.000	0.000	0.000*	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Dummy(Cutoff>=0)=1 × Cutoff	-0.003***	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
N	3486	1886	1794	1231
R^2 Within	0.231	0.459	0.061	0.256
R^2 Between	0.716	0.528	0.075	0.004
R^2 Overall	0.674	0.504	0.032	0.059
Panel C: Enforcement Shock Proxied by $TradeShock_{it}$ (FE=Pusher)				
Trade Shock	0.103***	0.159***	-0.040***	0.164***
	(0.009)	(0.008)	(0.008)	(0.012)
Positive Shock Impact Period	-0.092***	-0.022***	0.003	-0.007*
	(0.012)	(0.003)	(0.014)	(0.004)
Demand Surge Period	-0.041***	-0.009	-0.000	0.009
	(0.016)	(0.008)	(0.004)	(0.010)
Quality	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes
N	3485	1886	1794	1231
R^2 Within	0.410	0.425	0.035	0.368
R^2 Between	0.612	0.426	0.052	0.393
R^2 Overall	0.664	0.418	0.017	0.394
Panel D: Enforcement Shock proxied by $ShockWave_{it}$ (FE=Pusher)				
Enforcement Shock Impact Period	0.118***	0.148***	-0.038***	0.158***
	(0.008)	(0.009)	(0.006)	(0.013)
Positive Shock Impact Period	-0.088***	-0.022***	0.003	-0.005
	(0.012)	(0.004)	(0.014)	(0.003)
Demand Surve Period	-0.033**	-0.008	-0.003	0.014
	(0.015)	(0.007)	(0.004)	(0.009)
Quality	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes
N	3485	1886	1794	1231
R^2 Within	0.452	0.568	0.051	0.524
R^2 Between	0.606	0.434	0.055	0.405
R^2 Overall	0.675	0.482	0.019	0.432

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Cluster robust errors clustering at pusher's level are reported.

[2] Optimal MSERD bandwidth is the same as indicated in RD plot in Figure 3. CERRD method yields the one of the smallest bandwidth, which is 19, 21, 19, 27 for drugs from column (1) to (4). Degree of polynomial chosen is 3. RD estimates is very similar with and without control for quality of drug, RD estimates with quality controlled is reported in this table.

Table 3: **Impact of Shock on Price**

	(1) Ice	(2) Ketamine	(3) Esctasy	(4) Ermin
Panel A: RDD Cutoff=First day of Week 13				
RD Estimate (Kernel=Uniform, MSERD Optimal BW)	0.117***	0.109**	-0.025	-0.031
	(0.042)	(0.053)	(0.043)	(0.098)
RD Estimate (Kernel=Triangular, MSERD Optimal BW)	0.104**	0.122**	-0.029	-0.063
	(0.044)	(0.062)	(0.045)	(0.112)
RD Estimate (Kernel=Uniform, CERRD Optimal BW)	0.093*	0.131*	-0.053	-0.066
	(0.056)	(0.069)	(0.052)	(0.116)
RD Estimate (Kernel=Triangular, CERRD Optimal BW)	0.062	0.144*	-0.018	-0.137
	(0.058)	(0.076)	(0.053)	(0.141)
Observations	3468	1878	1785	1216
Panel B: Fixed Effects Regression				
Dummy(Cutoff>=0)=1	0.263***	0.167***	-0.018	0.088*
	(0.017)	(0.028)	(0.022)	(0.034)
Cutoff (First Observed Trading Day on 13th Week)	-0.001	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Dummy(Cutoff>=0)=1 × Cutoff	-0.002*	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Constant	5.116***	3.268***	3.218***	3.496***
	(0.036)	(0.031)	(0.041)	(0.047)
N	3469	1876	1781	1222
R^2 Within	0.194	0.108	0.005	0.016
R^2 Between	0.543	0.066	0.000	0.001
R^2 Overall	0.500	0.057	0.000	0.000
Panel C: Enforcement Shock Proxied by $TradeShock_{it}$				
Trade Shock	0.109***	-0.010	0.032***	0.055***
	(0.019)	(0.016)	(0.009)	(0.020)
Supply & Demand Condition	Yes	Yes	Yes	Yes
Quality & No. Drugs Bought	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes
N	3468	1876	1781	1222
R^2 Within	0.565	0.264	0.363	0.168
R^2 Between	0.716	0.306	0.222	0.297
R^2 Overall	0.688	0.292	0.284	0.252
Panel D: Enforcement Shock Proxied by $ShockWave_{it}$				
Enforcement Shock Impact Period	0.102***	0.039*	0.037***	0.045*
	(0.018)	(0.021)	(0.009)	(0.023)
Supply & Demand Condition	Yes	Yes	Yes	Yes
Quality & No. Drugs Bought	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes
N	3468	1876	1781	1222
R^2 Within	0.579	0.269	0.369	0.167
R^2 Between	0.693	0.301	0.223	0.296
R^2 Overall	0.691	0.294	0.284	0.250

