Illegal Drug Use and Government Policy: Evidence from a Darknet Marketplace*

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Abstract

This paper develops a structural model of demand for illegal drugs to study how consumers substitute between different drugs in response to government policies. We construct a unique longitudinal dataset by scraping a darknet marketplace that dominated Russia's retail illegal drug trade. We exploit novel micro-level moment conditions to identify correlations in preferences across drug types and consumers' degree of attachment to them. We estimate a median own-price elasticity of demand of -3, and find particularly high substitution within two classes of drugs: medium-risk stimulants and cannabis. We validate these estimates using exogenous variation in hashish prices. Using the estimated model, we find that cannabis legalization reduces the use of riskier drugs while increasing cannabis use: for every four additional doses of cannabis consumed, one fewer dose of another drug is consumed. We also use the model to quantify the impact of the introduction of new synthetic drugs, and to measure the extent to which substitution to other drug types offsets the impact of targeted interdiction.

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1. Introduction

The illegal drug trade is a global problem with implications for public health, violence, incarceration, unemployment, and property crime. In 2022, the U.S. government spent more than $40 billion to address this problem, roughly half on supply-side enforcement aimed at reducing drug availability and lowering use (National Drug Control Budget, 2023). However, the merits of supply-side enforcement remain debated (New York Times, 2023; The Economist, 2023).

Understanding how consumers substitute between different drug types is essential for evaluating the effects of government drug policies (see, e.g., Donahoe and Drake, 2025). Substitution can reduce the effectiveness of interventions targeting specific drugs, such as seizures or crop eradication: although consumption of the targeted drug may fall, this decline may be largely offset by substitution toward close substitutes. Conversely, substitution may strengthen the case for legalizing lower-risk drugs if it leads consumers to shift away from more dangerous drugs.

This paper studies the demand for illegal drugs and the impact of drug policies on consumption. Using unique, high-quality panel data covering Russia's drug market, we examine demand across a wide range of drug types. We begin by documenting heterogeneity in drug preferences. We then develop and estimate a demand model that accounts for these patterns. Finally, we apply the model to evaluate counterfactual drug policies.

Illegal drug markets are typically unobserved, which has constrained prior empirical research on drug demand. We overcome this by using data from Hydra, a darknet marketplace that operated from 2015 to 2022. Hydra was the largest darknet marketplace in the world and, in its later years, covered the majority of the retail drug trade in major Russian cities. By regularly scraping the platform for over a year, we compile a novel micro-level panel dataset of more than 3 million listings. Crucially, this dataset allows us to observe drug prices and estimate quantities sold in each location where the market operated.

We combine data on drug listings with an individual-level panel dataset of marketplace user reviews, which allows us to infer individual consumption patterns. Our findings reveal significant consumer heterogeneity. We find substantial persistence in drug choice: consumers most often purchase the same drug across multiple periods, though the degree of persistence varies by drug type — cocaine users, for example, are nearly twice less likely to purchase another drug than MDMA users. We also find that substitution tends to occur within groups of related drugs. Consumers who purchase amphetamine, MDMA, or mephedrone - three stimulants with similar effects — are substantially more likely to substitute toward one of the other two than toward another drug type. The substitution patterns we observe often diverge

from what pharmacological characteristics alone would predict. For example, mephedrone and $\alpha-$PVP, both stimulants classified as synthetic cathinones, show minimal substitution.

To capture the patterns we observe in the data, we develop a model that builds on the mixed logit framework (also known as BLP; see Berry, 1994; Berry et al., 1995). Because observable drug characteristics have little power to explain the consumption patterns in the data, we allow for preference heterogeneity by introducing random coefficients on dummies for each of the most popular drug types. These consumer-specific coefficients capture idiosyncratic attachment to each drug type.

To identify the covariance of random coefficients, a well-known challenge in BLP-type models, we exploit a novel set of moment conditions derived from our micro-level data on consumer reviews. These moments capture the correlation between users' choices, identifying covariances between random coefficients, in a manner analogous to second-choice data (Berry et al., 2004). As reviews can often be readily scraped from online platforms, our method may be applicable in other settings where demand is estimated using data from online marketplaces.

Our estimates reveal substantial price sensitivity among drug users, with a median price elasticity of -2.95. The higher elasticity relative to earlier studies may reflect our transaction-level data capturing a more representative cross-section of consumers than the common proxies targeting heavy users, and because the online marketplace setting — where prices are transparent, and purchases are deliberate — may itself increase price sensitivity. We validate our model by exploiting an exogenous supply-side shock that occurred during the study period, finding that our model closely predicts the observed response of consumption following the increase in hashish prices. We then employ our model to evaluate the impacts of several counterfactual supply-side drug policies.

First, we examine the potential impact of cannabis legalization on drug consumption. We model legalization as a reduction in the price of cannabis, which captures both the direct price declines observed following previous instances of legalization (Anderson et al., 2013; Hall et al., 2023) and, more broadly, reductions in non-monetary costs such as legal risk and stigma.[1] While legalization substantially increases cannabis consumption, it also reduces the consumption of riskier drugs: roughly one fewer non-cannabis dose is consumed for every four additional doses of cannabis. Substitution is not limited to medium-risk drugs but also extends to high-risk substances such as cocaine, suggesting that legalization may shift consumption away from the most harmful drugs.

[1]This interpretation requires that the influence of non-monetary cost reductions on utility is uniform across consumers and thus has a monetary equivalent. Jacobi and Sovinsky (2016) use survey data to explicitly incorporate the impact of reducing legal stigma and increasing accessibility in their structural model of marijuana demand.

Second, we study the impact of the emergence of new synthetic drugs on overall consumption. In particular, we focus on a class of synthetic drugs known as "bath salts," which have gained popularity in recent years (Prosser and Nelson, 2012) and account for nearly forty percent of all drugs sold on the marketplace. Using our model to simulate a counterfactual in which bath salts are unavailable, we find that their introduction increased total demand for illegal drugs by 36%, with only a third of bath salt consumption reflecting cannibalization of preexisting drug types. To our knowledge, this is the first study to evaluate the introduction of new drugs. Our results highlight the importance of efforts to prevent new drugs from entering the market, as their introduction can substantially expand overall drug use.

