Enforcement and Bargaining over Illicit Drug Wholesale Prices: Structural Evidence from a Transnational Asian Gang*

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Abstract

We estimate a structural model of multiproduct bargaining between a branch of a large transnational gang and pushers using data from detailed records kept by the gang. The model allows for the gang's relative bargaining power to differ for pushers with different characteristics, such as those with addictions or borrowing problems. Exploiting supply shocks in our data, we use the estimated model to study the effectiveness of various enforcement strategies. We find that targeting pushers is more effective at reducing quantities sold compared to targeting the gang's upstream supply chain.

Key words: Bargaining, Enforcement, Drugs, Crime
JEL Codes: C78, K42, L11

*The data used in this paper were obtained by Leong who first obtained approval to use this dataset to study the drug-selling market by writing to the appropriate Singaporean authorities. He obtained ethics approval from the Nanyang Technological University (NTU) IRB. As required by NTU IRB, we have solicited and incorporated feedback from the relevant authorities, lawyers, and ex-offenders into the current draft to ensure that we do not reveal any sensitive information that may jeopardize our own safety. Leong received a Singapore Ministry of Education Tier 1 grant for this research.

1 Introduction

The economics of transnational drug-selling gangs are of great interest to policymakers. Their activities create major negative externalities, such as addiction and crime, which are the focus of a number of large public policy initiatives. Understanding how different enforcement strategies affect prices and quantities throughout the supply chain are also relevant for designing optimal policing strategies, as many countries spend significant resources to reduce the consumption of illegal drugs. However, due to a lack of data on the trading activities of large drug gangs, little is understood about how prices and quantities are determined throughout the supply chain, and how different enforcement activities affect these prices and quantities.

In this paper, we study how prices and quantities are determined in the drug wholesale market by estimating a multiproduct structural bargaining model using detailed accounting records kept by the Singaporean branch of a large transnational gang. Our estimation exploits exogenous shocks to the gang's marginal costs, the largest being when the authorities successfully disrupted one of the gang's trafficking routes. We then use the estimated model to simulate a number of counterfactual enforcement strategies to explore the effectiveness of each strategy at reducing the total quantity sold on the market.

In our data, the gang recorded trades with 352 different pushers in four different illicit drugs of varying quality levels. These pushers are independent traders who sell drugs to end users. We observe 2,774 trades over the course of one year, where for each individual trade we observe the gang's unit costs, the bargained wholesale prices, and the quantities sold for each drug-quality pair. We also observe a host of characteristics for each pusher, such as demographics, business connections, and gambling and drug addictions. We also complement these data with interviews with over 100 ex-drug offenders and ex-drug users who were active in this market. Two large supply shocks occurred during our sample period. In one period, the authorities successfully intercepted a shipment and disrupted part of the gang's supply route, which caused the gang's unit costs to increase for a number of weeks. This particular disruption was significant not only because that route was compromised and had to be redirected, but also because the jockeys hired to transport the drugs were arrested and needed to be replaced. In another period, the gang's unit costs in ice (crystal meth) fell after the gang found a cheaper supplier.

We develop a structural model in which pushers decide each period how much, if any, of each drug to buy from the gang, where the wholesale prices are determined through Nash bargaining. We allow each pusher's bargaining weight to differ based on their observed characteristics, such as their demographics, business connections, and addictions. We also allow the parameters of the pushers' demand functions to change following the enforcement shock, which we use to identify the effectiveness of enforcement targeting this part of the gang's supply route.

Our model estimates show that borrowing problems and addiction to drugs and alcohol lower the bargaining power of the pushers. Those with gang affiliations and those with connections with businesses in which drugs are sold have higher bargaining power. Our estimated model is able to match the temporal variation in aggregate quantities and average wholesale prices for each drug in the data, and we use this model to simulate the effects of a number of counterfactual enforcement strategies.

Firstly, we use the estimated model to simulate what the total quantity sold on the market would have been in the absence of the enforcement shock. After the shock, the gang had to find a new supply route which increased unit costs, wholesale prices and end-user prices for approximately two months. Despite the large increase in wholesale prices, pusher demand was roughly similar to the no-shock scenario. In fact, the increase in end-user prices following the shock actually increased pusher demand in some drugs, despite the increase in wholesale prices. Given this result, we argue that targeting this part of the gang's supply route is not particularly effective at reducing the total quantity sold on the market.

Secondly, we estimate the effectiveness of the authorities targeting pushers. We do this by supposing the authorities manage to arrest a subset of the actively-trading pushers in one week. We find that such a policy leads to a large decrease in the total quantity sold in the following weeks. This is because the remaining pushers do not want to increase the total quantity they sell for fear of arrest. The penalties for being caught with large quantities of drugs are very severe in Singapore, as well as in many other countries. After approximately two months, the gang replaces the lost pushers and total sales return to normal. Due to a lack of data on the cost of enforcement, our results are not able to comment on the optimal level of enforcement (in the sense of Becker, 1968). However, market insiders we have spoken to agree that the cost of arresting pushers was much lower than successfully intercepting a large supply shipment during our sample period. The latter may involve months of work and large monetary incentives for informants. They also stated that these monetary rewards would sometimes be proportional to the market value of the drugs seized by the authorities as a result of the information provided, and these typically amounted to large sums. Therefore these counterfactual simulations suggest that if the goal is to reduce the quantity of illicit drugs sold on the market, then targeting pushers may be more effective than targeting the gang's shipments.[1]

One reason Southeast Asia is an interesting context in which to study this market is because of its large size. In 2018, 100 metric tons of methamphetamine were seized in Southeast Asia, compared to 68 tons in the US (NETI, 2019; UNODC, 2020). Singapore is an important transit point used by many transnational gangs in Southeast Asia (Emmers, 2003). Transnational gangs also view Singapore as a very attractive market because Singaporeans have very high spending power compared to other Asian countries (Teo, 2011). During our sample period, the GDP per capita of Singapore was more than 25 times that of China's.

This paper makes contributions to several strands of literature. Firstly, it contributes to the literature analyzing the effects of enforcement strategies on illegal drugs. Several papers have found that supply interventions only have small effects on lowering consumption. Dobkin et al. (2014) found

[1] In the Supplementary Appendix, we consider additional counterfactual experiments including one where we estimate the tax revenue that could be earned from legalizing ice.

that by targeting over-the-counter medicines that can be used to produce methamphetamine in the US, the number of production labs decreased but consumption was unchanged. Dobkin and Nicosia (2009) found that by the DEA shutting down suppliers of methamphetamine ingredients, the effects on prices and consumption were only temporary. Cunningham and Finlay (2016) also found short-lived price responses and small consumption responses from methamphetamine supply interventions. The literature has also studied the effects of enforcement on violence. Dell (2015) and Lindo and Padilla-Romo (2018) find that enforcement increased violence in Mexico and Gavrilova et al. (2019) find that medical marijuana laws reduced drug-related violence in the US. This paper contributes to this literature by using data from a gang's own records — rather than administrative data — to study the effectiveness of various enforcement strategies.

This paper also contributes to the literature on the structural estimation of models of the illicit drug market. Galenianos and Gavazza (2017) estimate a model of the interactions between sellers and end users, based on the theoretical model in Galenianos et al. (2012). Sellers face a trade-off between "cutting" the drug and reducing its quality to rip off new consumers, and selling them a high-quality product with the aim of building a long-term relationship. Janetos and Tilly (2017) study how online reviews mitigate adverse selection using a dynamic reputation model with scrapings from the dark web. Jacobi and Sovinsky (2016) study the effect of marijuana legalization on demand through increased access and reduced social stigma. Our paper differs from these by focusing on the relationship between the gang and pushers rather than the sellers and end users.

This paper also contributes to the literature on the estimation of structural bargaining models. Ho (2009) and Grennan (2013) estimate a bargaining model between hospitals and insurers and Crawford and Yurukoglu (2012) estimate a model with channel conglomerates and television distributors. While our bargaining model is based on these, it differs in two dimensions. Firstly, we allow pusher demand to be continuous over multiple products, rather than be discrete. Secondly, we allow the pusher's relative bargaining power to be a function of a large number of pusher characteristics.

A companion paper to this is Leong et al. (2019) who use the same dataset to study the causal effect of the enforcement shock on pusher demand using a regression discontinuity design. Finally, another related paper is Levitt and Venkatesh (2000), which to our knowledge is the only other paper in the economics literature which studies the financial records of drug-selling gangs. Their paper focuses on the compensation of gang members at different levels of the gang's hierarchy.

The remainder of our paper is organized as follows. Section 2 discusses the setting, market and data. Section 3 presents our bargaining model and Section 4 discusses estimation. Section 5 shows our model estimates and Section 6 presents our counterfactual simulations. Section 7 concludes.

2 Setting and Data

2.1 Overview

The gang we study is a now-defunct Singaporean branch of a large transnational gang that was active across several countries in Asia. The gang began operating in Singapore in the 1990s where it mainly sold four drugs: methylenedioxy-methamphetamine (ecstasy), nimetazepam (erimin), methamphetamine hydrochloride (ice, or crystal meth), and ketamine. We will refer to these drugs by their shorter trade name throughout this paper. This gang was the only gang selling ice in Singapore during our sample period, while there were many other gangs actively selling ecstasy, erimin and ketamine in the market. The gang imported ice, erimin, and ketamine from abroad while it sourced its supply of ecstasy locally. The gang then sold the drugs to pushers who then sold the drugs to end users. Pushers do not receive wages from the gang and are residual claimants on the profits they earn from trading. The supply chain is illustrated in Figure 1. The focus in this paper is how the gang and pushers bargained over wholesale prices and quantities of the drugs.[2]

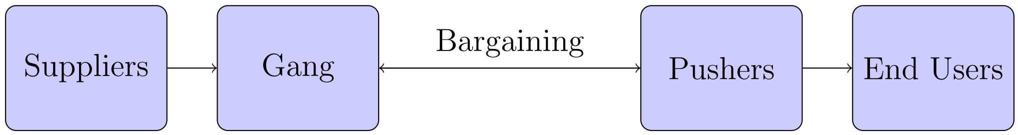


FIGURE 1: Drug supply chain

2.2 Trade Data

The gang recorded very detailed information about all of their dealings with each pusher in a ledger. For each trade the gang made with a pusher, they noted the date, the pusher's nickname, how many units of each drug were sold to the pusher, the quality levels of those drugs, the unit wholesale price paid by the pusher, and the gang's own unit costs of the drugs. They also recorded many details about the pushers, such as their education, borrowing behavior, and addictions. Our dataset is a digitized version of this accounting ledger which contains 2,774 trades between 352 different pushers over 51 weeks. Each trade can involve multiple products and we observe 8,402 trades in total at the product level. We have been instructed by the IRB not to reveal the exact time period that the ledger is from but we can reveal that our sample period is during the late 1990s. We also complement the trade data with interviews with 105 ex-drug offenders and ex-drug users who were active in this market during our sample period.[3]

One reason the gang kept such detailed records was to aid its decision-making as the gang was in its formative period operating in Singapore. They used the information to control their people and the flow of goods, and to predict demand during seasonal spikes. This branch of the gang also sometimes had to submit their accounting records to the international superiors of their

[2]See Leong et al. (2019) for a more extensive description of the gang's organizational structure.