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] In Panel A, Optimal MSERD bandwidth is the same as indicated in RD plot in Figure 3. CERRD method yields the one of the smallest bandwidth, which is 19, 21, 19, 27 for drugs from column (1) to (4). Degree of polynomial chosen is 3. RD estimates is very similar with and without control for quality of drug, RD estimates with quality controlled is reported in this table.

[2] Panel B-D are results based on fixed effects regression using pusher's fixed effects with errors clustered at pusher's level as well.

[3] In panel B, Cutoff is set on the first observed trading day on week 13th. Dummy variable is set to 1 if transaction occurred after the cutoff and 0 otherwise.

Table 4: **Impact on Pushers' Quantity**

Panel A: Donut RD				
RD Estimate (Triangular Kernal)	0.134	-0.047	-0.196	1.894
	(0.343)	(7.302)	(0.890)	(2.434)
RD Estimate (Triangular Kernal; with covariates)	0.365	-2.924	-0.093	0.928
	(0.332)	(6.060)	(0.898)	(2.149)
RD Estimate (Uniform Kernal)	2.535**	1.342	-0.218	-0.174
	(1.058)	(2.665)	(0.626)	(1.330)
RD Estimate (Uniform Kernal; with covariates)	1.250	1.918	-0.521	0.724
	(1.205)	(1.995)	(0.609)	(1.147)
Panel B: Pusher's Fixed Effects				
	(1)	(2)	(3)	(4)
Enforcement Shock Impact Period	0.051**	0.022	0.043	-0.032
	(0.024)	(0.026)	(0.026)	(0.040)
Positive Shock Impact Period	0.000	0.075**	0.055*	0.129***
	(0.027)	(0.029)	(0.028)	(0.045)
Demand Surge Period	0.092***	-0.005	-0.029	-0.082
	(0.029)	(0.041)	(0.038)	(0.054)
N	3026	1643	1528	1033
R^2 Within	0.291	0.435	0.333	0.302
R^2 Between	0.037	0.001	0.004	0.040
R^2 Overall	0.068	0.010	0.019	0.050
Panel C: Pusher's Fixed Effects (Early Pusher)				
Enforcement Shock Impact Period	0.176***	0.181***	0.094*	0.118*
	(0.042)	(0.044)	(0.050)	(0.067)
Positive Shock Impact Period	-0.461**	0.000	0.000	0.000
	(0.179)	(.)	(.)	(.)
Demand Surge Period	-0.088	-0.078	-0.031	-0.269***
	(0.058)	(0.060)	(0.061)	(0.093)
N	709	333	320	243
R^2 Within	0.203	0.506	0.476	0.313
R^2 Between	0.044	0.173	0.160	0.354
R^2 Overall	0.063	0.200	0.223	0.364
Panel C: Pusher's Fixed Effects (Early Pusher + Heavy Drug Addict)				
Enforcement Shock Impact Period	0.216***	0.091	-0.032	0.098
	(0.065)	(0.096)	(0.079)	(0.100)
Positive Shock Impact Period	-0.505*	0.000	0.000	0.000
	(0.273)	(.)	(.)	(.)
Demand Surge Period	0.022	-0.135	0.059	-0.064
	(0.096)	(0.107)	(0.094)	(0.133)
N	319	88	98	89
R^2 Within	0.176	0.616	0.581	0.358
R^2 Between	0.082	0.000	0.486	0.369
R^2 Overall	0.144	0.047	0.543	0.324

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Panel A presents Donut RD estimates with data 2 week apart from cutoff removed. Polynomial order of 1 used for ice and esctasy, and polynomial order of 2 used for ketamine and ermin. These choices of polynomial orders are made based on the fit with raw data. Optimal MSERD bandwidth are used . The covariates controlled are log price, days to next trading day. Quality is further controlled for ice and ketamine.

[2] Panel C presents fixed effect estimates using the subsample of pushers who joined the drug trade before the enforcement shock hits.

[3] Due to space limitation, we only reports the coefficient estimates of variables of key interest. Cluster robust errors clustering at pusher's level are reported.

