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Published

2022

Journal Title

Journal of the European Economic Association

Version

Version of Record (VoR)

DOI

10.1093/jeea/jvac003

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LAW ENFORCEMENT AND BARGAINING OVER ILLICIT DRUG PRICES: STRUCTURAL EVIDENCE FROM A GANG'S LEDGER

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Abstract
We estimate a structural model of 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. (JEL: C78, K42, L11)

Teaching Slides
A set of Teaching Slides to accompany this article are available online as Supplementary Data.

The editor in charge of this paper was Pierre Dubois.

Acknowledgments: 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 (number 2017-T1-001-076) and an NTU economics department grant (number 021156-00001) for this research. We thank seminar participants and discussants at Tilburg University, CEPR VIOS, Boston University, Yale University, IIOC, and EARIE for their helpful comments and suggestions. Walsh is a Research Affiliate at CEPR. The usual caveat applies.

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Journal of the European Economic Association 2022 20(3):1198–1230
https://doi.org/10.1093/jeea/jvac003

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 many large public policy initiatives. Understanding how different enforcement strategies affect prices and quantities throughout the supply chain is 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.

We study how prices and quantities are determined in the drug wholesale market by estimating a 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 disrupt one of the gang's trafficking routes. We then use the estimated model to simulate counterfactual enforcement strategies to explore the effectiveness of each strategy at reducing the total quantity sold in the market.

In our data, the gang recorded trades with 352 different pushers for four different illicit drugs of varying quality levels. These pushers are not employees of the gang but independent traders who sell drugs to end-users. We observe 2,774 trades over the course of one year, where for each 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 approximately two months. 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 for ice (also known as 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. As in Becker (1968), pushers take into account the risk of arrest in their demand decisions. The drug wholesale prices that pushers pay are determined through Nash bargaining, where each pusher's bargaining weight differs based on their trade history and 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 drug addictions lower the bargaining power of pushers. Those with longer trade histories, gang affiliations, and connections with businesses where drugs are sold have higher bargaining power. We use this model to simulate the effects of counterfactual enforcement strategies.

First, we use the estimated model to simulate what the total quantity sold in the market would have been in the absence of the enforcement shock. After the shock, the gang had to find a new supply route that which increased unit costs, wholesale prices, and end-user prices for certain drugs for approximately two months. Despite the large increase in wholesale prices, pushers supplied a similar quantity to the no-shock scenario. This is because end-user prices also increased in response to the shock. 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 in the market. This is in line with the predictions of Becker, Murphy, and Grossman (2006) for products with inelastic demand.

Second, we estimate the effectiveness of the authorities targeting pushers. We do this by supposing the authorities manage to arrest a small subset of the actively trading pushers in one week. We find that such a policy leads to a larger decrease in the total quantity sold in the following months. Targeting pushers with higher bargaining weights, such as those with nightclub connections, has an even larger effect. This is because pushers with higher bargaining weights pay lower wholesale prices and sell larger quantities. The remaining pushers also do not 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 Asian countries.[1]

Due to a lack of data on the cost of enforcement, our results are not able to comment on the optimal level of enforcement. 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.[2] Therefore, these counterfactual simulations suggest that if the goal is to reduce the quantity of illicit drugs sold in the market, then targeting pushers may be more effective than targeting the gang's shipments.

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 much higher spending power compared to other Asian countries (Teo 2011).[3]

We make contributions to several strands of literature. First, we contribute to the literature analyzing the effects of enforcement strategies on illegal drugs. Several

1. In Online Appendix A.13, we also consider a counterfactual experiment where we estimate a lower bound on the tax revenue that could be earned from legalizing ice.

2. Intercepting a shipment 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.

3. During our sample period, the GDP per capita of Singapore was more than 25 times that of China's.

studies have found that supply interventions have only small effects on lowering consumption (Dobkin and Nicosia 2009; Dobkin, Nicosia, and Weinberg 2014; Cunningham and Finlay 2016; Mejía and Restrepo 2016), whereas others have found significant effects of enforcement on violence (Dell 2015; Lindo and Padilla-Romo 2018; Gavrilova, Kamada, and Zoutman 2019; Castillo, Mejía, and Restrepo 2020). We contribute to this literature by using data from a gang's own records—rather than administrative data—to study the effectiveness of various enforcement strategies on the quantities sold in the market.

We also contribute to the literature on the structural estimation of models of the illicit drug market. Based on the model in Galenianos, Pacula, and Persico (2012) and Galenianos and Gavazza (2017) estimate a model of the interactions between sellers and end-users. 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. This paper differs from these by focusing on the upstream relationship between the gang and pushers rather than the sellers and end-users.

We also contribute to the literature on the estimation of structural bargaining models (Ho 2009; Crawford and Yurukoglu 2012; Grennan 2013; Ho and Lee 2017). Although our bargaining model is based on these, it differs in two dimensions. First, we allow pusher demand to be continuous over multiple products, rather than be discrete. Second, we allow the pusher's relative bargaining power to be a function of a large number of pusher characteristics and their trade history.

A companion paper to this is Lang et al. (2021), who use the same dataset to study the effect of the enforcement shock on pusher quantity choices 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 that studies the financial records of drug-selling gangs. They focus on the compensation of gang members at different levels of the gang's hierarchy.

2. Setting and Data

2.1. Overview

The gang we studied 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, but there were many other gangs actively selling ecstasy, erimin, and ketamine in the market. The gang imported ice, erimin, and ketamine from abroad, but it sourced its supply of ecstasy locally. The gang then sold the drugs to pushers, who then sold

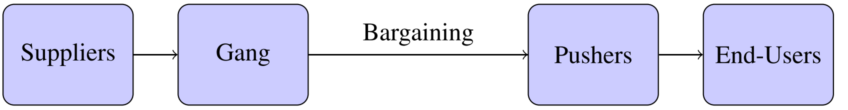

FIGURE 1. Drug supply chain.

the drugs to end-users. Pushers are not employees of the gang but are independent operators. They 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 of this paper is how the gang and pushers bargained over wholesale prices and quantities of the drugs.[4]

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 unit costs of the drugs. The ledger also contains paragraphs with detailed personal information for every pusher the gang traded with. Each of these paragraphs contains information on the pusher's family, other jobs, contacts, addictions, debt levels, conviction history, as well as basic demographic information. Our dataset is a digitized version of this accounting ledger, which contains 2,774 trades between 352 different pushers over 51 weeks.[5] 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 these data with interviews and surveys with 105 ex-drug offenders and ex-drug users who were active in this market during our sample period.[6]

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 predict demand during seasonal spikes and to control their people and the flow of goods. The gang obtained detailed personal information from all pushers it traded with to ensure they were not undercover agents. This branch of the gang also sometimes had to submit their accounting records to the international superiors of their 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 and pushers for these reasons. Drug-selling gangs in Southeast Asia have also been described as operating like multinational corporations (Allard 2019).

4. We refer the reader to Lang et al. (2021) for a more extensive description of the gang's organizational structure.

5. We can provide a redacted photograph of one page of the original book upon request.

6. We discuss data sources, data authentication, replication procedures, and how we carried out our interviews in Online Appendices A.2 and A.3.

TABLE 1. Summary statistics of completed trades.