[3]We discuss data sources, data authentication, replication procedures and how we carried out our interviews in the Supplementary Appendix.

organization. In interviews with ex-drug offenders, they noted that it was very common for large criminal organizations to record detailed data of their transactions. Drug-selling gangs in Southeast Asia have also been described to operate like multinational corporations (Allard, 2019).

The gang's record of the unit cost of each drug in a trade was calculated by taking the total cost of the shipment the drug came from and dividing by the total number of units in that shipment. The unit differs for each drug and is per tablet for ecstasy, per slab (10 pills) for erimin, and per gram for ice and ketamine. The gang had very frequent shipments (often several per day) and did not keep a large inventory. This cost is what the gang records as their cost for each particular trade. Since the gang kept such detailed records of their trades, especially for pecuniary matters, market insiders stated that the gang would have recorded other costs were they relevant for each trade.

The gang recorded three different quality levels for each drug. Over 95% of trades in ecstasy and erimin were of the same quality and, for ice and ketamine, over 99% of all trades were one of two qualities. Therefore for our analysis, we aggregate the quality levels for ecstasy and erimin into one quality and ice and ketamine into two qualities, leaving us with six different drug-quality pairs. We also aggregate trades that occurred between the same pusher and the gang in the same calendar week, taking the quantity-weighted average wholesale prices and costs where necessary. After both of these aggregation methods, the total number of trades becomes 2,536.

Average unit costs, wholesale prices, margins, and quantities for each drug are shown in Table 1. On average, the gang earned its largest margins on its sales of ice, which were 88% and 90% for low- and high-quality ice, respectively. For other drugs, the margins vary between 49% and 70%. The gang was able to sell ice at a higher margin because it was the only gang selling ice in the market during our sample period, while there were other gangs actively selling the other drugs.

Pushers also typically purchased small quantities of each drug in each trade. They did this to avoid the harsh sentences that come with larger quantities. Singapore has certain thresholds for the number of grams of a drug where drug

Product	Average unit cost	Average wholesale price	Average profit margin	Average quantity purchased	Total number of trades
Ecstasy	15.65	24.01	0.54	70.19	1791
Erimin	20.20	34.19	0.70	41.88	1222
Ice (High Quality)	88.69	165.94	0.90	10.30	1811
Ice (Low Quality)	78.89	146.11	0.88	10.95	1682
Ketamine (High Quality)	17.72	26.19	0.49	51.98	1144
Ketamine (Low Quality)	17.05	25.38	0.50	54.44	752

Prices are shown in Singaporean dollars, where US\$1≈ S\$1.70 during our sample period. Units for costs, wholesale prices and quantities are per tablet for ecstasy, per slab (10 pills) for erimin and per gram for both ice and ketamine. The gang calculates unit cost by dividing the total cost of the relevant shipment by shipment size.

Table 1: Summary statistics of completed trades.

trafficking is presumed, which can carry a life sentence. There are also higher thresholds that have a mandatory death penalty.[4] For ice, being caught with over 25 grams is presumed trafficking and being caught with over 250 grams carries a mandatory death sentence. Given these harsh penalties, pushers typically purchased small quantities of drugs frequently, rather than stockpiling large amounts. This can also be seen in Figure 2, which shows the frequency of pushers purchasing different quantities for each drug. 82% of trades involved less than 25g of ice and the largest quantity purchased at one time was 80g. Despite these thresholds, we do not observe any bunching of ice purchases just below 25g. Instead, the modal quantity of ice purchased is 10g. For other drugs, purchases over 200 units occur, but they are very rare. We also note that a pusher's primary use of the drugs was to sell to end users, although some pushers did use a very small fraction of their purchases for their own consumption.

Pushers also did not purchase a positive quantity of every drug in each trade. In fact, there were only 10 trades where a pusher purchased all 6 of the different drug-quality pairs. The modal pusher purchased 2 different products

[4]We summarize the maximum sentences from Singapore's Misuse of Drug Act in the Supplementary Appendix for the drugs in our data during our sample period.

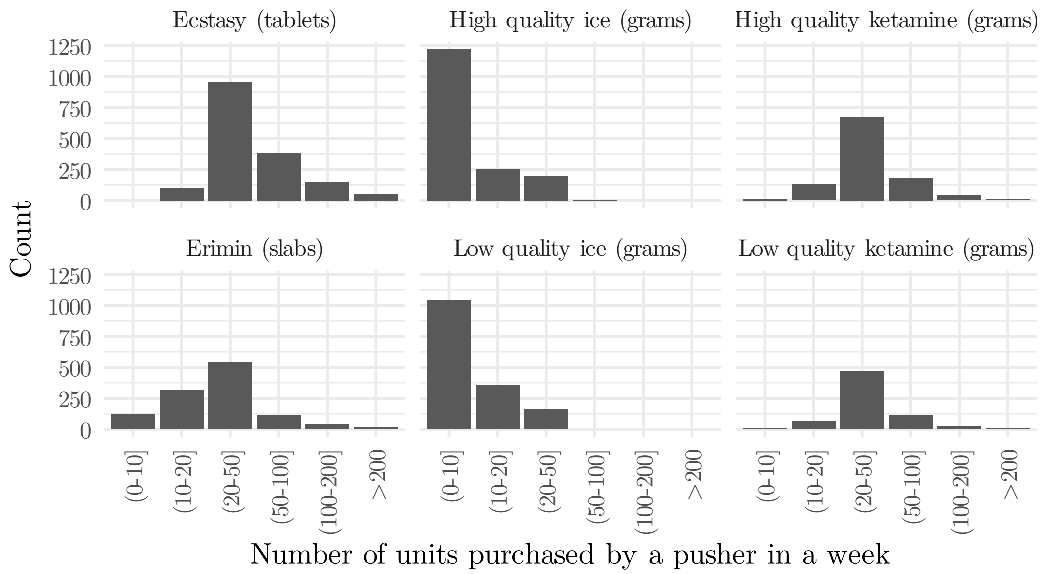


FIGURE 2: Histogram of weekly number of units purchased by pushers by product.

in a week and 69% of trades involved trades in fewer than 4 products. In our analysis, we model this as censored data and model selection into trading explicitly.

In our trade data, 216 of the 352 pushers bought two different qualities of the same drug on the same day. In trades where two qualities of the same drug were purchased, the wholesale price was on average 19% higher for the higher-quality version of the same drug. This is evidence that pushers knew the quality of the drugs when trading. Pushers were involved in multiple trades with the gang, with 98% of pushers having at least 4 trades with the gang over our year of data. Therefore, it is more likely that these trades were part of a long-term relationship rather than rip-off trades where the gang cheated the pusher, such as those studied in Galenianos et al. (2012) and Galenianos and Gavazza (2017) between sellers and end users. In interviews with ex-offenders, we were also told that pushers who purchased large quantities and those who had long-standing relationships with the gang were allowed to taste the products to determine their quality before purchase.

2.3 Pusher Characteristics Data

For each of the 352 pushers, we also observe a large number of pusher characteristics. Summary statistics of these characteristics are shown in Table 2. 96% of pushers are male and the median age is 30. Singaporean Chinese make up 88% of pushers, with the remainder either Malaysian Chinese or Singapore Indian. Most pushers have low education levels: 38% of pushers have only primary education, 5.7% are illiterate, and there are only 5 pushers with higher than secondary education. Pushers are often connected to the gang; 66% have some affiliation with the gang and 58% have a business connection, typically with karaoke establishments (KTVs), night clubs, or discotheques. Among pushers, 58.5% have been arrested before, and out of those arrested the median pusher spent 3 years in prison. Drug addiction is very common among pushers, with 39% having a light addiction, 30% having a heavy addiction and 43% having spent time in rehab.[5] Alcoholism is less common at 28%, but 62% and 58% have gambling addictions and borrowing problems, respectively.

Pushers started and stopped trading with the gang throughout the year, where the average pusher traded with the gang for 8 weeks. Figure 3 shows the number of active pushers by week in our data, where a pusher is active in a week if it purchased a positive quantity of any drug in that week. In the first two months, the number of pushers was smaller because the gang was still growing. Between weeks 10 and 49, the number of active pushers per week varied between 45 and 78. The number of pushers fell in the final two weeks as this was a holiday period. During the holiday period, there is a greater number of alternative employment opportunities which may lead to pusher exit, but there is also an increase in enforcement activities which would lead to more arrests.

There are several reasons why pushers entered into and exited out of trading, but in many cases, entry and exit were outside of a pusher's control. The gang recorded who made the introduction with each pusher. In most cases,

[5] There is a substantial literature documenting gang members engaging in drug use. See Fagan (1989), Esbensen and Huizinga (1993), Howell and Decker (1993), Harper et al. (2008) and Swahn et al. (2010).