Table 5: **Pushers' Profit Targeting**

	(1) Ice	(2) Ketamine	(3) Esctasy	(4) Ermin
Panel A: Dep Var: Log Price				
Dummy(Week>=21)=1	-0.133**	-0.050	0.524***	0.026
	(0.043)	(0.035)	(0.040)	(0.055)
Cutoff (First Observed Trading Day of 21st Week)	0.000	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Dummy(Week>=21)=1 × Cutoff	-0.002	-0.002	-0.024***	0.001
	(0.002)	(0.002)	(0.005)	(0.001)
N	392	165	141	121
R^2 Within	0.146	0.055	0.005	0.025
R^2 Between	0.003	0.029	0.095	0.022
R^2 Overall	0.035	0.031	0.016	0.040
Panel B: Dep Var: Log Price				
Post Shock	-0.051	-0.025	0.060	0.126
	(0.034)	(0.043)	(0.095)	(0.145)
Quality & No. Drugs Bought	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes
N	317	129	103	92
R^2 Within	0.677	0.160	0.312	0.073
R^2 Between	0.505	0.225	0.005	0.194
R^2 Overall	0.398	0.202	0.031	0.300
Panel C: Dep Var: Log Quantity				
Post Shock	-0.219*	-0.031	-0.055	-0.092
	(0.117)	(0.085)	(0.114)	(0.092)
Quality & No. Drugs Bought	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes
N	317	129	103	92
R^2 Within	0.094	0.307	0.431	0.602
R^2 Between	0.134	0.336	0.110	0.317
R^2 Overall	0.164	0.322	0.175	0.281

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Results based on fixed effects regression using pushers' fixed effects and with errors clustered at pusher's level.
[2] In all regressions, only subsample of early pushers are used.
[3] In panel A, Cutoff is set on the first observed trading day on week 21st. Dummy variable is set to 1 if transaction occurred after this cutoff and 0 otherwise.

Appendix A Additional Empirical Results

Figure A.1: Pusher's Join and Exit Pattern

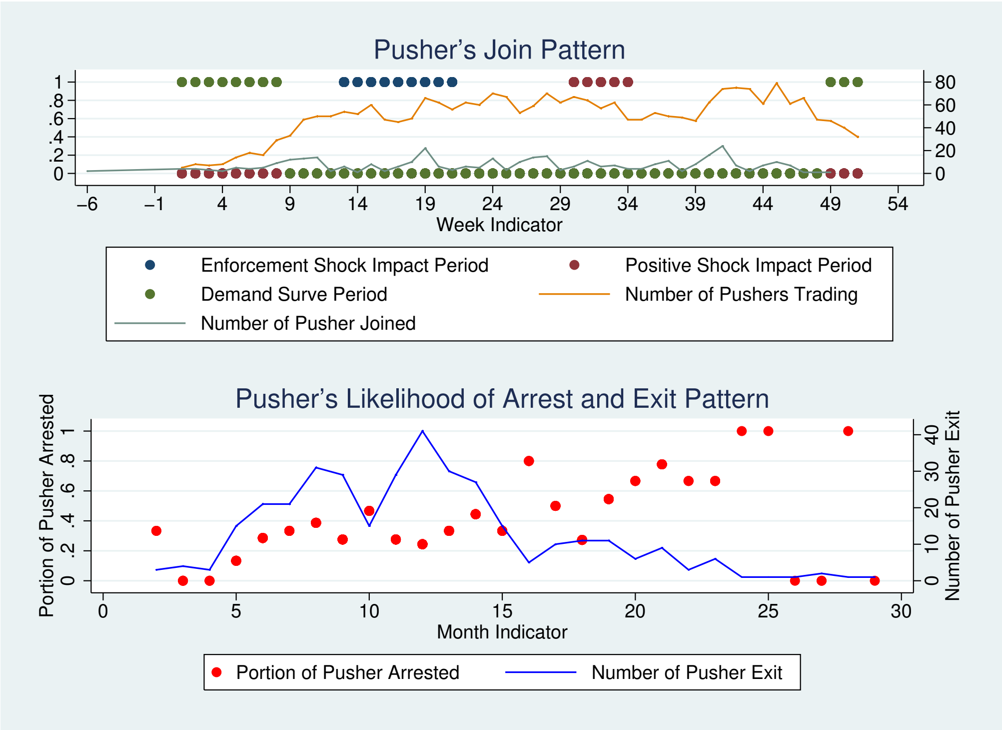


Table A1: **Pusher's Characteristics**

	%
Job Status	
Full-time	45.8
Jobless or Part-time	54.2
Gang member	
No	33.8
Yes	66.2
Arrested before	
No	41.5
Yes	58.5
Ever sent to Rehab	
Not a Drug Addicted	31.5
Yes	30.0
No	38.9
Frequency of Borrowing Money	
Never	2.6
Seldom	18.2
Sometimes	21.6
Usually	32.7
Always	25.0
Gambling addiction	
Never gamble	1.4
Seldom gamble	13.1
Sometimes gamble	23.0
Usually gamble	21.9
Super gambler	40.3
No. of Pushers	352