Third, we revisit the classic question of Becker et al. (2006) and show that drug enforcement can unintentionally increase total black market revenue. In our setting, this occurs when enforcement raises the price of amphetamine. Even though demand for amphetamine is elastic and its own revenue declines, the presence of close substitutes leads many consumers to shift toward other drugs. As a result, revenue from substitute drugs increases sufficiently to raise the total revenue in the black market.

Finally, we apply our estimates to examine the effects of targeted enforcement on total drug consumption. We simulate the elimination of individual drugs from the market, an outcome that successful supply-side interventions sometimes achieve in the short run. The impact on total drug use is the smallest for consumers of drugs that have close substitutes, such as amphetamine, cocaine, mephedrone, and MDMA. The largest effect occurs for $\alpha-$PVP, a drug with no close substitutes. For example, the share of consumption that shifts to substitute drugs is more than twice as large when amphetamine is eliminated than when $\alpha-$PVP is removed.

Our analysis has several limitations. First, we do not directly observe individual transactions. Instead, we approximate sales using listings and provide extensive evidence supporting the validity of this proxy. Nevertheless, our data, scraped from a dominant marketplace, are considerably richer and of higher quality than those previously used to study the demand for illegal drugs. Second, we model consumer preferences as static, implying that the stock of addiction is fixed. Therefore, our model primarily captures short-term substitution and cannot account for long-term dynamics, such as the possibility that lower-risk drugs may act as gateways to high-risk ones. Finally, our analysis focuses on how policies affect illegal drug consumption and does not study their potential effects on health outcomes, crime, or other social consequences.

Our paper makes two contributions to the literature on the estimation of demand for illegal drugs. First, by scraping a large marketplace, we obtain high-quality data on drug

consumption and prices.[2] The illegality of drug markets has long prevented researchers from accessing transaction data.[3] As a result, prior research on the demand for drugs has been forced to rely on proxy measures of consumption, such as emergency department visits (Caulkins, 2001; Dave, 2006), traffic fatalities (Anderson et al., 2013), toxicology tests of arrestees (Dave, 2008), self-reported information from surveys (DeSimone and Farrelly, 2003; Jacobi and Sovinsky, 2016; Van Ours and Williams, 2007), small-scale experiments (Jofre-Bonet and Petry, 2008; Olmstead et al., 2015), arrests (Mallatt, 2022), and user feedback on marijuana purchases (Davis et al., 2016). To estimate prices, researchers have often relied on recorded purchases made by undercover drug enforcement agents (Saffer and Chaloupka, 1999). However, this data has a low frequency, a number of methodological shortcomings (Manski et al., 2001), and over-represents large transactions (Horowitz, 2001).

Second, we are the first to model demand for a broad set of drug types, allowing us to estimate substitution patterns across drug types that together comprise nearly the entire market. In contrast, previous studies have predominantly considered substitution between just two drugs or sin goods (Alpert et al., 2018; DeSimone and Farrelly, 2003; Anderson et al., 2013; Powell et al., 2018).[4] In addition, the coverage of our dataset has allowed us to obtain the first estimates of price elasticities for newer synthetic drugs such as mephedrone.

The second strand of literature that our paper contributes to studies the effects of drug policies (see, e.g., Castillo et al., 2020; Cunningham and Finlay, 2016; Dobkin et al., 2014; Evans et al., 2019; Jacobi and Sovinsky, 2016; Mallatt, 2022). We present a structural demand model that allows us to study a range of counterfactuals. This is in contrast to papers such as Dobkin and Nicosia (2009); Moore and Schnepel (2021), which used event studies to estimate the impact of isolated large-scale shocks. These shocks are, by nature, rare, while our model can be used to assess routine policy responses. While prior papers have estimated structural demand models for illegal drugs, they have focused on particular drug types without accounting for substitution between drug types (Jacobi and Sovinsky, 2016; Kennedy et al., 1993; Galenianos et al., 2012; Adda et al., 2014; Mejia and Restrepo, 2016; Galenianos and Gavazza, 2017). By incorporating substitution across the full set of drug types, we are able to assess the impact of policies on total drug consumption.

[2]To the best of our knowledge, we are the first to utilize data scraped from a darknet marketplace for demand estimation. Other examples of papers in the economic literature that utilize data scraped from the dark web include Červenỳ and van Ours (2019), Bhaskar et al. (2019), and Espinosa (2019).

[3]A small number of papers have circumvented this constraint by studying settings where drugs that are typically illegal were instead legally traded. Van Ours (1995) and Liu et al. (1999) use transaction data from the regulated opium trade of the early 20th century. Hollenbeck and Uetake (2021) estimate the demand for legalized marijuana using the BLP framework.

[4]An exception is Ramful and Zhao (2009), who study the extensive margin of drug use for three drug types: marijuana, cocaine, and heroin. See Gallet (2014) for a meta-analysis of the literature on demand for illegal drugs.

The rest of the paper is organized as follows. Section 2 describes the context of illegal drugs and the operation of the marketplace. Section 3 describes the data we use. Section 4 presents our demand model and the details of its estimation. In Section 5, we apply our model to calculate the effects of several supply-side policies. Section 6 concludes.

2. Market for Illegal Drugs

For researchers, a central challenge in studying illegal drug markets is that they are rarely observable. In this paper, we overcome this limitation by leveraging a unique setting in which most retail drug transactions were concentrated on a single website, Hydra. In this section, we describe the platform and the relevant institutional context.

2.1. The Hydra marketplace

The Hydra marketplace operated on the Tor network, which allows for encryption and anonymization of traffic by routing it through a series of volunteer-run servers. The network can be accessed using a specialized browser that is available for free download. Because of the anonymization of traffic, the government cannot restrict access to websites on the Tor network in the same way it can with conventional websites.