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	1,791
Erimin	20.20	34.19	0.70	41.88	1,222
Ice (high-quality)	88.69	165.94	0.90	10.30	1,811
Ice (low-quality)	78.89	146.11	0.88	10.95	1,682
Ketamine (high-quality)	17.72	26.19	0.49	51.98	1,144
Ketamine (low-quality)	17.05	25.38	0.50	54.44	752

Notes. 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 the unit cost by dividing the total cost of the relevant shipment by the shipment size.

The gang's record of the unit cost of each drug in each 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 both 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. Because the gang kept such detailed records of their trades, especially for pecuniary matters, those we have interviewed 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 a single 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. We sum the quantity purchased by the pusher for each product in each week and take the quantity-weighted average wholesale prices and costs where necessary. After both of these aggregation methods, we are left with 2,536 trades.

Average unit costs, wholesale prices, margins, and quantities for each drug are shown in Table 1. On average, the gang earned the 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, whereas there were other gangs actively selling the other drugs.[7]

Pushers typically purchased small quantities of each drug in each trade. This can be seen in Figure 2, which shows the frequency of pushers purchasing different

7. From interviews with ex-drug offenders, the large gangs typically had a monopoly on at least one drug. Therefore, our gang is not unique in the market by having a monopoly on ice.

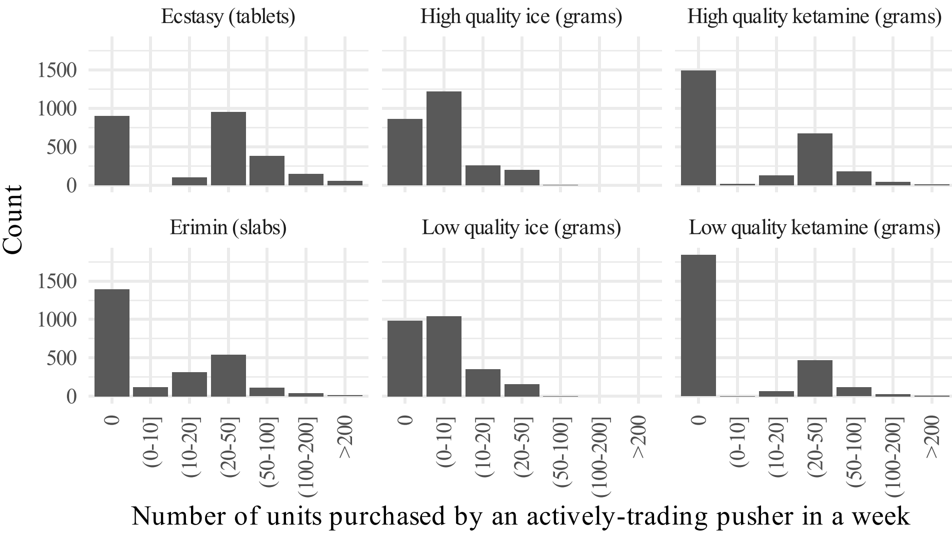

FIGURE 2. Histograms of weekly number of units purchased by a pusher.

quantities for each drug. 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 trafficking is presumed, which can carry a life sentence. There are also higher thresholds that have a mandatory death penalty.[8] All 105 of the ex-pushers we interviewed stated they knew the penalties associated with trafficking were more severe than possession. For ice, being caught with over 25 g is presumed trafficking, and being caught with over 250 g carries a mandatory death sentence. A total of 82% of trades involved less than 25 g of ice, and the largest quantity purchased at one time was 80 g. Despite these thresholds, we do not observe any bunching of ice purchases just below 25 g.[9] Instead, the modal quantity of ice purchased is 10 g. For other drugs, purchases of 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. There were only ten trades where a pusher purchased all six of the different drug-quality pairs. The modal pusher purchased two different products in a week and 69% of trades involved trades in fewer than four products. In our analysis, we model this as censored data and model selection into trading explicitly.

There is large variation in the wholesale prices pushers pay per unit for each drug.[10] Pushers who purchase larger quantities on average pay a lower wholesale price per

8. The maximum sentences from Singapore's Misuse of Drugs Act are shown in Online Appendix A.5.

9. We do not find evidence of bunching both before and after aggregating trades to the week level.

10. Online Appendix Figure A.1 shows histograms of the average margins by pusher for each product.

unit, but we do not observe bundle discounts for pushers who purchase several different types of drugs.[11] We also do not find evidence of frequent cross-subsidization across drugs. There are only 22 trades (0.26% of all trades) where the wholesale price was lower than the gang's unit costs. One ex-pusher we interviewed told us: "Do not think of the drug market like a vegetable market where you buy a few different types of vegetables and expect a [bundle] discount."[12]

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. It is also unlikely that the gang cheated pushers with bad-quality products, as 98% of pushers in our data had at least four trades with the gang over our year of data. Pushers ripped off with bad-quality products would be less likely to return. 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.

One underlying assumption in the model we present below is that there is no asymmetric information between the gang and each pusher when bargaining over wholesale prices. The pushers are informed of the gang's costs, and the gang is informed of the pushers' cost shocks. We believe this assumption fits our setting. From our data, we know the gang had considerable information about the pushers it sold to. The gang did this to ensure they were not undercover operatives. One ex-drug offender we interviewed stated that "if no one knows you well, it is impossible for you to buy or sell drugs. . . . We know everything about the people we deal with." The pushers also had knowledge of the gang's unit cost of drugs at the time. 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.

Another underlying assumption in our model is that pushers cannot trade drugs amongst each other, which would undercut the gang's ability to extract higher wholesale prices from pushers in weak bargaining positions. The weight thresholds that result in discrete jumps in punishment severity (such as the 25 g threshold for ice where drug trafficking is presumed) may have been an institutional feature that contributed to the gang's ability to bargain. 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, pushers that extract low wholesale prices would be able to buy large quantities for purposes of reselling to other pushers.

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11. We document the patterns we observe in our data regarding bulk and bundle discounts in Online Appendix A.4.

12. We note that the interviews we carried out for this paper were mostly conducted in Mandarin Chinese, and the quotations provided in this paper are translations. These translations exclude expletives used by the interviewees.

TABLE 2. Summary statistics of pusher characteristics.

	N	Mean	Standard deviation	Minimum	Median	Maximum
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
Singaporean Chinese	352	0.88	0.32	0	1	1
Malaysian Chinese	352	0.08	0.27	0	0	1
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	1,000	3,500
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

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.[13] Male pushers are 96%, and the median age is 30. Singaporean Chinese make up 88% of pushers, with the remainder being 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 five pushers with higher than secondary education. Two-thirds of pushers are connected to the gang and approximately half have a business connection, typically with karaoke establishments (KTVs), nightclubs, or discotheques.[14] A total

13. Unlike many survey datasets, the gang's information about the pushers it traded with have very few missing observations. This is because the gang's survival depended on thoroughly vetting the pushers it traded with.