	N	Mean	Std. Dev.	Min.	Median	Max.
Age	352	32.09	8.71	19	30	52
Female	352	0.04	0.19	0	0	1
Married	352	0.12	0.33	0	0	1
Has children	352	0.27	0.45	0	0	1
Ethnicity: Singaporean Chinese	352	0.88	0.32	0	1	1
Ethnicity: Malaysian Chinese	352	0.08	0.27	0	0	1
Ethnicity: Singapore Indian	352	0.04	0.20	0	0	1
Illiterate	352	0.06	0.23	0	0	1
Highest Education: Primary	352	0.38	0.49	0	0	1
Highest Education: Secondary	352	0.55	0.50	0	1	1
Highest Education: Higher	352	0.01	0.12	0	0	1
Unemployed	352	0.42	0.49	0	0	1
Employed part-time	352	0.12	0.33	0	0	1
Employed full-time	352	0.46	0.50	0	0	1
Monthly income (in $S)	350	858.86	838.40	0	1000	3500
Been in prison	352	0.59	0.49	0	1	1
Time spent in prison	352	2.03	2.45	0	1.4	14
Gang affiliation	352	0.66	0.47	0	1	1
Business connection with brothel	352	0.05	0.22	0	0	1
Business connection with KTV	352	0.38	0.49	0	0	1
Business connection with club/disco	352	0.24	0.43	0	0	1
Light drug addiction	352	0.39	0.49	0	0	1
Heavy drug addiction	352	0.30	0.46	0	0	1
Been in rehab	241	0.43	0.50	0	0	1
Alcoholic	352	0.28	0.45	0	0	1
Gambling addiction	352	0.62	0.49	0	1	1
Borrowing problem	352	0.58	0.49	0	1	1

Table 2: Summary statistics of pusher characteristics.

the gang recruited the pusher directly rather than the pusher approaching the gang. The majority of pushers were introduced to a gang member by their non-gang friends. They were also sometimes introduced to them by other gang members, other pushers or they were previous clients of the gang. The gang also hired new pushers at a steady rate. They ensured that the number of new pushers they hired at any given time would not be large enough to attract the attention of the authorities. In interviews with ex-offenders, one of the main reasons pushers decided to begin trading was that they were convinced by the gang or a peer that they could get rich quickly by selling drugs. Pushers are often drug addicts or have other addictions such as gambling and alcoholism, and often do not have an alternative to be able to feed their addiction or repay their debts.

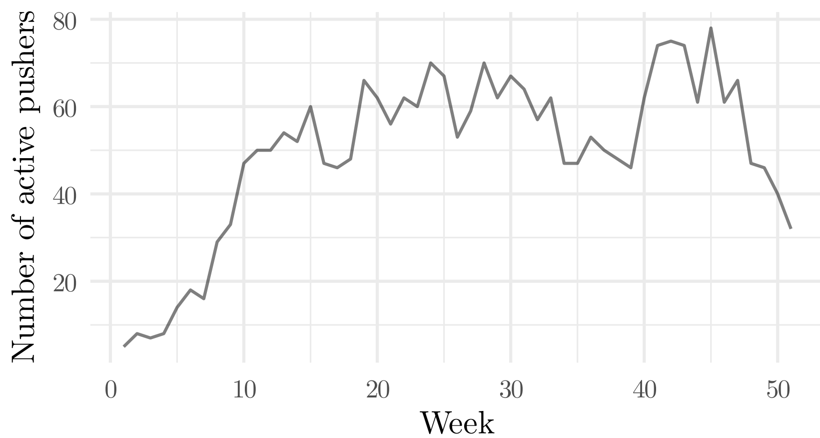


FIGURE 3: Number of active pushers trading per week

Our data also contains the reason why pushers stopped trading with the gang. At least 36% of pushers in our sample were arrested, while 57% of pushers stop trading for other reasons. The remaining 7% of pushers were fired by the gang. While some of the 57% may have been arrested, pushers were also free to stop selling for the gang without penalties. Internal gang rules prohibit the pushers from revealing anything they know about the gang if they choose to exit. Otherwise, these pushers would be subject to extreme punishment. According to market insiders, the top priority of the authorities is to seek out and eliminate drug-selling gangs that use any type of verbal or physical criminal force to intimidate anyone to get involved with the drug trade. The goal of the transnational gang leadership is to "avoid doing anything that may cause the authorities to focus on their operations and make as much money as possible." From interviews with ex-offenders, some pushers quit after selling drugs for a period of time, recalling they heard "God telling them to quit." Some pushers mentioned that their family convinced them to quit. Other pushers quit to pursue other lucrative illegal employment opportunities, often in the illegal gambling sector, which they chanced upon while selling drugs.

Pushers traded exclusively with one gang and did not trade with multiple gangs. They did this for several reasons. Firstly, all gangs would only sell to pushers that they knew and trusted. Pushers could not buy drugs from another gang without first spending time and resources to earn their trust. Secondly, it was common knowledge among pushers that all transnational gangs dealt with pushers in a similar way. Since pushers knew that the prices they would pay for drugs would be similar regardless of the gang they traded with, there would minimal financial benefit in trading with multiple gangs. Thirdly, there would be a higher risk of arrest in doing so. If pushers dealt with multiple gangs, they would have to reveal themselves to more people, and thus stand a higher risk of exposing themselves to undercover operatives.

2.4 End-User Market

We do not observe the interactions between the pushers and end users in our data, but from interviews with ex-offenders, ex-users, and police reports, we have information about the structure of the market in which they traded during our sample period. At the time, the end-user market in Singapore was highly competitive as there were many buyers and many pushers selling nearly identical products.[6] The search costs for trading were also low. A large proportion of trades occurred in the Geylang area, Singapore's red light district.[7] There are roughly 3.5km of road in Geylang, which was a hot spot for drug dealing (Lee, 2014). Gangs sold drugs on the street and in clubs and karaoke bars in the district. At least 10 different gangs and their respective pushers operated independently in different lanes of the district. Each gang, including the gang we study, claimed a few lanes as their turf.[8] In some instances, pushers paid rival gangs a fee to sell drugs on rival turf. From interviews with end users, a typical end user would contact 3-7 pushers before

[6]From the 1980s to the 1990s, there was significant growth in the number of new drug addicts in Singapore (Chua, 2016). For example, the number of heroin users was at its peak in the 1990s (Teo, 2011).

[7]From our surveys, 101 out of 105 respondents stated Geylang was the location with the most drug sales. See Li et al. (2018) for a more extensive description of Geylang.

[8]Most gangs in Asia will try to ensure that large scale violence does not break out across rival gangs when working in close proximity to one another in order to evade detection by the authorities. This is consistent with statements released by law enforcement officials. According to Allard (2019), the police in another Asian country claim that "the money is so big that long-standing, blood-soaked rivalries among Asian crime [drug] groups have been set aside in a united pursuit of gargantuan profits."

going to the district. For end users, it was easy to collect information about availability and prices as all the gangs were operating very close by. 97 of 105 of our survey respondents stated that they did not observe price differences for the same drug at the same time in a particular location, even across different gangs. There are also several other neighborhoods in Singapore that operated in a similar way, such as Bukit Merah and Tanjong Pagar. All these areas are collectively known as "Di San Qu". Because Singapore is a small country (50×27km in area), any end user was very close to an area where there were many pushers selling different drugs.

End users were often not worried about being the target of enforcement as individuals often obstructed police from entering into Geylang (Ministry of Home Affairs, 2014). Singapore had an "exceedingly low ratio" of police officers to population compared to cities such as Hong Kong, New York, and London (Hussain, 2014). During our sample period, the authorities did not have the modern technologies that are available to law enforcement today. This meant that the authorities faced challenges policing the large number of gangs in operation at the time. Ex-offenders we interviewed said that "unlike today, the drug situation at that time was a big problem". Furthermore, market insiders claim that Singapore started from a low base and acquired its modern-day reputation of strong enforcement over many years in part due to acquiring the necessary resources and the knowledge of the difficulties of conducting enforcement during this period.

End users also substitute easily across drugs. Approximately 80% of ex-users we have interviewed said they substituted from one drug to another depending on what was available. Different end users substitute to different drugs. For example, some substituted ice with heroin, while others substituted ice with erimin.

In interviews with ex-pushers, we asked what they would do if their own costs increased temporarily by 10-20%. The vast majority stated that they would not try to pass on any of this cost increase to end-user prices, further highlighting the competitiveness of the end-user market.

Given these features of the end-user market, we approximate the end-user

Product	Unit	Price (in S$)
Ecstasy	Tablet	43
Erimin	Pill	8
Ice (high quality)	Gram	280
Ice (low quality)	Gram	240
Ketamine (high quality)	Gram	50
Ketamine (low quality)	Gram	45

Table 3: End-user prices in Singaporean dollars

market as perfectly competitive in our model and assume that pushers take the end-user price as given. We assume that the end-user prices for each drug were fixed throughout our year of data, with the exception of the period following the enforcement shock (discussed further in the next subsection). We obtain end-user prices from various reports and from interviews with ex-drug offenders. The values from the reports fall within the ranges provided by the ex-drug offenders. Table 3 shows the end-user prices we use for each drug.[9] At these prices, pushers earn considerable gross margins over the wholesale price, with the median equal to 85%. However, pushers have a number of other costs, such as purchasing untraceable phone cards, vetting costs, transport costs, and in rarer cases, bribes. Therefore, their actual profit margins are much smaller than this. A majority of ex-pushers we have interviewed stated that they "didn't get rich from selling drugs". For instance, 104 of 105 of our survey respondents stated that they were not able to afford bail after being arrested.[10]

2.5 Enforcement and Supply Shocks

Our sample period contains shocks that had effects on the gang's unit costs for drugs. The largest of these was an enforcement shock where the authorities arrested some of the jockeys hired by the gang and seized their products. Jock-

[9] The sources to obtain these figures are described in detail in the Supplementary Appendix.

[10] Bail was set at roughly S$30,000-S$50,000 during our sample period.

eys are delivery experts hired by the gang to transport drugs from the supply source to the gang. The authorities intercepted the jockeys while transporting the drugs across the borders of a Southeast Asian country into Singapore. This event disrupted the gang's operations as the gang had to find other means to obtain the drugs, which raised their unit costs. After the enforcement event, new delivery routes and jockeys had to be secured, which took several weeks.