The marketplace began operation in 2015 (VICE, 2020) and primarily served the Russian market. After its predecessor RAMP was shut down by the Russian police in 2017, Hydra grew without any significant competition until its shutdown in 2022.[5] The unprecedented length of its existence allowed Hydra to become the largest darknet marketplace in the world. The U.S. Department of Justice estimated that Hydra accounted for 80% of all darknet market cryptocurrency transactions in 2021 (States of America V. Dmitry Olegovich Pavlov, 2022). U.S. Department of the Treasury (2022) estimates that the yearly revenue of Hydra in 2020 was $1.3 bln. At the time of its closure, Hydra had spread to the majority of cities in Russia and is thought to have been the most popular method to purchase drugs for retail consumption in several of the largest cities (Goonetilleke et al., 2023).

A key feature of Hydra is its distribution system, which allows us to approximate the quantities of drugs sold in each location. Unlike most darknet marketplaces, which rely primarily on legitimate postal services, Hydra used a dead-drop system (VICE, 2020). This system was first adopted by RAMP in response to a 2014 law requiring postal services to inspect packages for illegal substances (Saidashev and Meylakhs, 2021). To circumvent this, shops hired couriers to hide drugs across the city prior to purchase. The details of these

[5]The shutdown was a joint operation of German and U.S. law enforcement.

hidden drugs were then posted on the marketplace so that potential customers could select the listing that best suited their needs. Appendix Figure G.2 provides an example of a page with listings. After purchasing drugs with cryptocurrency, consumers received information about the exact location of the dead-drop (see Appendix Figure G.5 for an example). While a small proportion of drugs were still delivered via mail, the vast majority of retail sales were delivered via dead-drops.[6]

Similar to other darknet marketplaces (Janetos and Tilly, 2017), Hydra had a reputation system. Buyers could review purchases, providing both a numeric rating and detailed text comments.

One feature of the market is that sales of fentanyl and several other synthetic opioids were prohibited in the marketplace. Thus, our analysis is not informative about the demand for this drug. Goonetilleke et al. (2023) provides a detailed discussion of the scope, structure, and rules of Hydra.

2.2. Drug types

Table 1 describes the characteristics of the most popular drug types on Hydra.[7] The medical literature divides drugs according to their pharmacological effects. Stimulants, like MDMA (known as "ecstasy"), cocaine, amphetamine, and methamphetamine, increase the activity of the central nervous system. Two other types of stimulants are highly popular in Russia: mephedrone (known as "meow meow") and $\alpha-$PVP (known as "flakka"). These two drugs belong to the new family of drugs known as synthetic cathinones and are colloquially referred to as "bath salts." They emerged in the late 2000s and gained popularity in Russia, Europe and the U.S. in the early 2010s.

Depressants, like cannabis, opioids, and GHB, decrease the activity of the central nervous system. Cannabis can be distributed in different forms, the two most popular of which are marijuana buds and hashish. Hashish is produced by compressing and processing cannabis plants. Opioids, such as heroin and methadone, produce morphine-like effects and are commonly recognized for their potent effects and significant risks.[8] GHB is a substance that can be used for medical purposes but is also a popular recreational drug. Finally, for hallucinogens, such as LSD and psilocybin, the main effect is the altered perception of reality.

Drugs also differ in other dimensions. In particular, some drugs are considered "club"

[6]Drugs delivered via mail were primarily drugs that are particularly difficult for law enforcement to detect, such as LSD.

[7]See Manski et al. (2001) for a summary of the medical literature that examines the properties of illegal drugs.

[8]However, methadone can also be used for medical purposes, in particular, as a treatment for heroin addiction. Methadone therapy is not legal in Russia (Idrisov et al., 2017).

(or "party") drugs. These drugs are popular among younger individuals and are typically consumed at bars, nightclubs, concerts, and parties (Bowden-Jones and Abdulrahim, 2020). Drugs can also vary in their most common mode of administration, but each drug type typically can be administered in multiple ways. The mode of administration can impact the likelihood of developing dependence (Hatsukami and Fischman, 1996).

Table 1: Drug types most present on Hydra

Psychoactive class	Drug type	Club drug	Bath salt	Production	Administration	Form	Physical harm index	Dependence index	Overdose ratio
Stimulants	α-PVP	Y	Y	Synthetisized	Smoking, nasal, oral	Powder, crystal	—	—	—
	Amphetamine	Y	N	Synthetisized	Oral, nasal	Powder, crystal	1.81	1.67	—
	Cocaine	Y	N	Synthesized from organic compounds	Nasal	Powder	2.33	2.39	15
	MDMA	Y	N	Synthetisized	Oral	Pills, crystal	1.05	1.13	16
	Methamphetamine	Y	N	Synthetisized	Oral, smoking	Crystal, powder	—	—	10
	Mephedrone	Y	Y	Synthetisized	Oral, nasal	Powder, crystal	—	—	—
Depressants	GHB	Y	N	Synthesized	Oral	Liquid	0.86	1.19	8
	Hashish	N	N	Organic	Smoking	Resin	0.99	1.51	> 1000
	Heroin	N	N	Synthesized from organic compounds	Injection	Powder	2.78	3.00	6
	Marijuana	N	N	Organic	Smoking	Flowers, leaves	0.99	1.51	> 1000
	Methadone	N	N	Synthetisized	Oral	Powder	1.86	2.08	20
Hallucinogens	LSD	Y	N	Synthetisized	Oral	Saturated paper	1.13	1.23	1000
	Psilocybin	N	N	Organic	Oral	Mushrooms	—	—	1000

Note: This table describes characteristics of the most popular drugs sold on Hydra. "Club drug" indicates whether the drug is classified as a club drug, a group of psychoactive drugs often used at parties and clubs that heighten sensory perceptions and reduce inhibitions. "Administration" refers to the most common method of drug administration. "Form" refers to the most common substance forms in which drugs are sold. Harm and dependence indices come from Nutt et al. (2007). Overdose ratios, are defined as the ratio of the acute lethal dose to the dose most commonly used and are obtained from Gable (2004).