14. The gang has different units, such as the fighter unit or the intel unit. A pusher is affiliated with the gang if they were previously in one of these units. We note that someone cannot be in one of these units

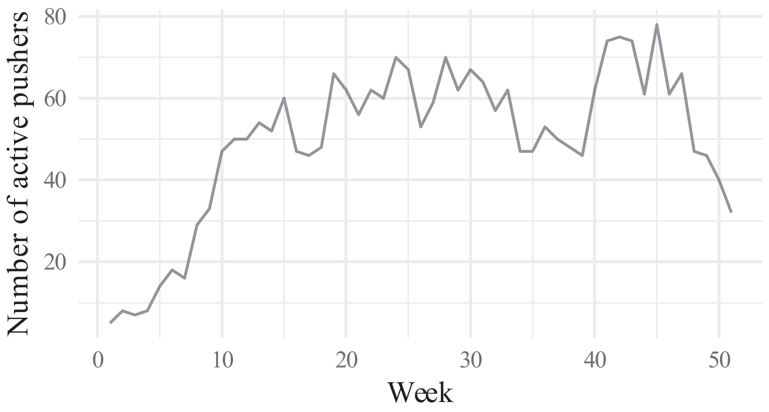

FIGURE 3. Number of active pushers trading per week.

of 58.5% have been arrested before, and out of those arrested the median pusher spent three 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.[15] Alcoholism is less common at 28%, but 62% and 58% have gambling addictions and borrowing problems, respectively.

The price discrimination that the gang engaged in can be related to the pusher characteristics. In Online Appendix Table A.2, we regress the gang's price-cost margin on many of these characteristics. We see that pushers with drug addictions on average pay higher prices, as they are more desperate for cash. Pushers with connections with businesses in which drugs are sold pay lower prices, as these pushers are more valuable to the gang. More experienced pushers, such as those with longer trade histories, also pay lower prices on average.

Pushers started and stopped trading with the gang throughout the year, where the median pusher traded with the gang for 7 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 are a greater number of alternative employment opportunities, but there is also an increase in enforcement activities, which would lead to more arrests. The majority of active pushers trade in consecutive weeks, although a smaller number of pushers will start and stop trading at different points in the year.

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and be a pusher at the same time. We refer the reader to Lang et al. (2021) for further information on the gang's organizational structure.

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

We take entry and exit into being a pusher as exogenous in our model. This is in part because our dataset is not well-suited to these decisions, but we also believe it is a reasonable assumption about the data, at least for answering our questions. Here, we describe the determinants of becoming a pusher. In general, there is no free entry into trading with the gang. The gang initiated the recruitment of pushers through their network of contacts. The gang recorded who made the introduction with each pusher in their ledger. 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 slow rate and never hired too many new pushers at one time. One ex-drug offender we interviewed stated "if we get too many members too quickly, the authorities will focus on us. We will do what everyone else does so we will look like the same as everyone else." For the same reason, the gang would ensure their total number of pushers did not greatly exceed that of rival gangs. In this sense, entry into becoming a pusher was affected by many factors that limit the role of endogenous entry.

Our data also contain the reason why pushers stopped trading with the gang. At least 36% of pushers in our sample were arrested, whereas 57% of pushers stop trading for other reasons. The remaining 7% of pushers were fired by the gang. Although some of the 57% may have been arrested, pushers were also free to stop selling for the gang without penalties. From interviews with ex-drug offenders, the arrival of an exogenous event (rather than conditions in the drug market) is what caused virtually all pushers they know of to quit selling drugs. Pushers often quit to pursue other lucrative illegal employment opportunities. These other employment opportunities were often in the illegal gambling sector, which they chanced upon while selling drugs. We do not observe these exact reasons for the pushers in our data, but they appear to be uncorrelated with market-related variables. In particular, one way to evaluate whether endogenous entry and exit is important for our questions about the effect of enforcement is to evaluate entry and exit during the enforcement period. In Online Appendix Figure A.2, we show the number of pusher entries and exits per week. There are no visible patterns nor any changes that coincide with major events such as the enforcement shock. In Online Appendix Table A.1, we run logit regressions of entry and exit on a dummy for the enforcement shock period and find no significant effect.[16]

In our model, we assume the pusher disagreement payoff is zero because pushers trade with only one gang. All 105 of the ex-pushers we have interviewed stated that they traded exclusively with one gang and did not trade with multiple gangs. They provided

16. Furthermore, 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."

several reasons for this. First, 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. Second, 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. Third, they knew it was unlikely that they would be able to obtain lower prices by trading with multiple gangs. One example response from an ex-pusher that we asked this question to was: "No, me and people I know do not do this . . . if you are no good, it doesn't matter how many people you visit, people will not give you anything good. We do not go here and there [different gangs] because there is no point."[17]

2.4. End-User Market

We do not observe the individual 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.[18] The search costs for trading were also low because a large proportion of trades occurred in the Geylang area, Singapore's red-light district.[19] There are roughly 3.5 km of road in Geylang, which was a hot spot for drug dealing (Lee 2014).

Pushers from different gangs sold drugs on the street and in clubs and karaoke bars in the district. Each gang, including the gang we study, claimed a few lanes as their turf. In some instances, pushers paid rival gangs a fee to sell drugs on rival turf.[20] According to the ex-pushers we have interviewed, selling drugs in Geylang was highly competitive between pushers, even between pushers of the same gang. For example, any pusher selling ice in our data would normally be at most 50 m away from another pusher selling the same products. Those we have interviewed stated that whenever a customer came to a place where drugs were sold, the pushers operating there would all

17. In Online Appendix A.6, we provide evidence from our interviews that the average pusher that trades with the gang we have data on is not substantially different to the average pusher trading with other large gangs that were in operation at the time.

18. 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). There were also many pushers from many gangs selling drugs at the time. From our interviews, there were 10 large gangs (those with over 350 members), 5 medium-sized gangs (between 150–350 members) and approximately 17 smaller gangs. These smaller gangs made up less than 10% of the market.

19. From our surveys, 101 out of 105 respondents stated Geylang was the location with the most drug sales. At any given time, pushers from all of the ten largest gangs were selling there. See Li, Lang, and Leong (2018) for a more extensive description of Geylang.

20. 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."

try to sell to that consumer. They also stated that this high degree of competitiveness was the same for all drugs sold in Geylang.[21]

From interviews with end-users, a typical end-user would contact three to seven pushers before 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. End-users were able to travel freely within Geylang to purchase drugs from the different lanes where different drugs were sold. A total of 92.4% of those we surveyed 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. Because Singapore is a small country (50×27 km in area), any end-user was very close to an area where many pushers were selling different drugs.

End-users were also less worried about being the target of enforcement because the authorities focused their efforts on targeting sellers. According to the ex-pushers we have interviewed, the authorities chose to focus their efforts on individuals that are in possession of large quantities of drugs instead of users, who typically possess much smaller quantities. They stated this was because the authorities lacked manpower and resources at the time. The penalties for possession and consumption are also much less severe than trafficking. Criminal organizations also often obstructed police from entering into Geylang, which protected end-users from enforcement activities (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 can 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, whereas 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%, while other pushers' costs remained the same. 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.

21. According to those we have interviewed, this was also the case for drugs that different gangs had a monopoly on. In our data, 313 of the 352 pushers in our data sold ice, and the median number of pushers selling ice in any given week was 42. Therefore, even though the gang we study had a monopoly on ice, the pushers that sold it competed with one another for customers.

TABLE 3. End-user prices in Singaporean dollars.

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

Given these features of the end-user market, we approximate the end-user market as 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).[22] We obtain end-user prices from various reports and from interviews with ex-drug offenders where they recalled the end-user prices from our sample period. 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.[23] At these prices, pushers earn considerable gross margins over the wholesale price, with the median equal to 85%. However, pushers have 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.[24]

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. Jockeys 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

22. We interviewed an additional 34 ex-pushers that operated during the time of our dataset and all 34 agreed that prices were stable over time except for after major shocks, such as the enforcement shock we observe in our setting. This is discussed further in the Online Appendix A.7.