Table A2: **Early Pusher's Exit Pattern by Month**

Exit Month	Not Had Shock	Had Shock	Total
2	2	0 2	
3	4	0 4	
4	2	1 3	
5	1	14 15	
6	0	7 7	
7	1	4 5	
8	1	2 3	
9	0	5 5	
10	0	3 3	
11	0	5 5	
12	0	4 4	
13	0	3 3	
14	0	2 2	
15	0	2 2	
16	0	1 1	
17	0	2 2	
18	0	1 1	
19	1	1 2	
21	0	2 2	
No. of Pushers	12	59	71

[1] Statistics calculated for pushers who joined before the enforcement shock occurred.

Figure A.2: Quantity v.s Price (Subsmpale of Earlypushers)

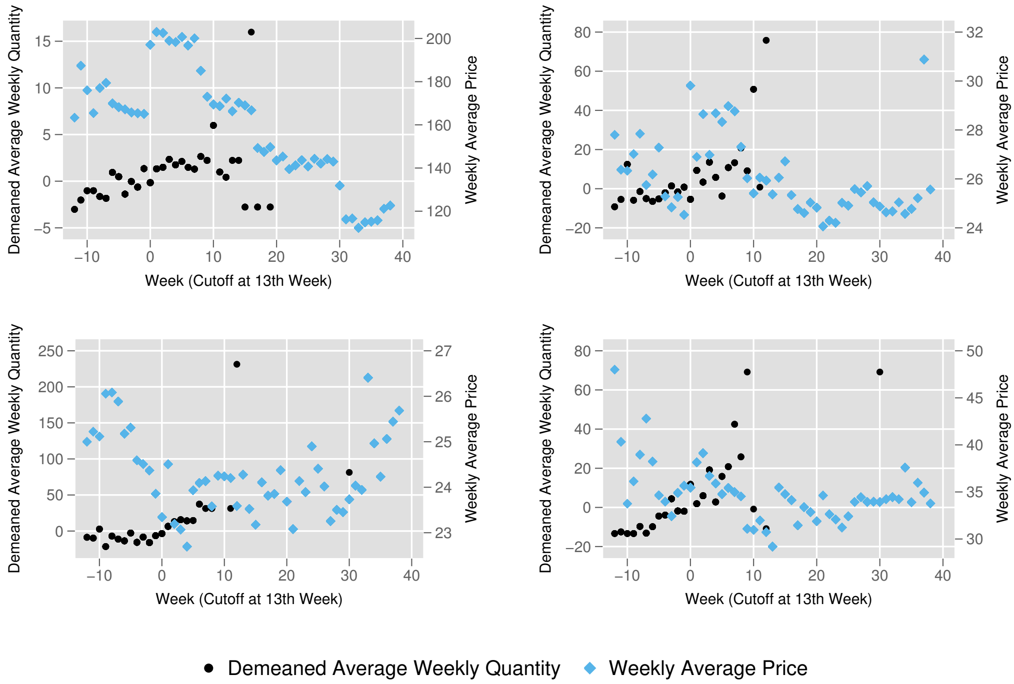


Figure A.3: Quantity v.s Price (Subsmpale of New Comers)