Figure 4 shows the average weekly unit cost to the gang and the wholesale price that pushers pay for each product. The enforcement shock occurred in week 13 and its effects lasted until week 21. This raised the unit costs of all drugs except ecstasy, which was sourced locally so was unaffected by the raid. We can see that the shock also correspondingly increased the weekly average wholesale price of the drugs. In week 30, the gang found a cheaper supplier for ice which lowered their unit costs by approximately 14%. This persisted for a number of weeks before falling again towards the end of the year. These cost savings were partially passed on to the pushers in the form of lower wholesale prices.

While there was a clearly visible change in unit costs and wholesale prices following the enforcement shock, the effect on total quantities purchased is less clear. Figure 5 shows the total quantity sold to all pushers each week for each product. There is considerable noise in the total quantity sold at the product-week level and there is no clear decrease in total quantities following the enforcement shock. However, from the figure, we do observe significantly less sold at the beginning and at the end of the year. This is mostly due to the number of active pushers during those times (see Figure 3).

Interviews with ex-offenders confirm that, at the time of the enforcement shock, there was only one large gang of jockeys that delivered drugs to virtually every gang in the country. Therefore, the supply disruption affected all gangs operating in Singapore and temporarily changed end-user prices in the market. Interviews with ex-offenders also confirm that end-user prices did indeed increase in these drugs following the shock. We will model the gang's residual demand curve and allow for market end-user prices to change in the period following the enforcement shock. The shock did not affect the gang's

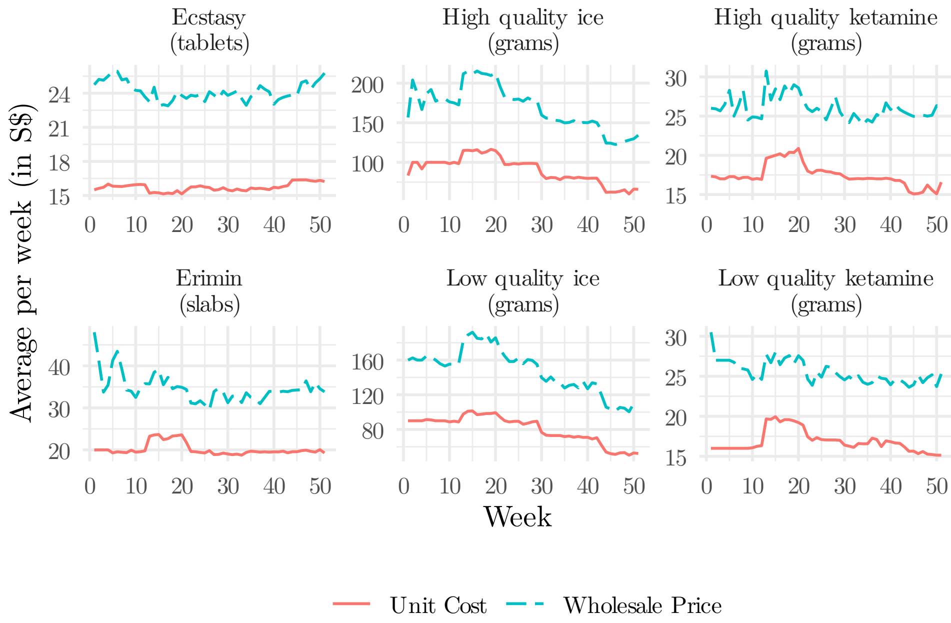


FIGURE 4: Average unit cost and wholesale price by week.

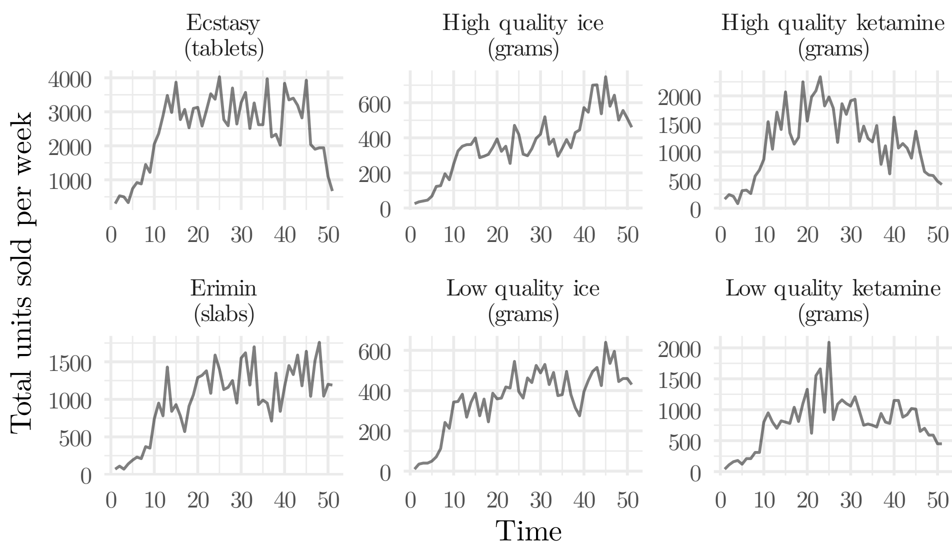


FIGURE 5: Total units sold per week.

unit costs for ecstasy, which was sourced locally. Interviews with ex-offenders indicated that other gangs also sourced ecstasy locally, so they also would not have been affected by the shock.[11]

We also note that during our sample period there were no other major events, such as a recession, other than the events already described, namely the enforcement shock and the large reductions in ice unit costs later in the year. We have confirmed this in interviews with ex-offenders who operated during the sample period.

3 Model

There is a set of N pushers, $\mathcal{N} = \{1, \ldots, N\}$, who trade with the gang. Each period t, a subset $\mathcal{N}_t \subset \mathcal{N}$ of the N pushers are actively trading and negotiate with the gang over the wholesale prices and quantities of each of the J different products. Each product is a drug-quality pair.[12] After the gang and pusher have come to an agreement on prices and quantities, the pushers sell the drugs to end users.

We first describe the payoff functions of pushers and the gang. We then discuss how prices and quantities are determined through Nash bargaining.

3.1 Pushers

If pusher i is active at time t ($i \in \mathcal{N}_t$), they can purchase a vector of quantities $\boldsymbol{q}_{it} \in \mathbb{R}^J_+$ of each product from the gang. Pusher i's payoff from purchasing

[11]Different Asian countries and regions have their own comparative advantages in producing different types of drugs, and these advantages evolve over time. For example, according to the US Department of State (2000), China is a major producer of drug precursor chemicals and emerging as a key production hub for ice and other synthetic drugs. Marijuana is grown throughout the Philippines, whereas Laos is a major source of opium. There is also evidence of ecstasy production in Singapore from a police bust that occurred near our sample period (The Straits Times, 1999).

[12]The six distinct products are (i) ecstasy, (ii) erimin (iii) high-quality ice, (iv) low-quality ice, (v) high-quality ketamine and (vi) low-quality ketamine.

quantities $\boldsymbol{q}_{it}$ is:

$$u_i\left(\boldsymbol{q}_{it}\right)=\sum_{j=1}^{J}\left(p_{jt}-w_{ijt}\right)q_{ijt}-\sum_{j=1}^{J}\left(\xi_{ijt}q_{ijt}+\frac{\kappa_{jt}q_{ijt}^{2}}{2}\right)$$

The pusher purchases product j at wholesale price w_{ijt} from the gang and sells to end users at price p_{jt}, which they take as given since the retail market for drugs is competitive. Pushers operate independently of one another and their payoffs do not depend on the actions of other pushers.

The term $\sum_{j=1}^{J}\left(\xi_{ijt}q_{ijt}+\frac{\kappa_{jt}q_{ijt}^{2}}{2}\right)$ represents the other monetary and non-monetary costs from selling drugs. The pusher's marginal cost for product j is $w_{ijt}+\xi_{ijt}+\kappa_{jt}q_{ijt}$ which increases linearly with quantity. The intercept varies with ξ_{ijt}, which is an idiosyncratic shock to the pusher's marginal cost. From interviews with ex-drug offenders, this can change week by week for a number of reasons, many of which are random and outside of the pusher's control. Pushers purchase untraceable phone cards on the black market and if suppliers are arrested the price of the cards may change. Pushers must also vet their customers to ensure they are not undercover officers. If the pusher has more customers that they are unfamiliar with in a certain week, this cost will increase. Many pushers rent a vehicle from friends or associates for short periods of time which can vary in cost. In rare instances, pushers may also need to bribe law enforcement officers.

Marginal costs are increasing in the quantity sold not only because the marginal cost of effort increases, but also because the penalties from selling larger quantities are greater. The more drugs a pusher sells, the greater risk of detection and the greater the penalty upon detection. This is because larger quantities can carry a longer jail sentence, a life sentence, or even the death penalty.[13]

Given this utility specification, pusher i's demand for product j at the

[13] In the pusher's utility function, we do not incorporate the legal thresholds for possessing different quantities of each drug that results in a discrete jump in the severity of punishment. We do this because we do not observe significant bunching just below these thresholds for the different drugs in our data.

wholesale price vector $\boldsymbol{w}_{it}$ is given by the following linear demand function:

$$q_{ijt}\left(\boldsymbol{w}_{it}\right)=\begin{cases}\frac{p_{jt}-w_{ijt}-\xi_{ijt}}{\kappa_{jt}} & \text{if } p_{jt}\geq w_{ijt}+\xi_{ijt}\\ 0 & \text{otherwise}\end{cases} \tag{1}$$

If a pusher is not active in period t, they cannot purchase any drugs. Entry and exit into trading are treated as exogenous and does not depend on prices or quantities sold. This is because there are many exogenous factors leading to entry and exit, such as arrests (see Section 2.3 for further details). Given this assumption, each pusher's demand in each period is static. This also has the consequence that pushers cannot stockpile drugs when prices are low. This is in line with our setting in which pushers typically purchase small quantities each week, partly explained by the harsh sentences upon detection. Ex-drug offenders also stated that they tried to sell all of their drugs as quickly as possible after the trade for this reason.