We characterize drug harmfulness along three dimensions: the overdose potential of Gable (2004), defined as the ratio of the acute lethal dose to the most commonly used dose, and the physical harm and dependence indices of Nutt et al. (2007).[9] Based on these measures, heroin is the most dangerous drug in our sample. Methadone and cocaine are also characterized by high levels of dependence and harm, while cannabis and MDMA score considerably lower. This data is unavailable for bath salts, which are newer drugs. However, Patocka et al. (2020) report a significant risk of overdose associated with α-PVP, and Winstock et al. (2011) document multiple harmful effects attributed to mephedrone. It should be noted that there is no universally accepted measure of total harm for drugs. For example, overdose potential does not account for risks from polydrug use. Furthermore, the indices of Nutt et al. (2007) have been widely debated, largely because of the difficulty of separating and correctly identifying individual and societal harms (Caulkins et al., 2011).

2.3. Production

Drugs differ significantly in production technology and whether they are imported or produced locally. In the Russian, U.S., or European markets, some drug types are entirely imported. For example, the production of cocaine requires the leaves of the coca plant, which is grown almost exclusively in Colombia, Peru, and Bolivia (UN Office on Drugs and Crime, 2022). Similarly, the production of heroin requires the opium poppy, which is mostly grown in Afghanistan (UN Office on Drugs and Crime, 2016). The origin is less clear for other drug types. Cannabis plants can be grown indoors, and, thus, marijuana can be both imported or produced locally. However, the production of hashish for the European market is mainly concentrated in Morocco and Afghanistan (UN Office on Drugs and Crime, 2016). There is evidence that bath salts for the Russian market are produced locally from precursors imported from chemical suppliers in China (Baza.io, 2020).

In the analysis, we leverage the differences in production across various drug types in two ways. First, we consider distance to the main ports as an instrument for price, under the assumption that the cost of cocaine and hashish increases with distance from the point of entry. Second, we use a policing shock that affected the supply of Moroccan hashish to validate our demand model.

[9] These indices are averages of expert-elicited scores, where 0 indicates no risk and 1, 2, and 3 represent some, moderate, and extreme risk, respectively.

2.4. Regulation

All drugs listed in Table 1 are classified as illegal substances in Russia, making the pickup of purchases on Hydra risky. Punishments for possession depend on the amount, with government-set thresholds for each drug (Government of Russia, 2012). The threshold closest to typical retail purchases is the "significant amount," exceeding which can result in a prison sentence. Moreover, the Russian legal system often over-classifies possession as an offense with intent to supply, which almost always results in incarceration, creating high risks for all consumers.[10] These legal risks may reduce demand for large dead-drops, which we account for in our demand estimation by including dead-drop size as a product characteristic.

The high risks associated with consumption imply that a legalization policy will increase demand for the legalized drug. In Section 5.1, to study the effects of legalization, we assume that a reduction in the non-monetary costs of consumption generates the same substitution patterns as a reduction in the price of the legalized drug.

3. Data

3.1. Datasets

Listings

Our first source of data contains information on listings on Hydra. We collected this data by scraping the Hydra website.[11] We describe the details of the scraping process in Appendix Section A.1. Our dataset covers all listings on the platform for 31 days between June 2019 and September 2020. See Appendix Table A.1 for the list of available dates.

Each shop could offer several products. For each product, the platform displays the listings offered by the shop. The platform allowed two types of listings: pre-order and instantaneous listings. Instantaneous listings provided the details about dead-drops that were already hidden in the city and could be purchased immediately. Pre-order listings allowed consumers to contact the shop to buy the drug, which was then deposited after the purchase was made. As noted by Goonetilleke et al. (2023), pre-order listings are more likely to be used for wholesale transactions or for more "exotic" drugs and, thus, constitute only

[10] Russian law distinguishes possession without intent to supply (Article 281) from possession with intent to supply (Article 281.1). In 2020, 56,556 people were convicted under Article 281, with 25% receiving prison terms. Under Article 281.1, 14,223 people were convicted, 92% of whom received prison sentences, and 65% for more than five years (Judicial Department, 2021a,b).

[11] We are indebted to Ekaterina Aleksandrova for her invaluable contribution to data collection efforts.

a small fraction of all purchases. Furthermore, they are only loosely connected to sales, as posting pre-order listings did not imply any pre-commitment on the shop's part. Therefore, we restrict our attention to instantaneous listings. Overall, we observe more than 3,410,000 instantaneous listings across 40 different drug types, 8,283 shops, and 1,337 different cities or towns.

As instantaneous listings describe the pre-hidden drugs, we observe the characteristics of each dead-drop, including the mode of hiding, amount (weight or counts), approximate location, and price. Our data also includes the information that was displayed as a part of the product's description: shop name and shop identifier, product name, drug type, and average ratings for the shop and product. Finally, we observe the approximate cumulative sales for the shop (this number was displayed by the platform; see Appendix Figure G.3 for an example). We restrict our analysis to retail listings, removing those that appear to be intended for redistribution, as we focus on estimating consumer behavior. We describe the details of data cleaning in Appendix Section A.2.

Definition of dose. There are two reasons why drug quantities cannot be directly compared across listings. First, drugs are sold in different substance forms. This occurs both within the same drug type – MDMA, for example, is sold as both pills and crystals – and across drug types – GHB is typically sold in liquid form, unlike most other drugs. Second, even within the same substance form, drug potency per gram can vary across different drugs. To address this issue, we normalize listed amounts using dose estimates for each drug-form combination. Doses represent the smallest frequently purchased amount within a given drug-form pair.[12] We present the details in Appendix Section A.3 and Appendix Table A.2.

Reviews

Our second dataset contains a large subset of customer reviews posted on the platform.[13] For each review, we observe the numeric rating, review text, purchased product, shop, reviewer's nickname, and the time when the review was posted. Our sample includes approximately 215,000 reviews. These reviews cover 784 shops on Hydra, representing 47% of the shops in our listings data.

[12] Our definition of a dose can be larger than the typical amount consumed if dead drops were intended to contain enough drugs for multiple consumptions.

[13] This dataset is purchased from a private firm that scraped several dozen darknet marketplaces and also provided data for United Nations Office on Drugs and Crime (2021). Details about the project can be found in Soska and Christin (2015) and Christin (2022).