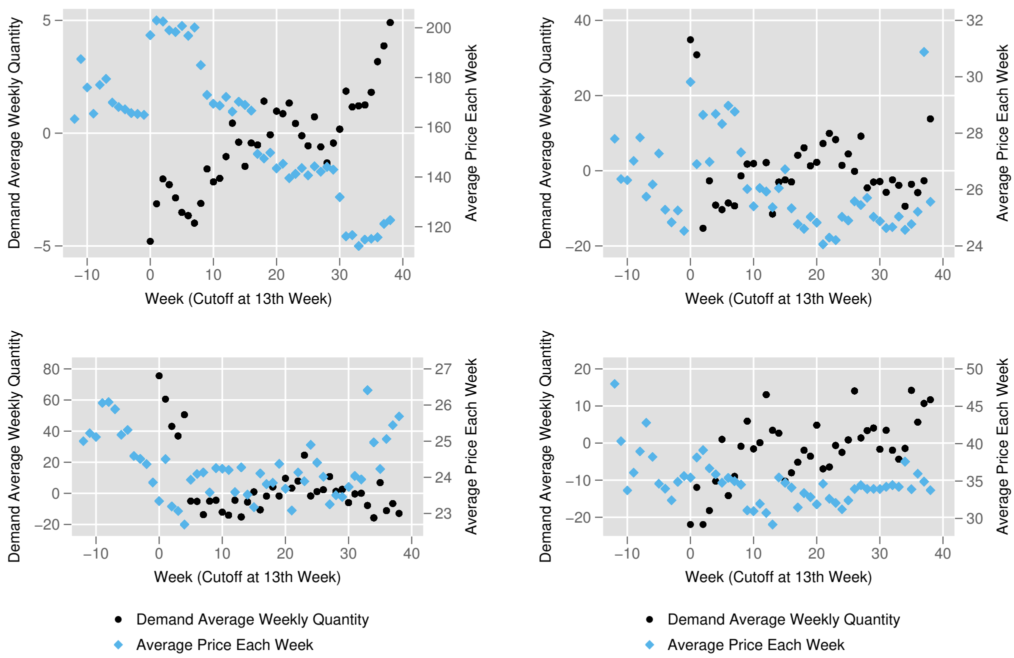
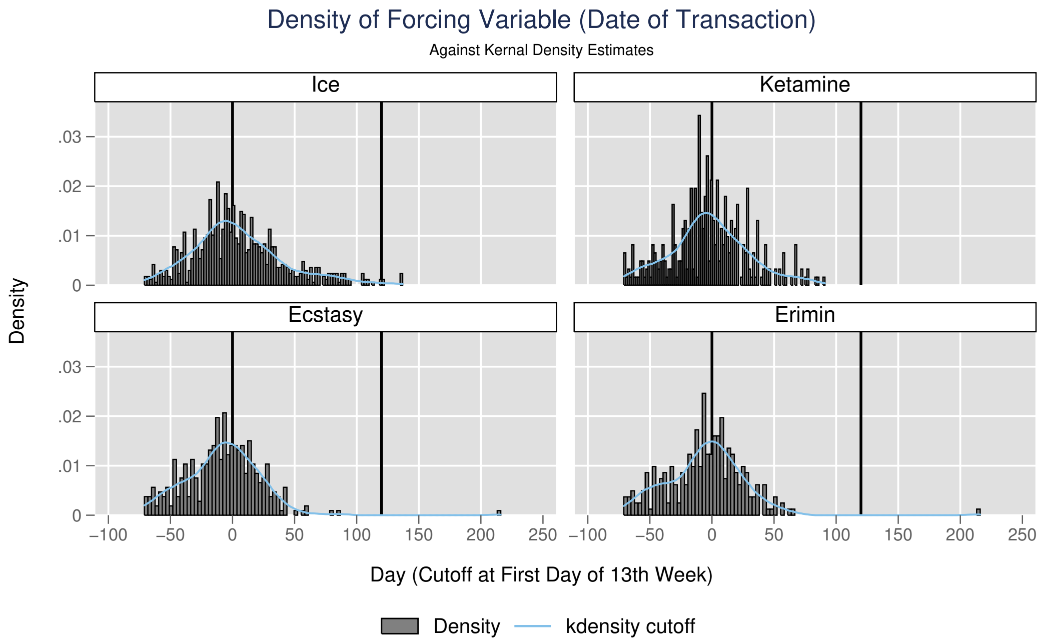
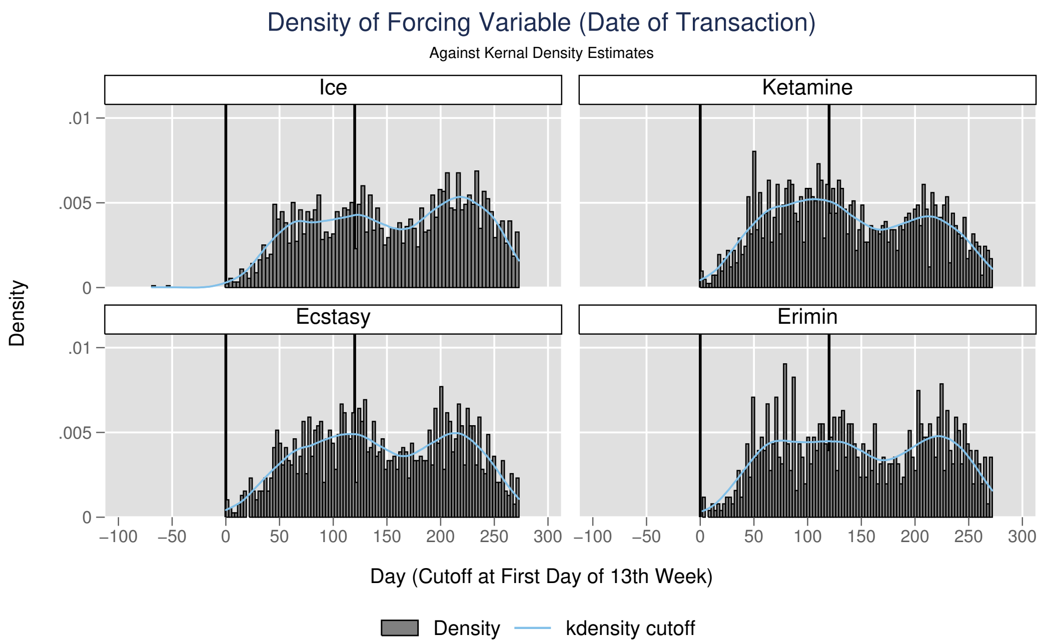