3.2 Gang Profits

The gang sells drugs to the actively-trading pushers in each period t. The marginal cost of drug j being sold to a pusher at time t is c_{jt}. We assume there are time-varying fixed costs for the gang (for example, storage costs, wages and costs associated with importing), but the gang has no fixed costs associated with each individual trade. Given the gang kept such detailed accounting records of their trades, the gang would likely have recorded any trade-specific fixed costs if there were any. The fixed costs in each time period are given by FC_t. The gang's profits in period t are then:

$$\pi_t\left(\{\boldsymbol{w}_{it}\}_{i\in\mathcal{N}_t}\right)=\sum_{i\in\mathcal{N}_t}\sum_{j=1}^{J}\left(w_{ijt}-c_{jt}\right)q_{ijt}\left(\boldsymbol{w}_{it}\right)-FC_t$$

The total payoff of the gang at time t is the sum of profits from trading with each pusher minus their time-varying fixed costs. We assume that the incentives of the gang members executing these trades are aligned with the gang and we abstract away from any principal-agent problems that may exist within the gang.

3.3 Nash Bargaining

We assume wholesales prices are determined through bilateral Nash bargaining between the gang and the pushers. At wholesale prices $\boldsymbol{w}_{it}$, pusher i's surplus from trade is given by their indirect utility function:

$$v_{it}\left(\boldsymbol{w}_{it}\right)=\sum_{j=1}^{J}\mathbb{1}\left\{p_{jt}\geq w_{ijt}+\xi_{ijt}\right\}\frac{\left(p_{jt}-w_{ijt}-\xi_{ijt}\right)^{2}}{2\kappa_{jt}} \tag{2}$$

where $\mathbb{1}\left\{p_{jt}\geq w_{ijt}+\xi_{ijt}\right\}$ equals 1 if $p_{ijt}\geq w_{ijt}+\xi_{ijt}$ and is zero otherwise. If the gang sells $\boldsymbol{q}_{it}$ to pusher i at time t at prices $\boldsymbol{w}_{it}$, the gang's surplus from that trade is equal to:

$$\pi_{it}\left(\boldsymbol{w}_{it}\right)=\sum_{j=1}^{J}\left(w_{ijt}-c_{jt}\right)q_{ijt}\left(\boldsymbol{w}_{it}\right) \tag{3}$$

The fixed cost is sunk and does not enter into the gang's surplus for an individual trade. The wholesale prices that result from bargaining are then those that maximize the Nash product of the gang's and pusher's surplus from trade:

$$\boldsymbol{w}_{it}=\underset{\widetilde{\boldsymbol{w}}_{it}\in\mathcal{W}_{it}}{\arg\max}\ \left[\pi_{it}\left(\widetilde{\boldsymbol{w}}_{it}\right)\right]^{1-\beta_i}\left[v_{it}\left(\widetilde{\boldsymbol{w}}_{it}\right)\right]^{\beta_i}$$

where $\beta_i\in(0,1)$ is pusher i's bargaining weight, $1-\beta_i$ is the gang's bargaining weight and:

$$\mathcal{W}_{it}=\left\{\widetilde{\boldsymbol{w}}_{it}\in\mathbb{R}^{J}:\widetilde{w}_{ijt}\in\left[c_{jt}+\xi_{ijt},p_{jt}\right]\cup\left\{p_{jt}-\xi_{ijt}\right\}\forall j\right\} \tag{4}$$

This is the set of possible wholesale prices at marginal costs, c_{jt}, the pusher's idiosyncratic shock, ξ_{ijt}, and end-user prices, p_{jt}. The negotiated wholesale price for product j must be between the sum of the gang's marginal cost and the pusher's idiosyncratic shock, $c_{jt}+\xi_{ijt}$, and the end-user price, p_{jt}. If

$c_{jt} + \xi_{ijt} > p_{jt}$, then $[c_{jt} + \xi_{ijt}, p_{jt}] = \varnothing$ and the wholesale price for product j that maximizes the Nash product is $p_{jt} - \xi_{ijt}$. At this wholesale price, no trade occurs in that drug as the pusher's demand is zero. This constraint does not permit the gang to cross-subsidize across drugs.

Taking derivatives of equation (4) with respect to w_{ijt} for the interior case of $p_{jt} > c_{jt} + \xi_{ijt}$ yields the first-order conditions:

$$\begin{aligned}(1-\beta_i)&\frac{\partial \pi_{it}(\boldsymbol{w}_{it})}{\partial w_{ijt}}\left[\pi_{it}(\boldsymbol{w}_{it})\right]^{-\beta_i}\left[v_{it}(\boldsymbol{w}_{it})\right]^{\beta_i}\\ +\,\beta_i&\frac{\partial v_{it}(\boldsymbol{w}_{it})}{\partial w_{ijt}}\left[v_{it}(\boldsymbol{w}_{it})\right]^{\beta_i-1}\left[\pi_{it}(\boldsymbol{w}_{it})\right]^{1-\beta_i}=0\end{aligned}$$

Using the expressions for $\pi_{it}(\boldsymbol{w}_{it})$ and $v_{it}(\boldsymbol{w}_{it})$ we obtain:

$$\begin{aligned}&(1-\beta_i)\left(p_{jt}+c_{jt}-2w_{ijt}-\xi_{ijt}\right)\left[\sum_{j'=1}^{J}\mathbb{1}\left\{p_{j't}>w_{ij't}+\xi_{ijt}\right\}\frac{\left(p_{j't}-w_{ij't}-\xi_{ijt}\right)^2}{2\kappa_{jt}}\right]\\ =&\beta_i\left(p_{jt}-w_{ijt}-\xi_{ijt}\right)\left[\sum_{j'=1}^{J}\left(w_{ij't}-c_{j't}\right)\mathbb{1}\left\{p_{j't}>w_{ij't}+\xi_{ijt}\right\}\frac{p_{j't}-w_{ij't}-\xi_{ijt}}{\kappa_{jt}}\right]\end{aligned} \tag{5}$$

which implicitly determines the optimal wholesale prices for all products where $p_{jt} > c_{jt} + \xi_{ijt}$. In general, there is no closed-form solution for the wholesale price vector $\boldsymbol{w}_{it}$, but iterative methods can be used to solve for it. To provide some intuition for this optimality condition, we can solve for the optimal wholesale price analytically in the special case where $p_{jt} > c_{jt} + \xi_{ijt}$ for a single product and $p_{j't} \leq c_{j't} + \xi_{ijt}$ for all other $J-1$ products $j' \neq j$. In this special case we obtain:

$$w_{ijt} = \beta_i c_{jt} + (1-\beta_i)\left(\frac{p_{jt} - \xi_{ijt} + c_{jt}}{2}\right)$$

If the pusher's bargaining coefficient β_i approaches one, which corresponds to the pusher holding all of the bargaining power, then the wholesale price approaches marginal cost c_{jt}. In this case, the pusher receives the entire surplus from the trade. As the pusher's bargaining coefficient approaches zero, which corresponds to the gang holding all of the bargaining power, then the wholesale price approaches $\frac{p_{ijt}-\xi_{ijt}+c_{jt}}{2}$ and the pusher's payoff equals zero. This is the price that a monopolist would charge given the pusher's linear demand curve.

We implicitly assume there is no asymmetric information between the gang and each pusher about each other's payoffs when bargaining over wholesale prices. From our data, we know the gang had considerable information about the pushers it sold to. Due to the legal penalties involved, the gang would conduct the necessary due diligence on each pusher to ensure that it was safe and profitable to work with them. The pushers also had knowledge of the gang's unit cost of drugs at the time. If the authorities seized any drug shipments that increased the gang's cost of obtaining drugs, this was made public knowledge in the media. Media articles typically included the location of the seizure, drug types, and total market value of drugs seized. Each gang's cost of drugs was also typically known in the drug-selling circles. Out of the 105 respondents we interviewed, 94 of them said that they had access to this type of information. Suppliers who tried to market to other gangs may also demonstrate that prominent gangs were their customers, thereby indirectly releasing this information to the market. Finally, we also assume that the disagreement payoff for the pusher is zero. This is because pushers cannot trade with rival gangs in the event of a disagreement.

We also note that the weight thresholds that result in discrete jumps in punishment severity (such as the 25g threshold for ice where drug trafficking is presumed) may have been an institutional feature that contributed to the gang's ability to price discriminate. The large penalties from being caught with larger quantities precluded pushers that bought at lower wholesale prices from making side trades. If all quantities had the same legal penalties, then this could have disrupted the gang's ability to price discriminate.

4 Estimation

4.1 Parameterization

We assume the bargaining weight for pusher i is a function of a large number of pusher characteristics, $\boldsymbol{x}_i$. We include variables such as sociodemographic characteristics and indicators for addictions, borrowing problems, and business connections. The vector of characteristics $\boldsymbol{x}_i$ does not have a t subscript because we only observe static pusher characteristics. For example, we do not observe pushers who develop addictions or large debts during our sample period. However, the median pusher trades with the gang for only 7 weeks and 94% of pushers trade with the gang for less than 16 weeks. Therefore, it is unlikely that our data fails to capture important temporal variation in pusher characteristics. We do not include the pusher's previous trade history in $\boldsymbol{x}_i$ as that would make the pusher's problem dynamic and would greatly increase the computational complexity of our estimation procedure.

For the bargaining weight, we adopt the following functional form:

$$\beta_i = \Phi\left(\boldsymbol{x}_i' \boldsymbol{\theta}_\beta\right)$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution and $\boldsymbol{\theta}_\beta$ is a vector of parameters to be estimated. This functional form is chosen to ensure the bargaining weights lie within the unit interval.

We assume the end-user prices p_{jt} are fixed throughout the year at the prices given in Table 3 with the exception of the period following the enforcement shock. Since the shock affected every gang in the country, it temporarily changed equilibrium prices in the end-user market. Ex-drug offenders we have interviewed also confirmed that end-user prices did increase temporarily following the shock. We parameterize end-user prices as:

$$p_{jt} = \bar{p}_j + \theta_{ej} e_t, \quad j = 1, \ldots, J$$

where each $\bar{p}_j$ is the corresponding price in Table 3 and $e_t = 1$ during the weeks following the enforcement shock and is zero otherwise. The terms θ_{ej} for each j are parameters to be estimated. Even though the enforcement shock did not affect the gangs' costs in ecstasy, we allow its market price to change as substitution from other drugs may affect the ecstasy market.