Other data

We use additional data sources to derive characteristics of products that are likely to be relevant from the consumers' perspective. We include these variables in the demand model. First, we use scrapes of the front page to identify whether a particular shop was advertised on the front page each month (see Section 2.1). Second, considering that consumers may prefer shops with established reputations, we incorporate into the model the duration of a shop's presence in the marketplace. To achieve this, we access historical data on the aggregate number of reviews on a shop-drug level. This data covers reviews left by Hydra users from six different cities since late 2016 and until 2021.[14] We use this information to identify the age of shops on Hydra.[15]

We use a 10% subsample of the Russian Census of 2010 to obtain city-level data on population and estimate the market size. While we observe listings from more than 1,000 cities, we restrict our attention to the country's largest cities. We exclude cities with a small Hydra presence (defined by the ratio of listings to population).[16] Our final sample includes 34 large cities.

3.2. Descriptive statistics

Table 2 presents summary statistics for the most popular drug types traded on Hydra. The four most popular drug types are stimulants: mephedrone, amphetamine, $\alpha-$PVP, and MDMA. They are followed by marijuana, hashish, and cocaine. The most expensive drug observed is cocaine, with an average price per dose of \$65. All other drugs are significantly cheaper, with the price per dose about three times lower. Among popular drugs, $\alpha-$PVP is the cheapest, with an average price per dose of \$14.

The last column of Table 2 shows that each drug type was sold by hundreds or thousands of shops. Goonetilleke et al. (2023) present additional evidence that Hydra had a high degree of competition. This motivates our approach to restrict attention to the demand side only. Changes in consumption would be driven by changes in demand if the supply of drugs is elastic.

Table 3 describes variation in prices of drug listings on Hydra. Several patterns are

[14] This data was purchased from an independent data collector, who also provided data for several media investigations (Knife Media, 2020; Proekt, 2019). As this data does not contain price information, we cannot use it for demand estimation.

[15] Each shop on the platform had a unique ID. We conclude that each new shop received an ID incremented by 1. Thus, we can establish the approximate date of registration for any merchant from its ID.

[16] We also observe an unusually high presence in satellite cities around Moscow, which we interpret as evidence that dead-drops hidden in these communities also serve consumers from Moscow. For this reason, we include these locations within the Moscow market.

Table 2: Summary statistics for select drug types on Hydra

	Daily Listings	Average Price ($ per dose)	Median Quantity	Market Share (doses)	# of Sellers
Mephedrone	11,168	23	2g	28%	2,200
Amphetamine	5,345	16	2g	15%	1,738
α-PVP	4,808	14	1g	11%	1,377
Marijuana	3,041	20	2g	8%	1,906
Hashish	3,040	16	2g	9%	1,831
MDMA (pill)	2,697	18	3 counts	7%	1,428
Cocaine	2,602	65	1g	6%	1,059
MDMA (crystal)	1,368	19	1g	4%	673
LSD	1,147	26	3 counts	3%	493
GHB	804	13	100ml	1%	76
Methadone	752	22	0.5g	2%	331
Heroin	293	20	0.5g	1%	201
Other Cannabis	705	13	2g	2%	690
Other Psychedelics	739	17	3 counts	2%	399
Other Stimulants	342	19	1g	1%	217
Other Opioids	11	30	1g	$< 1\%$	12

Note. This table shows summary statistics for the most popular drug types sold on Hydra. It is based on the main sample of 34 cities and 31 dates. Prices are converted to USD using an exchange rate of 74 RUB per USD.

noticeable. First, there is considerable price variation across shops, suggesting that product quality may vary across shops. To account for this, we include proxies for quality in our demand model. In particular, we include a set of shop characteristics, such as the shop's age and average rating. Appendix Table A.3 presents summary statistics of the variables that describe shops on the platform. Second, the last column of Table 3 shows that the proportion of price variation that occurred over time was the largest for hashish. This is explained by the policing shock to the supply of this drug that occurred during the sample period. In Section 4.3, we use this variation to validate our model estimates.

3.3. Proxies for sales

Because we cannot directly observe sales on Hydra, we use instantaneous listings as a proxy. To compute market shares for different products, we assume that the number of listings with specific characteristics is proportional to the number of sales with the same characteristics. This assumption is motivated by the fact that depositing each dead-drop was expensive for shops and required a substantial payment to the courier (Goonetilleke et al., 2023). Therefore, posted listings represent a strong commitment to sell.

The credibility of this assumption is supported by the strong correlations between listings

Table 3: Variation in prices

	Price per gram			Variation		
Drug type	Mean	Median	Std	Shop	City	Time
α-PVP	24	23	5	29.7%	18.3%	29.3%
Amphetamine	15	14	4	68.1%	6.7%	0.3%
Cocaine	124	122	23	63.7%	7.4%	2.3%
Hashish	15	12	6	20.2%	3.7%	61.0%
Marijuana	19	18	5	34.9%	5.2%	38.1%
MDMA	35	34	8	65.9%	11.4%	3.1%
Mephedrone	21	21	5	45.3%	18.3%	0.8%

Note. The variation due to each factor represents the ratio of the total variance explained by corresponding fixed effects in the regression of price on shop-level, city-level, and date-level fixed effects. For consistency, this analysis only uses the median quantity for each drug type. Prices are converted to USD using an exchange rate of 74 RUB per USD.

and several other proxies for sales. First, because the platform reports rounded cumulative sales for each shop, we can calculate the change in total sales between the beginning and end of our observation period. Table 4 shows that the correlation between this change and the number of listings is 0.7.

Second, the number of reviews is another proxy for sales. Table 4 shows that the correlation between reviews and listings on the shop level is 0.62. Importantly, because these proxies are noisy, we would expect the observed correlations to be lower than the true correlation between listings and sales. In particular, changes in total sales are affected by substantial rounding error,[17] and the total number of reviews in our dataset suffers from incomplete scraping coverage.

Finally, trends in listings closely track changes in cryptocurrency inflows to Hydra. Flashpoint, Chainanalysis (2021) estimate monthly Hydra revenues by counting Bitcoin transactions to wallets that analysts identified as belonging to Hydra. Appendix Figure A.1 shows that the dynamics of listings and cryptocurrency inflows exhibit similar patterns.