Figure A.4: Density of Forcing Variable (Early Pushers)

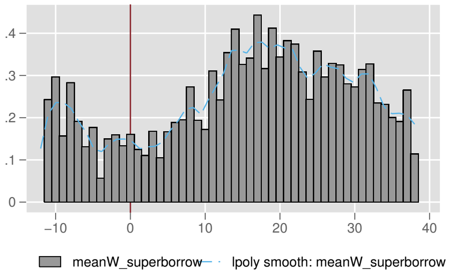


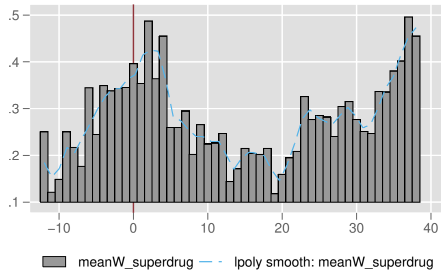
Note: Bin Num=100

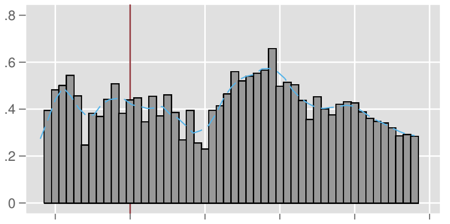
Figure A.5: Density of Forcing Variable (Non-Early Pushers)