23. The sources we used to obtain these figures are described in detail in Online Appendix A.7. We also discuss confirmatory evidence from ex-pushers we interviewed and the consequences of any measurement error in these data for our model estimates and counterfactual simulations.

24. Bail was set at roughly S$30,000–S$50,000 during our sample period.

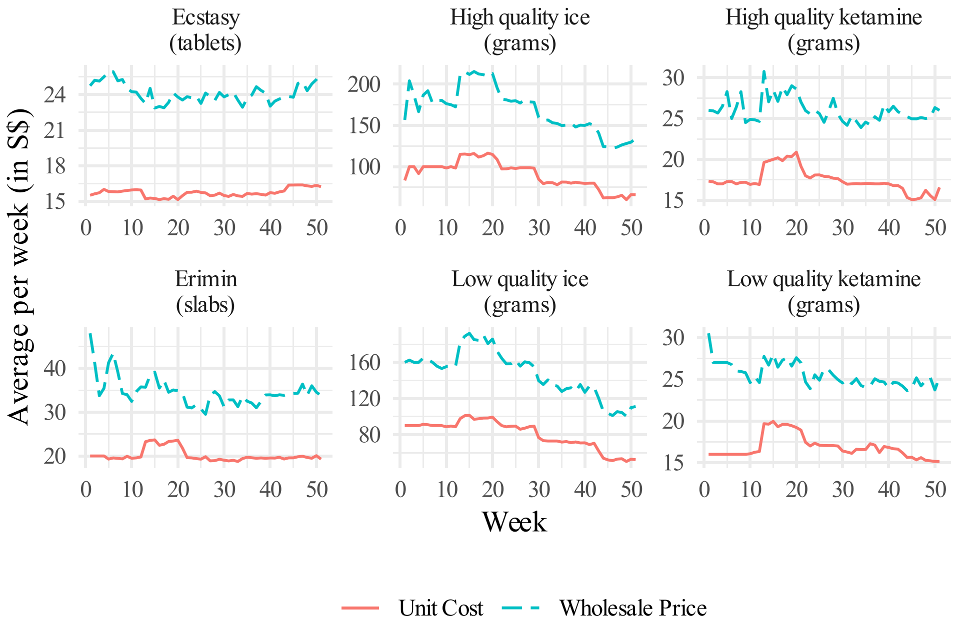

FIGURE 4. Average unit cost and wholesale price by week.

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.[25] 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 several weeks before falling again toward the end of the year. These cost savings were partially passed on to the pushers in the form of lower wholesale prices.

Although there was a clear change in unit costs and wholesale prices following the enforcement shock, its effect on quantities is less clear. Figure 5 shows the total quantity sold to all pushers in each week for each product. There is considerable noise in the total quantity sold at the product-week level, and there is no clear change in total quantities following the enforcement shock. However, from the figure, we do observe significantly less sold at the beginning and end of the year. This is mostly due to the number of active pushers during those times (see Figure 3).[26]

25. The unit costs for ecstasy fluctuated between S\$15–S\$17 per unit throughout the year, but these fluctuations were not related to the arrests of the jockeys.

26. The lower quantities observed at the beginning of the year are unlikely to be due to learning. The gang we studied was active in several other Asian countries before trading in Singapore and therefore had

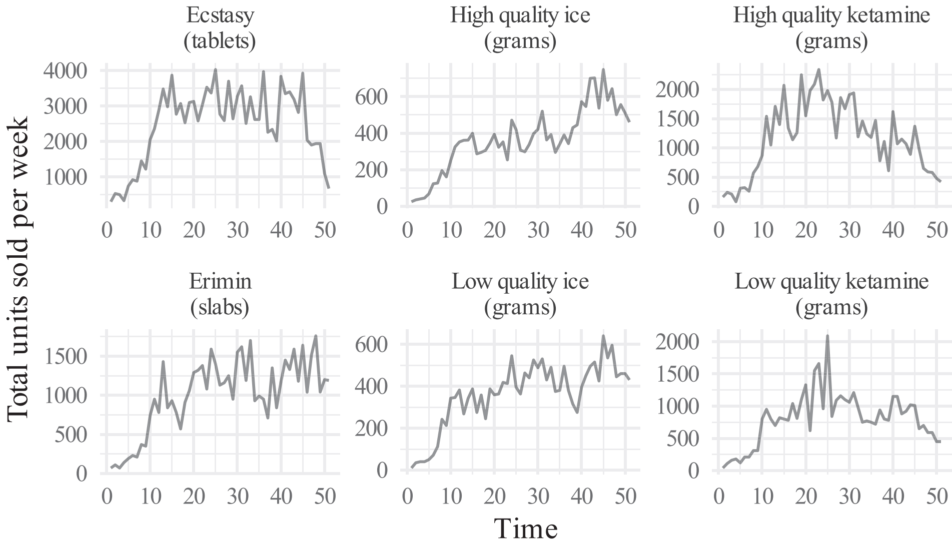

FIGURE 5. Total units sold per week.

Interviews with ex-drug 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.[27] 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 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.[28]

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

obtained the relevant knowledge and experience to run their operations there. They also hired experienced people to run their operations and would have collected any necessary information before entering the market.

27. We note that if a single pusher's costs increase, then pushers will not charge a higher price to end-users. However, if the costs increase for all pushers (through the gangs passing on cost increases), then the end-user price of the product may adjust.

28. 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 is 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).

and the large reductions in ice unit costs later in the year. We have confirmed this in interviews with ex-drug offenders who operated during the sample period.

3. Model

3.1. Overview

In this section, we develop a model designed to capture the key features of the illicit drug market in our setting. These features are as follows: (1) The gang obtains drugs from their suppliers and sells the drugs to pushers. (2) Pushers are not employees of the gang and do not obtain a fixed wage. Rather, pushers earn profits by reselling the drugs to end-users. (3) The gang engages in price discrimination and charges different pushers different prices for the same drug. (4) Pushers typically buy small quantities of any drug at one time because the penalty upon arrest is increasing in quantity. (5) Pushers only purchase a subset of all products in any given week. (6) Pushers take the end-user price as given because the end-user market is competitive.

We model the payoffs of the gang and the pushers and assume that wholesale prices are determined through bilateral Nash bargaining. We then estimate the parameters of this model and use it to simulate the effectiveness of various enforcement strategies.

3.2. Pushers

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 pushers is actively trading. If pusher i is actively trading at time t, they choose quantities q_{ijt} for each product $j = 1, \ldots, J$ to maximize their expected payoff. Each product j is a drug-quality pair. We follow Becker (1968) and model the expected payoff from purchasing the vector $\boldsymbol{q}_{it} \in \mathbb{R}_+^J$ as

$$u_i(\boldsymbol{q}_{it}) = \sum_{j=1}^{J} (p_{jt} - w_{ijt} - \xi_{ijt}) q_{ijt} - \alpha_t K_t(\boldsymbol{q}_{it}).$$

Pushers sell product j to end-users at price p_{jt}. Pushers take the end-user price as given because the retail market for drugs is competitive. The pusher purchases product j from the gang at wholesale price w_{ijt}. The term ξ_{ijt} is an idiosyncratic cost representing other monetary and non-monetary costs from selling drugs. These costs are correlated over time within a drug and are correlated across drugs within a time period. The probability of arrest in each period is α_t and the disutility from arrest is $K_t(\boldsymbol{q}_{it})$, which depends on quantity. This is because pushers who are caught selling larger quantities face more severe punishment. Following Becker (1968), we assume the payoff from selling drugs is earned both when arrested and not arrested.[29]

29. The pusher payoff specification we use differs from an earlier draft of this paper. We discuss these differences in Online Appendix A.10.