To compute market shares based on listings, it is sufficient that listings are proportional to sales. We discuss this assumption is detail in Appendix Section A.5. We expect that a single listing typically corresponds to several transactions, since couriers likely deposited multiple dead-drops in the same neighborhood. If a shop had several dead-drops of the same drug type, amount, hiding mode, and price in approximately the same location, these

[17] For example the platform displayed the same cumulative sales for shops with 149,000 and 100,000 actual sales.

Table 4: Correlations between different proxies for sales

	Listings	Cumulative sales	ΔCumulative sales	Reviews
Listings	-	0.74	0.70	0.62
Cumulative sales	0.74	-	0.93	0.65
ΔCumulative sales	0.70	0.93	-	0.70
Reviews	0.62	0.65	0.70	-

Note. This table presents correlations between several shop-level proxies for sales. "Listings" and "reviews" refer to total values aggregated over the study period for each shop. "Cumulative sales" denotes the rounded total number of sales for the shop as displayed by the platform. "ΔCumulative sales" represents the change in this cumulative measure between the first and last days the shop is observed in the data.

dead-drops appeared on the marketplace under a single listing.[18]

Because our analysis is based on market shares of different drug types, it is important that the ratio of listings to dead-drops does not differ systematically across drug types. To verify this, we use reviews as a proxy for sales and compare the market shares of each drug type computed from listings with those computed from reviews (Appendix Table A.5). We find that the shares generated by the two measures are overall very similar. This supports our assumption that sales are proportional to listings.

3.4. Proxies for quality

Potential heterogeneity in unobserved quality poses an identification problem for demand estimation. Because quality is likely positively correlated with both price and demand, omitting it from the model can bias price sensitivity estimates downward. In our context, "quality" reflects the purity and potency of the drug or the ease of recovering the dead drop. To account for variation in quality across listings, we incorporate quality into the analysis by using user ratings as a proxy. However, there are three major concerns about using ratings as a proxy for quality. First, ratings left by users on online platforms are likely to be a function of both quality *and price*.[19] Luca and Reshef (2021) find that ratings can be highly

[18]This feature of the platform was described in the instructions published on the website.

[19]This is possible under two feasible models of consumer behavior. First, users can rate not the quality of goods purchased but their net utility, which decreases with price. Second, users can rate based on their satisfaction relative to the reference point of expected quality, which, in turn, is likely to be positively correlated with price.

responsive to prices: they estimated that a price increase of 1% leads to a 3%-5% decrease in the average rating. Second, Filippas et al. (2022) show that ratings on online platforms are subject to inflation. Finally, ratings on Hydra had very low granularity: 94% of all reviews we observe had ratings 10/10, with an average rating of 9.6 (see Appendix Table A.4). Thus, ratings can contain limited information about underlying product quality.

To address the issue, we employ natural language processing techniques to construct another measure of quality. We determine the sentiment of each review in our dataset and use the average sentiment score of reviews for each shop as an additional proxy for quality. Further details about the text analysis are provided in Appendix B.

3.5. Reviewer behavior

Review data provide a unique opportunity to study the behavior of individual consumers. We identify reviews made by specific consumers using usernames displayed on the platform. To study choices made by the same consumer over time, we focus on users who posted at least two reviews. This gives a sample of 43,381 users and a total of 132,855 reviews. Appendix Table A.4 reports summary statistics for our review data. Figure 1 presents a matrix of drugs' market shares conditional on reviewing a particular drug. Each element P_{jk} of this matrix represents the probability that, conditional on a randomly selected review for drug j, another randomly selected review by the same user in a different period is for drug k.[20]

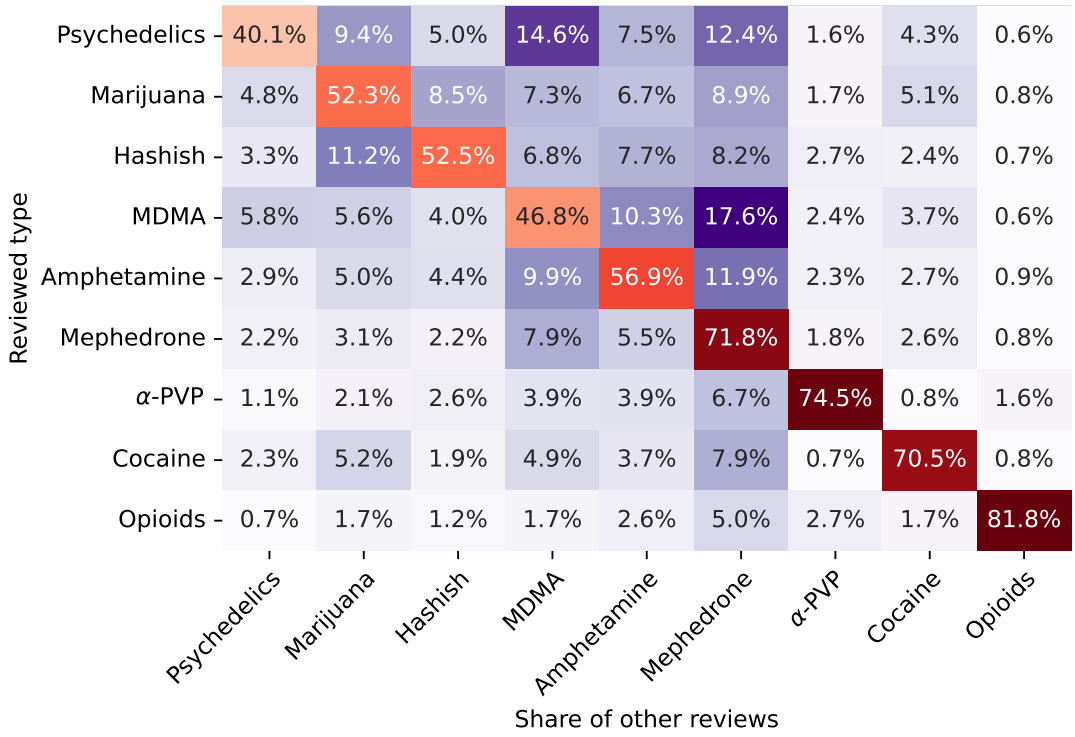
Several patterns emerge in Figure 1. First, the diagonal elements of the matrix are the largest, indicating that conditional on consuming a given drug, most consumers purchase the same drug in other periods. However, the degree of attachment differs between drugs. For example, the share of opioids is very large conditional on reviewing an opioid, even though opioids have a small market share. Cocaine consumers also have a high probability of consuming cocaine in other periods. This is consistent with the dependence index (DI) reported in Table 1, which is the largest for opioids and cocaine (heroin has a DI equal to 3.0 and cocaine has a DI of 2.33). Moreover, the ranking of drugs by dependence index coincides with the ranking by diagonal elements for the most popular drugs. While a DI is not available for the two bath salts, $\alpha-$PVP and mephedrone, our estimates indicate that