We also allow the slope of the pusher's marginal cost function to change in the period following the enforcement shock:

$$\kappa_{jt} = \kappa_j + \kappa_j^e e_t, \quad j = 1, \ldots, J$$

Each κ_j and κ_j^e are parameters to be estimated. We assume that for each j, the idiosyncratic shocks ξ_{ijt} are draws from a normal distribution with mean μ_j and variance σ_j^2, which are further parameters to be estimated.

The gang's surplus from a trade is given by $\pi_{it}(\boldsymbol{w}_{it}) = \sum_{j=1}^{J} (w_{ijt} - c_{jt}) q_{ijt}$. The wholesale price and quantities are directly observed in the data. We assume that the unit cost recorded by the gang approximates the gang's actual marginal cost for a trade. Since the gang kept such detailed records of all their dealings with pushers, if there were any other meaningful costs associated with a particular trade, they would have recorded it in their ledger. Therefore, we treat the gang's surplus $\pi_{it}(\boldsymbol{w}_{it})$ as fully observed in our data and therefore it does not require parameterization.[14]

Finally, we also need to specify $\mathcal{N}_t$, the set of active pushers in each week as we assume entry and exit into trading is exogenous. We specify the weeks each pusher is active as follows. A pusher is active if it purchased a positive quantity of at least one drug in a week or purchased a positive quantity in both the preceding and following week. Under this assumption, the median number of active pushers per week is 64 and there are 3,023 pusher-weeks.

[14]In principle, we could allow for the gang's actual marginal cost to be the unit cost in the data plus a mean-zero shock. However, the variance of this shock is not separately identified from σ_j^2, which is the variance of the pusher's idiosyncratic shock, ξ_{ijt}. We discuss the reason for this in the Supplementary Appendix.

4.2 Simulated Method of Moments

The full vector of parameters to be estimated is:

$$\boldsymbol{\theta} = \left(\boldsymbol{\theta}_\beta, \left\{\theta_{ej}, \mu_j, \sigma_j, \kappa_j, \kappa_j^e\right\}_{j=1}^J\right)$$

We use simulated method of moments to estimate $\boldsymbol{\theta}$ using the continuous-updating estimator (Hansen et al., 1996). Given a trial value of the parameter vector $\boldsymbol{\theta}$ and draws of ξ_{ijt} for each j, we can calculate the wholesale prices $\boldsymbol{w}_{it}$ that satisfy the Nash bargaining first-order conditions in equation (5). Since we do not have a closed-form solution for $\boldsymbol{w}_{it}$, we do this by finding the fixed point of the function $\boldsymbol{\Omega}(\boldsymbol{w}_{it})$, whose jth element is:

$$\Omega_j(\boldsymbol{w}_{it}) = p_{jt} - \xi_{ijt} - \frac{(1-\beta_i)(p_{jt} - \xi_{ijt} + c_{jt} - 2w_{ijt})\, v_{it}(\boldsymbol{w}_{it})}{\beta_i \pi_{it}(\boldsymbol{w}_{it})}$$

A trade can only occur in a drug if $p_{jt} > c_{jt} + \xi_{ijt}$ as we do not allow for cross-subsidization.[15] In the range $w_{ijt} \in (c_{jt} + \xi_{ijt}, p_{ijt})$, the function $\Omega_j(\boldsymbol{w}_{it})$ is increasing in w_{ijt} and we can find the fixed point using bisection. A complete description of this procedure is given in the Supplementary Appendix. Once we have found the vector of wholesale prices satisfying $\boldsymbol{w}_{it} = \boldsymbol{\Omega}(\boldsymbol{w}_{it})$, we can calculate pusher demand for each product using equation (1).

Let $\widetilde{w}_{ijts}(\boldsymbol{\theta})$ and $\widetilde{q}_{ijts}(\boldsymbol{\theta})$ be the simulated wholesale price and quantity in simulation s with the trial parameter vector $\boldsymbol{\theta}$. With ns simulations, we obtain estimates of the expected wholesale price and quantity for drug j for pusher i at time t conditional on trading according to:

$$\widetilde{w}_{ijt}(\boldsymbol{\theta}) = \frac{\sum_{s=1}^{ns} \mathbb{1}\{\widetilde{q}_{ijts}(\boldsymbol{\theta}) > 0\}\, \widetilde{w}_{ijts}}{\sum_{s=1}^{ns} \mathbb{1}\{\widetilde{q}_{ijts}(\boldsymbol{\theta}) > 0\}}$$

$$\widetilde{q}_{ijt}(\boldsymbol{\theta}) = \frac{\sum_{s=1}^{ns} \mathbb{1}\{\widetilde{q}_{ijts}(\boldsymbol{\theta}) > 0\}\, \widetilde{q}_{ijts}}{\sum_{s=1}^{ns} \mathbb{1}\{\widetilde{q}_{ijts}(\boldsymbol{\theta}) > 0\}}$$

We also calculate the participation probability $\widetilde{\rho}_{ijt}(\boldsymbol{\theta})$ for pusher i making a

[15] In simulations with different parameter values, we found that cross-subsidization was never optimal. Removing the option of cross-subsidization also reduces the computational burden of calculating the optimal wholesale prices.

trade in drug j at time t using:

$$\widetilde{\rho}_{ijt}\left(\boldsymbol{\theta}\right) = \frac{\sum_{s=1}^{ns} \mathbb{1}\left\{q_{ijts} > 0\right\}}{ns}$$

To calculate $\widetilde{w}_{ijt}\left(\boldsymbol{\theta}\right)$, $\widetilde{q}_{ijt}\left(\boldsymbol{\theta}\right)$ and $\widetilde{\rho}_{ijt}\left(\boldsymbol{\theta}\right)$, we use $ns = 10{,}000$ where our draws for ξ_{ijt} are from a J-dimensional Halton sequence. For each observation i, j, t, in the data, our model has three errors. For trades in products that occurred in the data (those observations where $q_{ijt} > 0$), these are the error in the wholesale price, $w_{ijt} - \widetilde{w}_{ijt}\left(\boldsymbol{\theta}\right)$, the error in the quantity, $q_{ijt} - \widetilde{q}_{ijt}\left(\boldsymbol{\theta}\right)$, and the error in the participation probability, $1 - \widetilde{\rho}_{ijt}\left(\boldsymbol{\theta}\right)$. For trades that did not occur in the data (those observations where $q_{ijt} = 0$), there is only the error in the participation probability, $-\widetilde{\rho}_{ijt}\left(\boldsymbol{\theta}\right)$. Together, the model error for one observation can be represented by:

$$\boldsymbol{e}_{ijt}\left(\boldsymbol{\theta}\right) = \begin{pmatrix} \mathbb{1}\left\{q_{ijt} > 0\right\}\left(w_{ijt} - \widetilde{w}_{ijt}\left(\boldsymbol{\theta}\right)\right) \\ \mathbb{1}\left\{q_{ijt} > 0\right\}\left(q_{ijt} - \widetilde{q}_{ijt}\left(\boldsymbol{\theta}\right)\right) \\ \mathbb{1}\left\{q_{ijt} > 0\right\} - \widetilde{\rho}_{ijt}\left(\boldsymbol{\theta}\right) \end{pmatrix}$$

Since we use the continuous-updating weight matrix, it accounts for the error being scaled differently depending on if it is the error in the wholesale price, quantity or participation probability. For instruments, we use the full set of product-week dummies and the interaction of each pusher characteristic, $\boldsymbol{x}_i$, with each product dummy. Our objective function for estimating $\boldsymbol{\theta}$ is then:

$$\widehat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \left(\sum_{t=1}^{T}\sum_{i\in\mathcal{N}_t}\sum_{j=1}^{J}\boldsymbol{Z}_{ijt}'\boldsymbol{e}_{ijt}\left(\boldsymbol{\theta}\right)\right)' \boldsymbol{W}\left(\boldsymbol{\theta}\right)\left(\sum_{t=1}^{T}\sum_{i\in\mathcal{N}_t}\sum_{j=1}^{J}\boldsymbol{Z}_{ijt}'\boldsymbol{e}_{ijt}\left(\boldsymbol{\theta}\right)\right)$$

where $\boldsymbol{Z}_{ijt}$ is the instrument matrix for observation i, j, t and $\boldsymbol{W}\left(\boldsymbol{\theta}\right)$ is the continuous-updating weight matrix. To account for simulation error when calculating standard errors, we inflate the variance-covariance matrix by $1+\frac{1}{ns}$.

5 Estimation Results

Table 4 shows the simulated method of moments parameter estimates. Heavy drug addictions, alcoholism, and borrowing problems reduce a pusher's bargaining power. This is intuitive, as these pushers are more desperate for cash. Gambling addictions do not affect the bargaining parameter, but this may be explained by 70% of pushers with gambling addictions having a borrowing problem. Older pushers, unemployed pushers, and those with a gang affiliation have more bargaining power. These pushers are likely to be more experienced traders. Business connections with brothels and night clubs are more valuable to pushers than connections with karaoke establishments. There is also some evidence of price discrimination across nationality and ethnicity, where Malaysian Chinese have less bargaining power and Singapore Indians have more bargaining power than the base group of Singaporean Chinese. Ex-drug offenders stated that the small number of Indian pushers (13 in our data) were more valuable to the gang because it opened up the Indian market to them, which raised their bargaining power. Those with primary education have greater bargaining power than illiterate pushers, but having further education does not improve one's bargaining power. This may also be related to experience on the street.

Figure 6 shows a histogram of the estimated pusher bargaining weights. We can see that the gang has relatively more bargaining power than most pushers. 86% of the estimated pusher bargaining weights are below 0.5 and the median bargaining weight is 0.36. There is also considerable variation across pushers, with bargaining weights varying between 0.13 and 0.84.