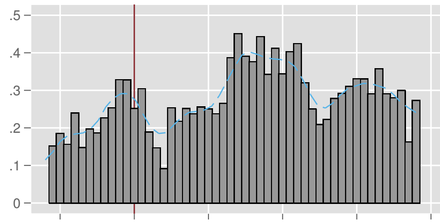


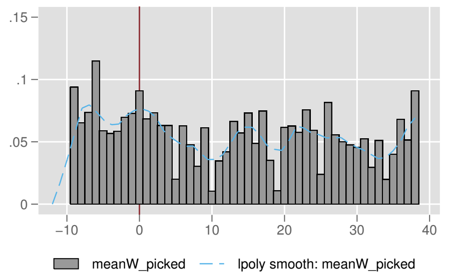
Note: Bin Num=100

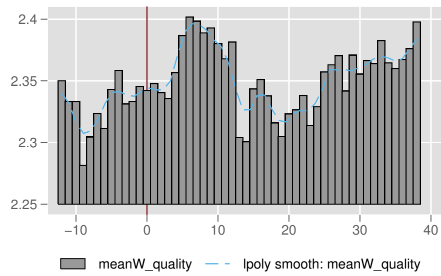

meanW_superborrow
lpoly smooth: meanW_superborrow

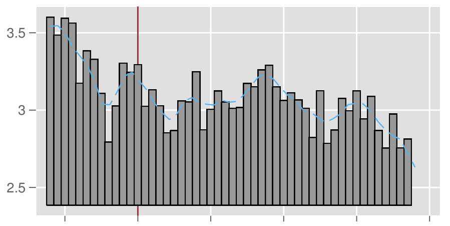

meanW_superdrug
lpoly smooth: meanW_superdrug

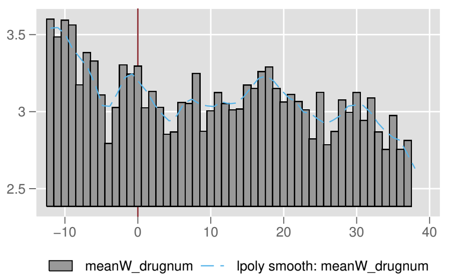


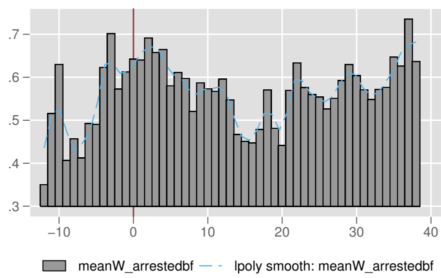


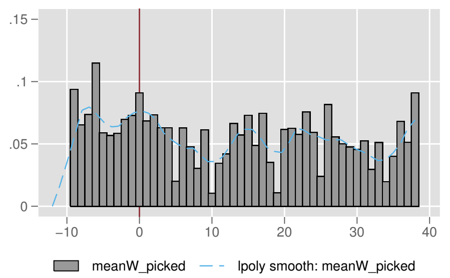

meanW_picked
lpoly smooth: meanW_picked


meanW_quality
lpoly smooth: meanW_quality




meanW_drugnum
lpoly smooth: meanW_drugnum


meanW_arrestedbf
lpoly smooth: meanW_arrestedbf


meanW_picked
lpoly smooth: meanW_picked

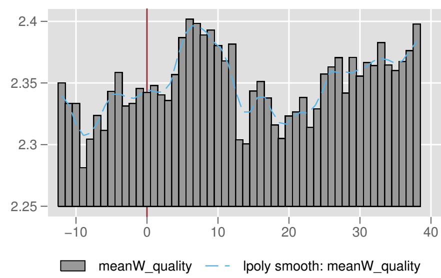

meanW_quality
lpoly smooth: meanW_quality

Table A3: **Impact of Shock on Order and Trade Level Cost**

	(1) Ice	(2) Ketamine	(3) Esctasy	(4) Ermin
Panel A: Shock=Order Level Shock				
Event (Base= No Shock)	ref.	ref.	ref.	ref.
Perceived Enforcement Shock	0.115^{***}	0.145^{***}	-0.036^{***}	0.184^{***}
	(0.011)	(0.008)	(0.003)	(0.018)
Positive Supply Shock	-0.040^{***}	-0.029^{***}	-0.018^{**}	-0.003
	(0.008)	(0.006)	(0.007)	(0.007)
Demand Surge	-0.112^{***}	-0.085^{***}	0.031^{***}	-0.009
	(0.018)	(0.008)	(0.011)	(0.008)
N	3508	1900	1784	1231
R^2	0.670	0.434	0.101	0.411
Panel B: Shock=Trade Level Shock				
Event (Base= No Shock)	ref.	ref.	ref.	ref.
Perceived Enforcement Shock	0.101^{***}	0.135^{***}	-0.024^{**}	0.151^{***}
	(0.012)	(0.010)	(0.010)	(0.017)
Positive Supply Shock	-0.025^{**}	-0.003	-0.021^{***}	-0.009
	(0.010)	(0.006)	(0.006)	(0.007)
Demand Surge	-0.125^{***}	-0.055^{***}	0.020^{**}	0.009
	(0.011)	(0.011)	(0.008)	(0.007)
N	3508	1900	1784	1231
R^2	0.702	0.524	0.110	0.493
Panel C: Shock=Shock Impact Period				
Event (Base= No Shock)	ref.	ref.	ref.	ref.
Perceived Shock Wave	0.116^{***}	0.139^{***}	-0.027^{**}	0.152^{***}
	(0.012)	(0.010)	(0.011)	(0.017)
High Demand Period	-0.097^{***}	-0.047^{***}	0.013	0.008
	(0.015)	(0.010)	(0.011)	(0.007)
Positive Supply Shock	0.049^{***}	0.021^{**}	-0.023^{***}	-0.002
	(0.012)	(0.008)	(0.008)	(0.006)
N	3508	1900	1784	1231
R^2	0.698	0.522	0.113	0.492

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Due to space limitation, we only reports the coefficient estimates of variables of key interest. Cluster robust errors clustering at pusher's level are reported.