[20] For $j \neq k$, the elements P_{jk} of this matrix are given by the share of k in all other reviews by the same user weighted by the number of reviews this user left for j:

$$P_{jk} = \sum_{i:R_i>1} \frac{R_{ij}}{\sum_{i':R_{i'}>1} R_{i'j}} \frac{R_{ik}}{R_i - 1} = \frac{1}{\mathbb{E}\big[R_{ij} \mid R_i > 1\big]} \mathbb{E}\Big[\frac{R_{ij}R_{ik}}{R_i - 1} \mid R_i > 1\Big]. \tag{1}$$

For $j = k$, the elements are $P_{jj} = \big(\sum_{i:R_i>1} R_{ij}(R_{ij}-1)/(R_i-1)\big)/\big(\sum_{i':R_{i'}>1} R_{i'j}\big)$. Here, R_{ij} is the total number of observed reviews for product j by user i and $R_i = \sum_j R_{ij}$ is the total number reviews by user i.

Figure 1. Conditional shares of different drug types



Note: Each element P_{jk} of this matrix represents the probability that for a random review for drug j, a random different review by the same user is for drug k. Opioids include heroin and methadone. Psychedelics include mushrooms and LSD.

consumers of these drugs exhibit a high degree of attachment, suggesting that dependence on bath salts is comparable to that of cocaine.

Second, the matrix provides evidence of substitution between drug types. For four popular drug types (amphetamine, hashish, marijuana, and MDMA), the diagonal elements are around 50%, indicating that consumers are almost as likely to buy another drug in other periods as they are to buy the same drug type.

Third, substitution is more likely to occur within certain product groups. The cluster of amphetamine, MDMA, and mephedrone is particularly notable: for consumers who purchased one of these three drugs, the two most likely alternatives are the other two. For example, MDMA users' next most likely choices are mephedrone (17.7%) and amphetamine (10.5%), and similar patterns hold for amphetamine buyers (mephedrone 11.9%, MDMA 9.9%) and mephedrone buyers (MDMA 7.8%, amphetamine 5.5%). As discussed in Section 2.2, all three are stimulants, share the same mode of administration, and fall into the category of club drugs, and medical studies have found strong similarities in their induced

effects (Poyatos et al., 2022). However, substitution patterns we observe could not be predicted *ex ante* solely on the basis of drug characteristics. For example, $\alpha-$PVP is another popular stimulant with similar characteristics, yet consumers of MDMA, mephedrone, and amphetamine rarely switch to this drug.

Another cluster in Figure 1 is hashish and marijuana. These two drugs are produced from cannabis plants, belong to the same psychoactive class, and have the same administration. Marijuana is the second choice for hashish consumers in our data.[21] At the same time, these two drugs have substantial flow to and from the three stimulants mentioned above.

The heterogeneity in preferences evident in Figure 1 highlights the need to incorporate consumer heterogeneity into our demand model. A model without consumer heterogeneity – for instance, the standard multinomial logit model – would fail to generate realistic predictions about substitution. In the next section, we develop a demand model that can reproduce the observed patterns.

4. Demand Model

To account for the taste heterogeneity documented in Section 3.5, we use the BLP approach, which was introduced in Berry (1994) and Berry et al. (1995). Because we are particularly interested in substitution between different drug types, we define products as individual drug types, such as cocaine or mephedrone. The indirect utility that a consumer i can obtain from buying a drug of type j in city c on date t is given by

$$U_{ijct} = -\alpha p_{jct} + x_{jct}\beta + \sum_{g \in G} \lambda_i^g I(j \in g) + \xi_{jct} + \varepsilon_{ijct}, \tag{2}$$

where p_{jct} is the average price per dose of drug j in city c on date t, x_{jct} is a vector of observed product characteristics, ξ_{jct} are unobserved product characteristics, and ε_{ijct} are taste shocks independent from other random variables.

Product characteristics x_{jct} include dummies for each drug type, number of doses, hiding method, substance form, and proxies for quality and marketing activities by shops.[22] We also include date-level fixed effects to account for the growth of the platform and potential differences in drug consumption across seasons and days of the week. We include time trends

[21] The same is not true for marijuana, for which the second choice is mephedrone. This can be explained by the increased enforcement of hashish in the study period which resulted in a drop in its market share (see Section 4.3).

[22] Due to aggregation, categorical characteristics (e.g., hiding type) are converted to the proportion of listings that have this characteristic. Continuous characteristics are converted to the average across all listings within the given product.

for mephedrone and amphetamine because these drugs exhibited growth in popularity over our sample period. Preferences for price p_{jct} and product characteristics x_{jct} are given by α and β and are the same for all consumers.

We include random coefficients for individual drug types $g \in G$. These random coefficients allow us to incorporate idiosyncratic attachment to particular drugs and correlation in preferences for different drug types. Random coefficients vary across consumers and are given by

$$\begin{pmatrix} \lambda_i^1 \\ \vdots \\ \lambda_i^K \end{pmatrix} = \Sigma \begin{pmatrix} \nu_i^1 \\ \vdots \\ \nu_i^K \end{pmatrix}, \tag{3}$$

where we assume that ν_i are drawn from the multivariate standard normal distribution, and, thus, the covariance between random coefficients is equal to $\Sigma\Sigma'$. Because including multiple random coefficients is computationally expensive, we limit their number to $K = 6$. Therefore, we include them only for the drug types with the largest market shares, defining G $=\{\alpha$-PVP, amphetamine, cannabis, cocaine, MDMA, mephedrone$\}$. Together, these drugs cover 88% of the total drug consumption. Cannabis aggregates hashish and marijuana into a common dummy variable given their similarity; otherwise, we do not impose any *ex ante* restrictions.