Focusing now on the pusher demand parameter estimates, we first note that since wholesale prices and unit costs for ice are higher per unit compared to the other products, we change the unit for ice from 1g to 0.2g (a typical serving size) for estimation. We do this so that the ice parameters are scaled similarly to the other products. From the estimates, we see that the means of the cost shocks are relatively high compared to the typical gross margins pushers receive. The average gross margin for each product in the

Bargaining coefficients $\boldsymbol{\theta}_\beta$					
Constant	−1.026	(0.077)	Unemployed	0.090	(0.020)
Heavy drug addict	−0.088	(0.025)	Age	0.016	(0.001)
Alcoholic	−0.106	(0.022)	Female	0.195	(0.058)
Gambling addict	0.019	(0.022)	Malaysian Chinese	−0.360	(0.051)
Borrowing problem	−0.130	(0.019)	Singapore Indian	0.112	(0.047)
Been in prison	−0.159	(0.023)	Married	−0.035	(0.031)
Gang affiliation	0.161	(0.022)	Has children	0.192	(0.027)
Has connection with brothel	0.525	(0.035)	Has primary education	0.091	(0.047)
Has connection with KTV	0.141	(0.021)	Has secondary education	−0.085	(0.021)
Has connection with club/disco	0.415	(0.020)			

Pusher Demand Parameters

	Ecstasy	Erimin	High Quality Ice	Low Quality Ice	High Quality Ketamine	Low Quality Ketamine
Marginal cost mean μ_j	25.29	81.47	32.73	34.58	49.79	62.53
	(0.09)	(0.11)	(0.11)	(0.09)	(0.18)	(0.08)
Marginal cost standard deviation σ_j	26.47	53.23	44.47	42.82	32.63	38.33
	(0.28)	(0.20)	(0.17)	(0.35)	(0.14)	(0.06)
Marginal cost slope κ_j	0.24	0.68	0.48	0.36	0.29	0.26
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Change during enforcement period κ_j^e	−0.01	−0.03	0.21	0.22	−0.04	0.04
	(0.02)	(0.04)	(0.03)	(0.02)	(0.01)	(0.02)
Enforcement shock price change θ_{ej}	−0.08	1.71	28.38	24.33	2.29	1.25
	(0.44)	(0.80)	(0.59)	(0.50)	(0.49)	(0.62)

Standard errors in parentheses.

Table 4: Parameter estimates.

data varies between S$18.85 and S$45.92. This partly explains why pushers do not purchase a positive quantity of each drug in each period in which they are active. Only pushers with a favorable draw of their cost shock purchase in a period. We estimate that the price of a serving of ice increased substantially following the enforcement shock. The price for high- and low-quality ice increased by S$27.76 and S$23.91 respectively. The estimated price changes for the other drugs are much smaller. Ex-drug offenders we have interviewed recalled similar prices changes after the enforcement shock. The increase in the pushers' marginal cost slope also increased substantially for ice relative to other products.

In order to assess the model's fit, we simulate trades according to the estimated model to obtain the predicted total quantity sold and average wholesale prices for each traded product for each week. For these simulations, we use pseudorandom normal draws for the pushers' cost shocks, ξ_{ijt}. For each time

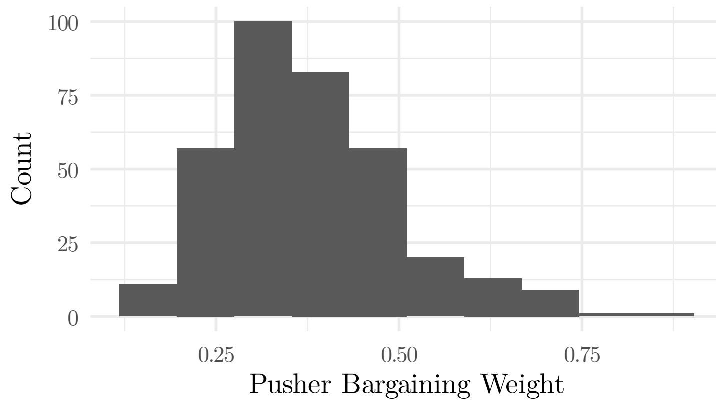
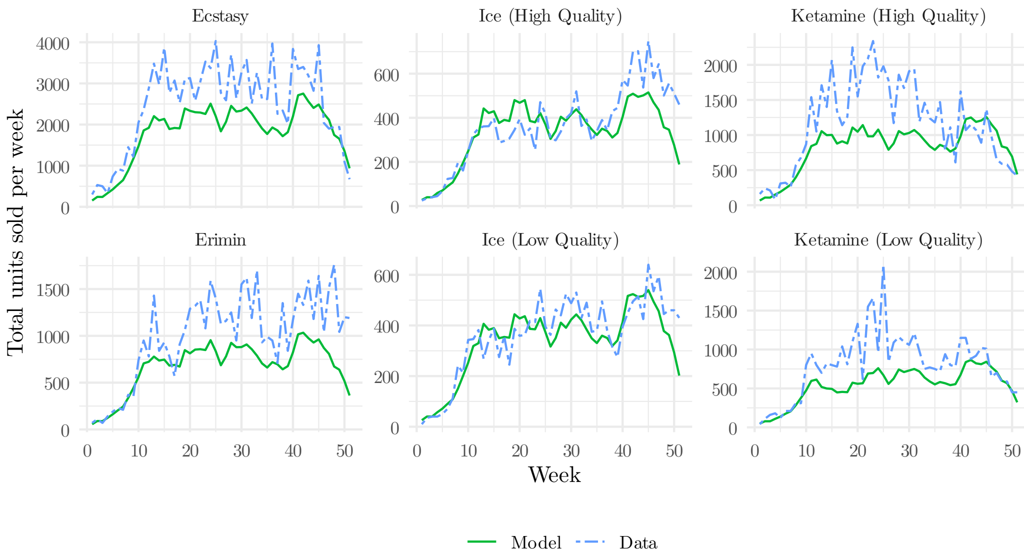
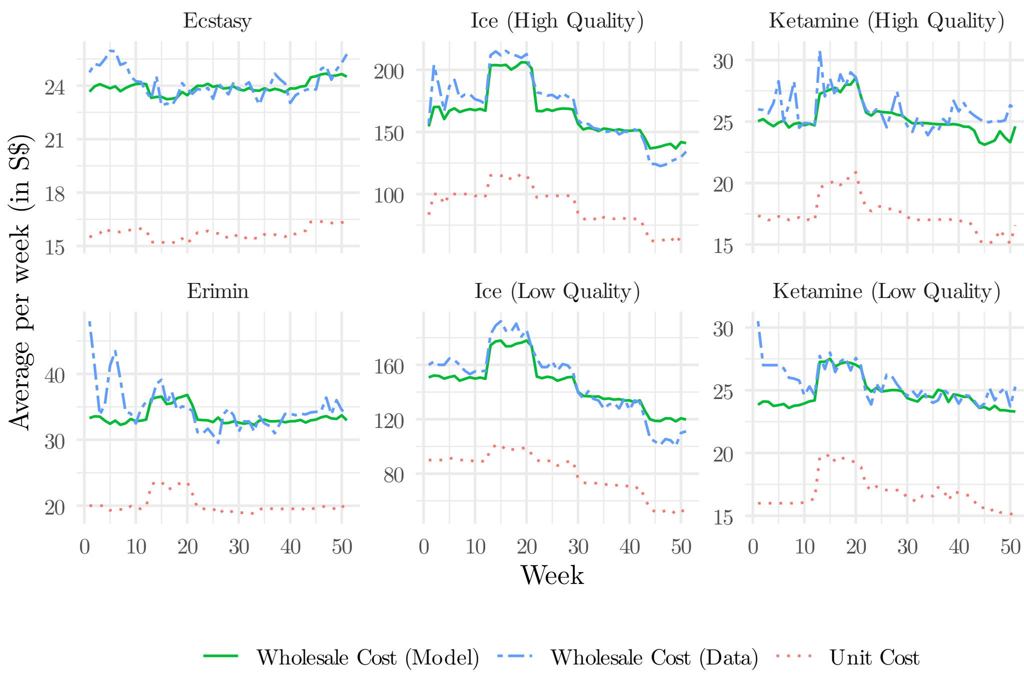


Figure 6: Histogram of estimated pusher bargaining weights.

period in which each pusher is active, we draw J shocks and calculate the optimal wholesale prices using the fixed point approach and compute the demanded quantities. We do this for every active pusher and sum the quantity purchased of each drug in that period. We then take the average total quantity and average wholesale price per week from 10,000 simulations. Figure 7 demonstrates how our model fits with the data at the estimated parameters after simulating trades according to this procedure. Figure 7a shows the predicted total sales of each drug in each week against the data. While weekly sales in the data is noisy, the model is able to match the broader patterns in the data relatively well. However, the model underpredicts the total quantity in certain weeks for certain products. This is partly due to a small number of pushers who purchase very large quantities in the data (as high as 600 units), while the model predicts that they purchase similar quantities to the remaining pushers. Figure 7b shows the average predicted wholesale price for completed trades against the data. The model predicts the overall pattern very well, although the model's predictions do not capture the noise in the average wholesale price at the beginning of the year. This is likely due to the smaller number of active pushers in those weeks.



(A) Predicted weekly sales by drug versus data.



(B) Predicted average weekly wholesale price by drug versus data.

FIGURE 7: Model fit.

6 Counterfactuals

6.1 No Enforcement Shock

For our first counterfactual experiment, we use the estimated model to simulate the counterfactual wholesale prices and quantities that would be observed if the enforcement shock did not occur. In the data, the enforcement shock raised marginal costs for all drugs except for ecstasy. During the period of the enforcement shock, which occurred in weeks 13 to 21, we set the marginal cost of each drug c_{jt} to its level in week 12. For weeks 22 onward, we use the same marginal costs observed in the data. In the model, we allowed the end-user prices and the slopes of marginal cost for each drug to change during the enforcement shock. We set these parameters equal to their values outside the enforcement shock period. In Figure 3 we saw that the enforcement shock had little effect on the total number of active pushers, so we assume the total number of active pushers remains the same as observed in the data. We simulate trades according to the same procedure when describing how we evaluate the model's fit in Figure 7.

Figure 8 shows the total sales of each product in each week for this counterfactual experiment together with the baseline model's predictions. Outside of weeks 13 to 21, the total sales are identical because all model primitives are the same. During the period following the shock, however, we can see that the shock did not have a very large effect on the total number of units sold per week. In fact, the pushers actually purchased more ice as a result of the enforcement shock since end-user prices increased.[16] Ex-offenders we have interviewed recalled selling larger quantities following the shock, despite the rise in wholesale prices.[17] Pushers often have addictions to satisfy or have debts to repay, and are not dissuaded by the higher wholesale prices and higher levels of enforcement and continue to sell at pre-shock levels. Even though this delivery

[16]While pushers purchased higher quantities of ice in the absence of the enforcement shock, the frequency of trades above the presumed trafficking threshold of 25g did not increase.