We assume the disutility from arrest is a quadratic function of quantity given by[30]

$$K_t(\boldsymbol{q}_{it}) = \frac{1}{2}\sum_{j=1}^{J} \kappa_{jt} q_{ijt}^2.$$

Pushers make static demand decisions in each period t. Taking first-order conditions, pusher i's demand for product j at the wholesale price vector $\boldsymbol{w}_{it}$ is given by

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

We assume pushers are not forward-looking in their quantity choice. In our setting, pushers do not stockpile drugs when prices are low. In our data, we observe pushers buying small quantities each week, partly explained by the harsh sentences upon detection. Ex-pushers we have interviewed also stated that they tried to sell all of their drugs as quickly as possible after each trade for this reason. Pushers also do not trade with the gang for long periods of time. The median pusher trades with the gang for only 7 weeks, and 94% of pushers trade with the gang for less than 4 months.[31]

Our payoff specification also assumes pushers are risk neutral. Experimental evidence such as in Block and Gerety (1995) and Khadjavi (2018) has found that criminals are significantly less risk averse than non-criminals. Our own qualitative interviews and survey data also suggest pushers are willing to accept risk for higher expected returns. This evidence is discussed further in Online Appendix A.8.

3.3. *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, assistant 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 pecuniary 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

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

30. We choose here not to 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 that would allow us to identify the effects of these thresholds.

31. See Online Appendix A. 9 for information from our qualitative interviews, survey data, and relevant literature that further supports this assumption.

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 further 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.

3.4. 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 trading is given by their indirect utility function:

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

where $\mathbb{1}\{p_{jt} \geq w_{ijt} + \xi_{ijt}\}$ equals 1 if $p_{jt} \geq w_{ijt} + \xi_{ijt}$ and is zero otherwise. We assume pushers trade exclusively with one gang and have a zero disagreement payoff. 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

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

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 trading

$$\boldsymbol{w}_{it} = \underset{\widetilde{\boldsymbol{w}}_{it} \in \mathcal{W}_{it}}{\arg\max} \; [\pi_{it}(\widetilde{\boldsymbol{w}}_{it})]^{1-\beta_{it}} [v_{it}(\widetilde{\boldsymbol{w}}_{it})]^{\beta_{it}}, \tag{4}$$

where $\beta_{it} \in (0, 1)$ is pusher i's bargaining weight, $1 - \beta_{it}$ is the gang's bargaining weight, and

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

This is the set of possible wholesale prices at the gang's marginal costs, c_{jt}, the pusher's idiosyncratic marginal cost, 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 marginal cost, $c_{jt} + \xi_{ijt}$, 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, along with our specification of the bargaining model, does not permit the gang to cross-subsidize across drugs. We do not observe evidence of cross-subsidization in our setting.[32]

32. As discussed in 2.2, our raw data contains only 22 trades (0.26% of all trades) where the wholesale price was lower than the gang's unit costs.

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:

$$(1-\beta_{it})(p_{jt}+c_{jt}-2w_{ijt}-\xi_{ijt})\left[\sum_{j'=1}^{J}\mathbb{1}\{p_{j't}>w_{ij't}+\xi_{ijt}\}\frac{(p_{j't}-w_{ij't}-\xi_{ijt})^2}{2\alpha_t\kappa_{jt}}\right]$$
$$=\beta_{it}(p_{jt}-w_{ijt}-\xi_{ijt})\left[\sum_{j'=1}^{J}(w_{ij't}-c_{j't})\mathbb{1}\{p_{j't}>w_{ij't}+\xi_{ijt}\}\frac{p_{j't}-w_{ij't}-\xi_{ijt}}{\alpha_t\kappa_{jt}}\right], \tag{5}$$

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 $p_{j't} \leq c_{j't} + \xi_{ij't}$ for all other $J-1$ products $j' \neq j$. In this special case we obtain

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

If the pusher's bargaining coefficient β_{it} approaches one, which corresponds to the pusher holding all of the bargaining power, then the wholesale price approaches the gang's 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, the wholesale price approaches $(p_{ijt} - \xi_{ijt} + c_{jt})/2$ and the pusher's payoff is zero. This is the price that a monopolist would charge.

4. Estimation

4.1. Parameterization

We assume the bargaining weight for pusher i at time t is a function of their characteristics and trade history with the gang. We include sociodemographic variables and indicators for addictions, borrowing problems, and business connections. The majority of the characteristics do not vary over time in our sample. For example, we do not observe pushers who develop addictions or large debts during our sample period. 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 intertemporal variation in pusher characteristics is important. To capture how the bargaining relationship may vary over time for a pusher, we allow the bargaining weight to vary with the number of trades pusher i completed before week t. For the bargaining weight, we adopt the following functional form:

$$\beta_{it} = \Phi\big(\boldsymbol{x}'_{it}\boldsymbol{\theta}^{\beta}\big),$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution, the vector $\boldsymbol{x}_{it}$ contains the pusher characteristics and trade history 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. As the shock affected all pushers from every gang in the country, it temporarily changed equilibrium prices in the end-user market. We parameterize end-user prices as

$$p_{jt} = \bar{p}_j + \theta^e_j e_t, \quad j = 1, \ldots, J,$$

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^e_j for each j are parameters to be estimated. Even though the enforcement shock did not affect the gangs' costs of ecstasy, we allow its market price to change as potential substitution from other drugs may affect the ecstasy market.

The idiosyncratic marginal costs ξ_{ijt} are an important element of the econometric model. To interpret these shocks, we rely on our interview evidence about the setting. From interviews with ex-drug offenders, pusher marginal costs can change week by week for several reasons. 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. These idiosyncratic costs also have a product-specific component, which represents the cost of finding consumers for that particular drug in a week. We allow these cost shocks to be correlated over time for a pusher within a drug, and we also allow them to be correlated across drugs within a time period. If a pusher's regular customers demand more of a product in one period, it is possible they may demand more of it in the following period. Similarly, if a pusher's customers mix complementary drugs together, these shocks may be correlated across products. Specifically, we model these shocks according to

$$\xi_{ijt} = \rho_j \xi_{ijt-1} + \nu_{ijt} \quad \text{for } j = 1, \ldots, J \quad \text{and} \quad \boldsymbol{\nu}_{it} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}).$$

The shock for pusher i for product j in a period t is a function of its lagged value ξ_{ijt-1}, and a contemporaneous shock ν_{ijt} drawn from a multivariate normal distribution, which permits the shocks to be correlated across drugs, j. Each of the ρ_j, μ_j, and elements σ_{jk} of $\boldsymbol{\Sigma}$ are parameters to be estimated.