Table A4: **Impact of Shock on Order and Trade Level Price**

	(1) Ice	(2) Ketamine	(3) Esctasy	(4) Ermin
Panel A: Shock=Order Level Shock				
Event (Base= No Shock)	ref.	ref.	ref.	ref.
Perceived Enforcement Shock	0.096***	0.020	0.021	0.061**
	(0.017)	(0.013)	(0.019)	(0.030)
Positive Supply Shock	0.023	0.013	0.038**	0.013
	(0.017)	(0.009)	(0.015)	(0.014)
Demand Surge	0.032*	0.044***	0.038***	0.070***
	(0.017)	(0.013)	(0.010)	(0.021)
N	3491	1890	1771	1222
R^2	0.710	0.387	0.439	0.326
Panel B: Shock=Trade Level Shock				
Event (Base= No Shock)	ref.	ref.	ref.	ref.
Perceived Enforcement Shock	0.098***	0.025*	0.011	0.044*
	(0.016)	(0.013)	(0.014)	(0.025)
Positive Supply Shock	0.025	0.014	0.037***	0.013
	(0.017)	(0.009)	(0.014)	(0.013)
Demand Surge	0.026	0.040***	0.037***	0.069***
	(0.017)	(0.012)	(0.010)	(0.020)
N	3491	1890	1771	1222
R^2	0.711	0.387	0.439	0.325
Panel C: Shock=Shock Wave				
Event (Base= No Shock)	ref.	ref.	ref.	ref.
Perceived Enforcement Shock	0.078***	0.035**	0.019	0.014
	(0.014)	(0.016)	(0.013)	(0.033)
Positive Supply Shock	0.012	-0.006	0.010	-0.007
	(0.015)	(0.009)	(0.012)	(0.016)
Demand Surge	0.004	0.032***	0.032***	0.062***
	(0.013)	(0.010)	(0.008)	(0.018)
N	3491	1890	1771	1222
R^2	0.712	0.390	0.437	0.327

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Due to space limitation, we only reports the coefficient estimates of variables of key interest. Cluster robust errors clustering at pusher's level are reported.

Table A5: **Assistants' Cost Pass-Through**

	(1) Ice	(2) Ketamine	(3) Esctasy	(4) Ermin
Panel A: Dep Var: Log Price (Subsample:Early Pusher)				
Log Unit Cost	0.869***	0.236	2.010**	1.055***
	(0.162)	(0.287)	(0.848)	(0.385)
Enforcement Shock Impact Period	0.076	1.839	2.586	0.668
	(0.396)	(1.633)	(2.778)	(0.775)
Enforcement Shock Impact Period × Log Unit Cost	-0.002	-0.582	-0.909	-0.246
	(0.088)	(0.534)	(1.010)	(0.266)
Order Characteristics	Yes	Yes	Yes	Yes
Pusher's Characteristics	Yes	Yes	Yes	Yes
N	808	377	369	281
R^2	0.723	0.479	0.357	0.351
Panel A: Dep Var: Log Price (Full Sample)				
Log Unit Cost	0.470***	0.531***	0.855***	0.088
	(0.108)	(0.060)	(0.118)	(0.080)
Enforcement Shock Impact Period	-0.531	0.579	0.747	-0.836***
	(0.323)	(0.516)	(0.577)	(0.247)
Enforcement Shock Impact Period × Log Unit Cost	0.136*	-0.184	-0.260	0.291***
	(0.071)	(0.170)	(0.211)	(0.082)
N	3468	1876	1781	1222
R^2	0.580	0.270	0.371	0.172

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
[1] Results based on fixed effects regression using pushers' fixed effects and with errors clustered at pusher's level.
[2] In all regressions, only subsample of early pushers are used.

Table A6: **Impact of Shock on Assistant's Profit**

	(1) Ice	(2) Ketamine	(3) Esctasy	(4) Ermin
Panel A: Dep Var: Log Total Weekly Trading Quantity				
Enforcement Shock Impact Period	0.534**	-0.124	-0.047	0.138
	(0.228)	(0.218)	(0.130)	(0.208)
Positive Shock Impact Period	0.011	0.216	0.059	0.037
	(0.222)	(0.176)	(0.158)	(0.242)
Demand Surve Period	-1.226***	-1.454***	-0.990***	-1.156***
	(0.167)	(0.160)	(0.155)	(0.220)
Log Average Price Each Week	-2.516***	1.094	-5.165**	-2.713**
	(0.490)	(1.485)	(1.948)	(1.055)
N	51	51	51	51
R^2	0.690	0.749	0.768	0.649
Panel B: Dep Var: Log Profit Marin				
Enforcement Shock Impact Period	0.042***	-0.135***	0.027*	-0.173***
	(0.010)	(0.015)	(0.014)	(0.021)
Positive Shock Impact Period	0.006	-0.027*	0.050***	-0.037
	(0.011)	(0.017)	(0.015)	(0.023)
Demand Surve Period	0.069***	0.124***	0.059***	0.079***
	(0.012)	(0.021)	(0.018)	(0.025)
N	3446	1864	1769	1203
R^2	0.090	0.345	0.397	0.216

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
[1] In panel B, we also control for log quantity of drug, quality of drug and time trend.