[17]See the Supplementary Appendix for the counterfactual wholesale prices. The Supplementary Appendix also includes a decomposition where we simulate trades when only unit costs increase from the enforcement shock but end-user prices do not adjust.

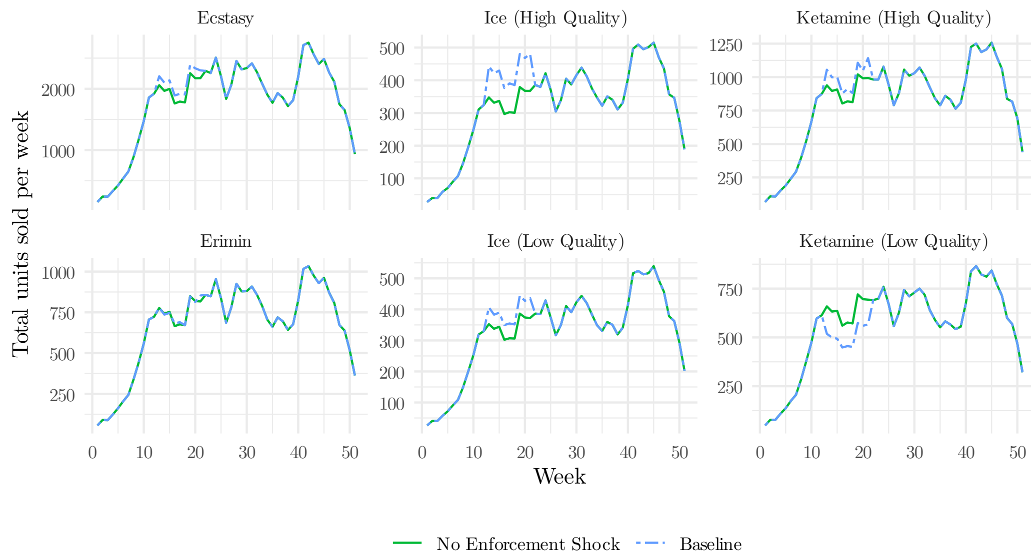


FIGURE 8: Total sales of each drug in each week, no enforcement shock versus baseline.

route was shut down, the gang was quick to find an alternative (although a more costly one), before costs returned pre-shock levels after some weeks.

6.2 Targeting Pushers

Targeting the source of drugs may be ineffective, as in this particular case, the gang sourced the drugs using a different route and the pushers still had a large incentive to sell, despite the higher wholesale prices that were passed onto them. Enforcement could instead focus its efforts on the pushers. In this counterfactual, we consider the effect of a large raid on pushers. We suppose that in week 26 of our data that law enforcement successfully arrests a random subset of 50 of the active pushers $\mathcal{N}_a$ in that week, where $\mathcal{N}_a \subset \mathcal{N}_{26}$ with $|\mathcal{N}_a| = 50$. We choose week 26 because no other shocks occurred in that week and the number of active pushers is close to the median value. We assume that for these 50 pushers measures are taken such that they do not purchase any products for all following weeks. For example, they are sent to jail or are monitored in future time periods and are threatened with very harsh penalties

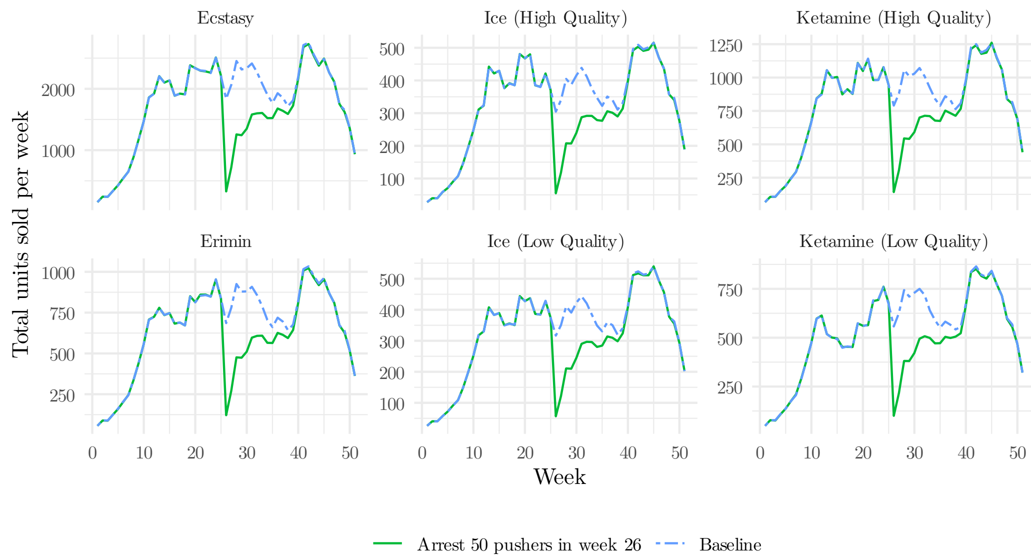


FIGURE 9: Total sales of each drug in each week, pusher raid versus baseline.

if they are caught again. Therefore the set of active pushers in each week in this counterfactual, $\mathcal{N}_t^{TP}$, always excludes these arrested pushers after week 26, i.e. $\mathcal{N}_t^{TP} = \mathcal{N}_t \setminus \mathcal{N}_a$ for all $t \geq 26$ while $\mathcal{N}_t^{TP} = \mathcal{N}_t$ for all $t < 26$.

The results from this counterfactual experiment are shown in Figure 9. We can see that in week 26 there is a large drop in total sales of all drugs, as the arrested pushers make up a large fraction of the active pushers in that week. Over time, however, the effect slowly wears off as these pushers are replaced by new pushers, and after approximately 10 weeks total sales return to normal. Such a policy could be effective, however, if a raid on pushers were to be carried out repeatedly. This is because most pushers in our data only trade with the gang for less than 9 weeks. However, if raids were performed repeatedly and pushers expected them, the pusher demand parameters may change in response due to the higher risks that pushers face.[18]

The survey data we have collected show that when any large-scale pusher raid like this happens, the gang would not respond by immediately increasing

[18]In the Supplementary Appendix, we show the results of arresting pushers continuously throughout the year assuming the demand parameters are unchanged. We also show the effect of targeting specific types of pushers, such as those with previous convictions.

its hiring activities to replace the lost pushers. We asked each respondent what the recruitment strategy of their gang was when a sizable number of their pushers (more than 20) were arrested. Almost all the respondents claimed that the gang would slowly replace the lost pushers over the following weeks, which is similar to what occurs in this counterfactual. They stated that if the gang were to immediately hire more pushers during or immediately after a raid, they would attract the attention of the authorities and become their main focus in enforcement efforts. They believed that the authorities would view their actions as a challenge and focus their efforts on dismantling their gang. Since there were many gangs in operation at the time, if the gang were not the main focus of enforcement efforts, the probability of getting caught would be much lower than if they were the main target. Therefore the gang's optimal response would not be to expand too quickly but rather, as they phrased it, "wait until things quietened down" before resuming hiring activities at its normal slow and gradual rate.

Obtaining accurate information on the difference in cost between different enforcement strategies is difficult, but it is likely that large supply busts are much more costly than targeting pushers. According to interviews with ex-offenders, large supply busts often took months of planning with significant manpower, often involving multiple departments cooperating across several countries. Most of all, ex-offenders told us that they believe that informants that contributed information that led to successful drug raids were entitled to monetary payouts which were a fraction of the total market value of the drugs seized, which is usually very large. Targeting pushers, on the other hand, is much less costly. The authorities always have undercover operatives on the streets at any given time. When they believe a pusher is a threat, they will proceed to arrest that pusher. Since the authorities know where the pusher operates, it does not require a lot of manpower to arrest them. Ex-offenders also stated that once a pusher is targeted by the authorities, it is very difficult to escape.

6.3 Discussion on External Validity

Our setting is similar to other Asian countries in many ways, and as a result, we argue our results have validity in other countries. Many other countries, including China and India, have a death penalty for drug trafficking. Countries with capital punishment for such offenses have a combined population of over 3 billion.[19] Therefore the behavior of the pushers with regards to the harsh penalties for drug trafficking may be similar in these other countries.

The structure of the end-user market in Singapore is also similar to other Asian countries. Ex-offenders who we have interviewed that were active in Malaysia or China at different points in time stated that highly competitive markets such as those in Geylang were also present in those countries.

Finally, the operations and organizational structures of transnational gangs are more similar to each other than local street gangs.[20] According to market insiders we have spoken to, the gang we study is similar in demographics to other gangs. Our transnational gang is also active across several countries across Asia and would apply similar business practices across those countries.

7 Conclusion

In this paper, we develop a multiproduct bargaining model between the Singaporean branch of a large transnational gang and pushers. We do this using detailed transaction data kept by the gang, together with detailed information on pusher characteristics, such as addictions and business connections. Our sample period also contains aggregate shocks, which we exploit in estimation. One shock involved the authorities successfully disrupting part of the gang's supply route which raised marginal costs for most products for several weeks. We use the estimated model to evaluate the effect of this enforcement shock by simulating the total sales of each drug in the absence of the shock. While

[19]Other Asian countries that have adopted capital punishment for drug crimes include Bangladesh, Indonesia, Laos, Myanmar, Thailand, and Vietnam (Leechaianan and Longmire, 2013).

[20]See the Supplementary Appendix for a further discussion on the differences between transnational gangs and local street gangs.

marginal costs and wholesale prices were affected by the shock, its effect on the total quantity sold was limited. We contrast this with an alternative policy where law enforcement focuses its efforts on arresting the pushers. We find that such a policy is more effective at reducing the quantity sold on the market, and argue that such an approach is less costly. This is evidence that taking a tough stance against pushers, a policy adopted by Singapore, is an effective strategy for reducing the total quantity of illegal drugs that is brought to the market.[21]

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[21] "Singapore is relatively drug-free, and the administration is under control" (Phillips, 2018).

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