The probability of arrest and the disutility from arrest enter into the pusher's indirect utility and demand functions as the product $\alpha_t \kappa_{jt}$. We do not separately identify α_t

and κ_{jt}, but we parameterize the product of these terms as

$$\alpha_t \kappa_{jt} = \theta_j^{\alpha\kappa} + \theta_j^{\alpha\kappa e} e_t \quad \text{for } j = 1, \ldots, J.$$

Each drug has a base $\theta_j^{\alpha\kappa}$ term, which is allowed to change during the enforcement shock by $\theta_j^{\alpha\kappa e}$.[33]

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. As 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.[34]

Finally, we also need to specify $\mathcal{N}_t$, the set of active pushers in each week as we treat entry and exit into trading as exogenous. In estimation, a pusher is active if it purchased a positive quantity of at least one drug in a week.

4.2. *Simulated Method of Moments*

The full vector of parameters to be estimated is

$$\boldsymbol{\theta} = \left(\boldsymbol{\theta}^{\beta}, \left\{\theta_j^{e}, \rho_j, \mu_j, \{\sigma_{jk}\}_{k=j}^{J}, \theta_j^{\alpha\kappa}, \theta_j^{\alpha\kappa e}\right\}_{j=1}^{J}\right).$$

We estimate $\boldsymbol{\theta}$ using the continuous-updating simulated method of moments estimator (Hansen, Heaton, and Yaron 1996). Given a trial value of the parameter vector $\boldsymbol{\theta}$, we can simulate paths of the cost shocks ξ_{ijt} for each pusher. With these cost shocks, we can calculate the wholesale prices $\boldsymbol{w}_{it}$ that satisfy the Nash bargaining first-order conditions in equation (5). As we do not have a closed-form solution for $\boldsymbol{w}_{it}$, we compute the vector of wholesale prices using iterative methods. Our fixed point procedure is described in detail in Online Appendix A.12. Once we have computed the bargained vector of wholesale prices, we can calculate pusher demand for each product using the demand function in equation (1).

Let $\widetilde{w}_{ijts}(\boldsymbol{\theta})$ and $\tilde{q}_{ijts}(\boldsymbol{\theta})$ 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

33. We could also allow pusher heterogeneity to enter into $\alpha_t \kappa_{jt}$ and thereby allow the expected disutility terms to vary over i. However, after some experimentation with this approach we have found that our more parsimonious specification is able to capture the main patterns observed in the data well.

34. 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, in our data the variance of this shock is not separately identified from the variance of the pushers' cost shocks. We discuss this point formally in Online Appendix A.11.

on trading according to

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

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

We also calculate the participation probability $\tilde{r}_{ijt}(\boldsymbol{\theta})$ for pusher i who is active at time t making a trade in drug j using

$$\tilde{r}_{ijt}(\boldsymbol{\theta}) = \frac{\sum_{s=1}^{ns} \mathbb{1}\{q_{ijts} > 0\}}{ns}.$$

To calculate $\widetilde{w}_{ijt}(\boldsymbol{\theta})$, $\tilde{q}_{ijt}(\boldsymbol{\theta})$, and $\tilde{r}_{ijt}(\boldsymbol{\theta})$, we simulate $ns = 1{,}000$ paths of ξ_{ijt} over time for each pusher. For moments, we match the average wholesale price, quantity, and participation probability for each product-week combination with their counterparts in the data. The empirical counterpart of the participation probability is an indicator if pusher i purchased any of product j at time t in the data. As we use a continuous-updating weight matrix, it accounts for the moments being scaled differently for different outcomes and products. To account for simulation error when calculating standard errors, we inflate the variance-covariance matrix by $1 + 1/ns$. We cluster standard errors at the pusher level.

We now provide a heuristic discussion of what variation in our data identifies each of our parameters. The bargaining coefficient parameters $\boldsymbol{\theta}^{\beta}$ are identified through variation in wholesale prices across pushers with different characteristics. The changes in the end-user prices of each product during the enforcement shock period, θ_j^e, are identified through the pass-through of the gang's unit cost increases on wholesale prices. The pusher cost means, μ_j, and the expected disutility terms, $\theta_j^{\alpha\kappa}$, are identified through the quantities pushers purchase given the wholesale price. Conditional on purchasing a product, μ_j enters into the intercept of the linear pusher demand function and $\theta_j^{\alpha\kappa}$ enters into the slope. Thus the $\theta_j^{\alpha\kappa}$ are identified through changes in the pusher's demand from changes in the wholesale price. The changes in the expected disutility terms, $\theta_j^{\alpha\kappa e}$, are identified through the changes in the pushers' demanded quantities during the enforcement shock period. The pusher cost standard deviations, σ_j, are identified through the average proportion of weeks active pushers purchase the product. The cost autocorrelations, ρ_j, are identified by the frequency of the same pusher purchasing the same product across weeks. Finally, the cost correlations across products are identified by the frequency of pairs of products begin purchased together by pushers.

5. Estimation Results

Table 4 shows the estimates of our bargaining coefficient parameters, $\boldsymbol{\theta}_{\beta}$. Heavy drug addictions and borrowing problems reduce a pusher's bargaining power. This is

TABLE 4. Bargaining parameter estimates. Standard errors in parentheses.

Constant	−1.751	(0.080)	Club connection	1.836	(0.206)
Trade history	0.164	(0.018)	Unemployed	0.082	(0.037)
Heavy drug addict	−0.114	(0.041)	Age	0.013	(0.001)
Alcoholic	−0.055	(0.035)	Female	0.242	(0.190)
Gambling addict	0.019	(0.014)	Malaysian Chinese	−0.804	(0.233)
Borrowing problem	−0.110	(0.039)	Singapore Indian	0.098	(0.114)
Been in prison	−0.218	(0.050)	Married	−0.029	(0.042)
Gang affiliation	0.223	(0.053)	Has children	0.146	(0.059)
Brothel connection	0.807	(0.210)	Has primary education	0.070	(0.025)
KTV connection	0.157	(0.045)	Has secondary education	−0.108	(0.038)

intuitive, as these pushers are more desperate for cash. Gambling addictions do not have a statistically significant effect on 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 gang affiliations have more bargaining power. This is because these pushers are often more experienced traders. Business connections with brothels and nightclubs are more valuable to pushers than connections with karaoke establishments.

There is also some evidence of price discrimination across nationality, ethnicity, and gender. Malaysian Chinese have less bargaining power and Singapore Indians have more bargaining power than the base group of Singaporean Chinese. Although not statistically significant, 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. Similarly, the female pushers (13 in our data) were also valuable to the gang because it further opened up the female market to them. 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.[35]

Figure 6 shows a histogram of the average estimated bargaining weights by pusher. We can see that the gang has relatively more bargaining power than most pushers. A total of 73% of the estimated pusher bargaining weights are below 0.5, and the median bargaining weight is 0.28. There is also considerable heterogeneity across pushers, with bargaining weights spanning the entire unit interval.[36]

The remaining parameter estimates, which relate to the pusher demand function, are shown in Table 5. We first note that because wholesale prices and unit costs for ice are much higher per unit compared to the other products, we change the unit for ice from 1 g to 0.2 g (a typical serving size) for estimation. We do this so that the parameters related to ice are scaled similarly to the parameters related to other products. From the estimates, we see that the means of the cost shocks are relatively

35. In Online Appendix Table A.2, we show a regression of the gang's mark-up on these characteristics. Our structural estimates are consistent with these reduced-form estimates.

36. In Online Appendix Figure A.3, we show the histogram of bargaining weights for all pusher-weeks.

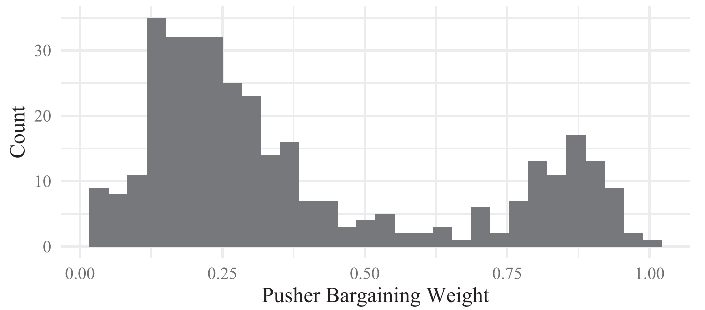

FIGURE 6. Histogram of the average estimated bargaining weights by pusher.

TABLE 5. Pusher demand estimates. Standard errors in parentheses.

	Ecstasy	Erimin	High-quality ice	Low-quality ice	High-quality ketamine	Low-quality ketamine
Expected disutility $\theta_j^{\alpha\kappa}$	0.22	0.60	0.49	0.38	0.30	0.28
	(0.01)	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)
Change during enforcement period $\theta_j^{\alpha\kappa e}$	−0.03	0.01	0.17	0.21	−0.03	0.02
	(0.02)	(0.07)	(0.06)	(0.03)	(0.02)	(0.03)
Enforcement period price change θ_j^{e}	−0.21	0.76	21.80	21.64	5.07	−0.17
	(0.34)	(2.19)	(1.57)	(0.63)	(0.80)	(1.37)
Pusher cost mean μ_j	10.04	57.05	20.35	21.58	32.90	40.57
	(0.08)	(0.35)	(0.36)	(0.15)	(0.12)	(0.08)
Pusher cost standard deviation σ_j	22.25	48.97	43.60	39.98	31.13	36.36
	(0.34)	(1.58)	(0.79)	(0.66)	(0.82)	(0.14)
Pusher cost autocorrelation ρ_j	0.44	0.14	0.09	0.10	0.19	0.20
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Pusher cost correlations across products:						
Ecstasy	1.00	0.15	0.11	0.11	0.09	0.05
		(0.03)	(0.03)	(0.02)	(0.02)	(0.01)
Erimin	—	1.00	0.06	0.10	0.08	0.10
			(0.01)	(0.01)	(0.04)	(0.01)
High-quality ice	—	—	1.00	0.19	0.13	0.12
				(0.01)	(0.04)	(0.01)
Low-quality ice	—	—	—	1.00	0.09	0.10
					(0.01)	(0.00)
High-quality ketamine	—	—	—	—	1.00	0.18
						(0.01)
Low-quality ketamine	—	—	—	—	—	1.00

high compared to the typical gross margins pushers receive. The average gross margin for each product in the 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.

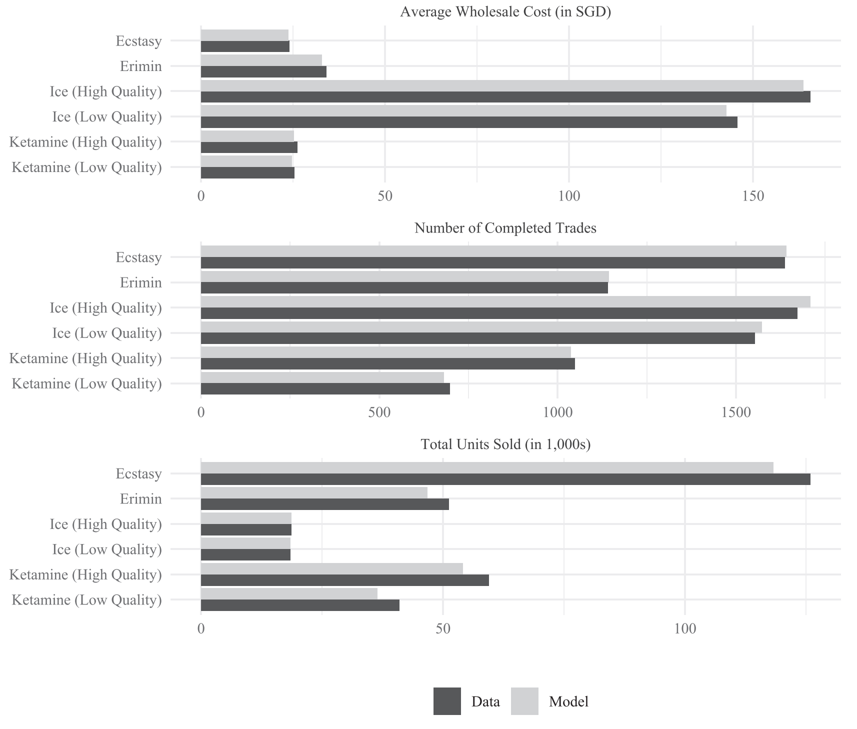

FIGURE 7. Model fit.

We estimate that the price of a serving of ice increased by approximately S$22 following the enforcement shock. Ex-drug offenders we have interviewed recalled similar price changes after the enforcement shock. One ex-pusher we interviewed told us that extremely high pass-through is common for ice. The estimated price changes for the other drugs are close to zero, except for high-quality ketamine, which increased by approximately 10%. The expected disutility parameter also increased substantially for ice, whereas there was no statistically significant change for the other products.

In order to assess the model's fit, we simulate trades according to the estimated model parameters to obtain the predicted average wholesale price, the number of completed trades and the total quantity sold for each product. We take the average of 1,000 simulations. The results are shown in Figure 7. The model matches these aggregate outcomes relatively well, although the predicted quantities are less accurate for ketamine where we have fewer observations.[37]

37. In Online Appendix Figure A.4, we also show the predicted model outcomes of each drug in each week against the data. Although weekly sales in the data are noisy, the model is able to match the broader patterns in the data relatively well. The model predictions are less accurate for ketamine in certain weeks. This is because, in the majority of weeks, there are fewer than 20 trades in these products.

TABLE 6. No enforcement shock counterfactual: total sales in 1,000s of units.

	Ecstasy	Erimin	High-quality ice	Low-quality ice	High-quality ketamine	Low-quality ketamine
Enforcement shock (baseline)	118.29	46.77	18.67	18.42	54.07	36.43
No enforcement shock	115.00	47.49	18.23	18.13	52.15	37.77
Shock where only unit costs change	114.99	46.70	17.97	17.95	50.83	36.82
Shock with no end-user price adjustment	118.23	46.57	17.20	16.88	51.64	36.46

6. Counterfactual Simulations

We now use the estimated model to simulate a number of counterfactual policy experiments. We first estimate the effect of the enforcement shock on the total quantity sold by simulating the trades that would have occurred in the absence of the shock. We then contrast this to a policy where the authorities target pushers with certain characteristics.

6.1. No Enforcement Shock

For our first counterfactual experiment, we use the estimated model to simulate the counterfactual total quantity sold if the enforcement shock had not occurred. In our data, the enforcement shock raised marginal costs for all drugs except for ecstasy. During the period of the enforcement shock, which occurred in weeks 13–21, we set the marginal cost of each affected drug c_{jt} to its level in week 12. For weeks 22 onward, we use the same marginal costs observed in the data as they had then returned close to pre-shock levels. In the model, we allowed the end-user prices and the expected disutility of arrest 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.

Table 6 summarizes the results of this counterfactual experiment.[38] The first row shows the total quantity sold for each product under the baseline case when the enforcement shock occurs, and the second row shows the counterfactual scenario when it does not occur. We can see that the enforcement shock did not substantially reduce the total quantity sold by the pushers in the market. In fact, the total sales increased by a small amount in certain drugs. Ex-offenders we have interviewed recalled selling larger quantities following the shock, despite the rise in wholesale

38. Online Appendix Figure A.5 shows the average wholesale price and total quantity for every drug-week under this counterfactual scenario.

prices.[39] Although the wholesale prices increased following the shock, end-user prices also increased, partially offsetting the wholesale price increase. Therefore, pushers continued to purchase similar quantities.

To decompose the effect of the end-user price change and the change in the expected disutility parameters, $\theta_j^{\alpha\kappa e}$, we simulate two further counterfactual scenarios. First, we simulate what would have happened if only the gang's marginal costs had changed but the end-user prices and the expected disutility parameters had not adjusted. This is shown in row 3 of Table 6. Here, the gang passes the cost increase onto pushers in the form of higher wholesale prices, and pushers purchase smaller quantities. Relative to the no-shock scenario, total quantities fall between 1%–2.5% for affected products. Second, we next consider what happens if both the gang's costs and expected disutility parameters changed, but end-user prices remained the same. This is shown in row 4 of Table 6. Here the total sales fall even further in most products: Total quantities fall between 1%–7% for affected products. Therefore, the small effect of the enforcement shock on quantities is largely due to the end-user price adjustment.[40]

We note that because there are other gangs actively selling ecstasy, erimin, and ketamine during our sample period, we can evaluate the effect of the enforcement shock only on the total quantity sold by the gang we observe in our data. However, the gang we study is the only gang selling ice during our sample period, so our results represent the effect of the enforcement shock on the total quantity of ice sold in the country.

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 raid on pushers on the total quantity sold.

We suppose that in week 26 of our data that law enforcement successfully arrests 20 of the active pushers in that week. Because this represents a small share of the total number of active pushers, market insiders we have spoken to claim that "arresting 10–20 pushers would not affect [end-user] prices." Moreover, due to the increasing penalties associated with being caught with larger quantities, the remaining pushers would not increase the quantity they sell each week to make up for the smaller number

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

40. The price elasticity of demand for addictive drugs is likely to be small in the short run. This has been discussed in the influential work of Becker and Murphy (1988), and empirical evidence for this is discussed in Castillo, Mejía, and Restrepo (2020). For short-run price changes, addicted consumers often continue purchasing, but the drug attracts fewer new customers. For long-run price changes, both types of consumers may substitute. Therefore, for the short-run price change in our case, it is highly plausible that end-users continued to purchase quantities similar to pre-shock period. This issue is discussed further in Online Appendix A.14.

TABLE 7. Targeting pushers counterfactual: total sales in 1,000s of units.

	Ecstasy	Erimin	High-quality ice	Low-quality ice	High-quality ketamine	Low-quality ketamine
Baseline	118.29	46.77	18.67	18.42	54.07	36.43
Arrest 20 pushers randomly	114.29	45.10	18.06	17.82	52.33	35.16
Arrest 20 previously convicted pushers	114.31	45.10	18.06	17.81	52.29	35.15
Gang hires back 20 pushers	118.16	46.71	18.65	18.40	54.01	36.39
Arrest 20 pushers with club connections	111.20	43.84	17.57	17.32	50.95	34.15
Gang hires back 20 pushers	115.59	45.70	18.26	18.02	52.88	35.62

of pushers. Our data has substantial variation in the number of active pushers throughout the year, and we do not find any evidence that pushers purchase larger quantities during weeks where there are fewer other active pushers.[41] 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 20 pushers, once they are arrested they are no longer active for the remainder of the year.

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 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 were arrested. Almost all the respondents claimed that the gang would slowly replace the lost pushers over the following weeks. 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. As there were many gangs in operation at the time, if the gang was 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 their normal slow and gradual rate. Based on this evidence, for this counterfactual, we assume that the gang continued its hiring at the rate we observe in the data. However, we also compare this to the less likely scenario where the gang immediately replaces all the arrested pushers immediately following the raid. For these replaced pushers, we randomly draw pushers with replacement from our sample of pushers. This allows us to calculate a lower bound of the effect of this policy.

We consider three different types of raids. We first consider what would happen if 20 random pushers were arrested. We then consider targeted arrests where the authorities arrest 20 ex-convicts or 20 pushers with nightclub connections. The results from this counterfactual experiment are shown in Table 7. When 20 random pushers

41. Regression estimates with this evidence are shown in Online Appendix Table A.3.

are arrested, the total quantity falls by approximately 3%–4% in all products. If the authorities instead arrest 20 previously convicted pushers, the fall in quantity is very similar. This is because, on average, previously convicted pushers buy similar quantities to the average pusher. If the gang were to immediately hire back 20 pushers, the total quantities are very similar to the baseline case. This is because the replaced pushers are similar to the previously convicted pushers.

When the authorities target pushers with nightclub connections, the total quantity falls by approximately 5%–6% for each product. Even if the gang immediately hires back 20 pushers, the total quantity still falls by approximately 2%. This is because the replaced pushers have fewer business connections and purchase smaller quantities on average. Although the gang may replace a small number of the arrested pushers in response to the raid, it is unlikely they would replace all 20 for the reasons listed above. Therefore, we expect the effect to be closer to 5%–6% than the estimated lower bound of 2%. This result suggests that targeting pushers with relatively more bargaining power, such as those with nightclub connections, is an effective strategy to lower the total quantity sold. Furthermore, pushers with nightclub connections earn much larger gross profits than the average pusher. Therefore, this policy also targets those who gain the most from trading.

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. These 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. Because 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.[42] Therefore, the behavior

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

of the pushers regarding 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 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.[43] According to market insiders we have spoken to, the gang we studying 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

We develop a multiproduct bargaining model between the Singaporean branch of a large transnational gang and pushers. We estimate this model using detailed transaction data kept by the gang, together with detailed information on the pushers, such as their addictions and business connections. We use our estimated model to simulate the effects of different enforcement strategies on the total quantity of drugs sold. We first consider the effectiveness of targeting delivery routes. During our sample period, the authorities successfully intercepted a large shipment and disrupted the gang's supply route. The gang quickly found a new supplier, but the shock raised its marginal costs for several weeks.

We find that although these cost increases led to price increases further down the supply chain, the total quantity sold by the gang was largely unaffected. A natural explanation is that addictive drugs such as ice often have small short-run price elasticities. We then consider an alternative policy where law enforcement focuses its efforts on arresting a subset of the actively trading pushers. We find that such a policy is more effective at reducing the quantity sold in the market, and argue that such an approach is less costly. Arresting a small number of pushers will have little effect on market prices, and the remaining pushers do not increase the quantity they sell due to the harsh penalties associated with being caught with larger quantities. Such a policy is even more effective if the authorities target pushers who have greater bargaining power over the gang, even if the gang responds by immediately recruiting new pushers. 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 sold.[44]

43. See Online Appendix A.15 for a further discussion on the differences between transnational gangs and local street gangs.

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

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Supplementary Data

Supplementary data are available at *JEEA* online.