The interpretation of type-specific random coefficients is the following. A large value of $\mathbb{V}ar(\lambda^j)$ implies that a substantial fraction of consumers will have a large draw of λ^j and are likely to purchase drug j in many periods, being unwilling to substitute other drug types for it. A high value of $cov(\lambda^j, \lambda^k)$, where $k \neq j$, implies that consumers who have a large draw of λ^j are likely to also have a large draw of λ^k. In this case, a large proportion of consumers of drug j would be willing to substitute it for drug k. These type-specific random coefficients allow our specification to account for the heterogeneity in consumption patterns that we observe in Section 3.5.[23]

The unobserved product characteristics ξ_{jct} are common across all consumers for each market-drug combination and can be correlated with p_{jct}. This accounts for potential endogeneity, for example, driven by unobserved quality or because drug sellers strategically respond to aggregate-level demand shocks by adjusting prices. Consumers can also choose the outside option of not purchasing any drug, for which the indirect utility is normalized to be mean-zero: $U_{i0ct} = \varepsilon_{i0ct}$. On each date, the consumer chooses the option that provides the highest indirect utility. For policy implications, we interpret the outside option as for-

[23]Heterogeneity in drug consumption is also widely discussed in addiction studies, see Reuter (2010). In particular, one can expect that males consume more drugs (Pacula, 1997) or that younger people may prefer party drugs.

going drug consumption rather than shifting to offline markets. We believe this assumption is reasonable given that Hydra covered the vast majority of the overall drug market in the cities in our sample.[24]

The discrete choice framework restricts cross-price elasticities to be non-negative, precluding complementarity by construction. As discussed in Section 1, there has been limited research into cross price elasticities, and prior research has focused on only a small number of drug pairs. However, the research that does exist has tended to point to illegal drugs being either substitutes or independent goods. Studies have found that legal cannabis substitutes for prescription opioids (Powell et al., 2018), and that ecstasy and cannabis substitute for cocaine among recreational polysubstance users (Goudie et al., 2007). Meanwhile, other drug pairs, such as heroin and marijuana, have been estimated to be effectively independent, with cross-price elasticities close to zero (Olmstead et al., 2015). The main exception is heroin and cocaine, which several studies find to be complements, possibly reflecting the use of "speedballs" (see, e.g., Olmstead et al., 2015). However, these studies primarily focus on dependent users (see, e.g., Olmstead et al., 2015; Jofre-Bonet and Petry, 2008), a population unlikely to be representative of the recreational users who comprise the bulk of our sample. The discrete choice restriction is therefore unlikely to be a binding constraint for the drug pairs and population of interest in this paper.

Discussion. An alternative approach would be to model drugs in characteristic space. However, it is inherently challenging to identify a set of characteristics that would adequately capture the relevant differences between drugs for several reasons. To begin with, measuring attributes such as "pleasure," likely a key driver of drug consumption, is particularly difficult due to the lack of consensus on how to quantify them. Moreover, in cases where a well-defined measure does exist, such as the overdose ratio, they are not available for all types of drugs. Finally, the characteristics provided in the medical and chemistry literature are typically categorical, grouping substances into broader classes. The example of $\alpha-$PVP highlights that a simple categorization by psychoactive class fails to capture the relevant substitution patterns, as discussed in Section 3.5. At the same time, introducing dummies for many different categorizations would rapidly inflate the dimensionality of the characteristic space.

4.1. Estimation

Identification of the non-linear parameters (in our case, the covariances of random coefficients) in the mixed logit model is a well-known challenge because it requires a large number

[24] Alternatively, our policy simulations are valid if Hydra is representative of the overall drug market, so that substitution patterns in offline markets mirror those observed on the platform.

of IVs, and aggregate data often does not have sufficient variation. To solve this issue, we use micro-moment conditions that describe the reviewing behavior of consumers. In our demand model, two products, j and k, are close substitutes if their random coefficients are correlated. In this case, people who review drug j would also often review drug k. Thus, the panel structure of our review data can help identify the covariances between random coefficients.

Micro-moments using reviews

We capture correlation in tastes for particular drug types by matching co-movements of purchases for drugs j and k across consumers in the data for different pairs (j, k). We infer purchases from reviews. Specifically, our micro moments are averages of $R_{ij}R_{ik}$, where R_{ij} is the total number of observed reviews for product j by user i:

$$R_{ij} = \sum_t R_{ijt}, \;\; R_{ijt} = I(\text{review by } i \text{ for drug type } j \text{ on date } t). \tag{4}$$

Intuitively, if consumers who like drug j usually like drug k, then a consumer who has reviewed drug j is likely to have also reviewed drug k and $R_{ij}R_{ik}$ should be larger on average, all else being equal.

Our sample is subject to selection because it only has users with at least one review observed. Thus, the appropriate model counterpart of the product of reviews in the data is

$$\mathbb{E}\Big[R_{ij}R_{ik} \mid R_i > 0\Big] = \frac{\mathbb{E}R_{ij}R_{ik}}{\mathbb{P}\big(R_i > 0\big)}, \tag{5}$$

where $R_i = \sum_j R_{ij}$ is the total number of observed reviews by consumer i. The moments defined by equation 5 can be approximated using averages over N simulated consumers:[25]

$$\mathbb{E}\Big[R_{ij}R_{ik} \mid R_i > 0\Big] \approx \frac{\frac{1}{N}\sum_{i=1}^{N}\mathbb{E}\big[R_{ij}R_{ik} \mid i\big]}{\frac{1}{N}\sum_{i=1}^{N}\mathbb{P}\big(R_i > 0 \mid i\big)}. \tag{6}$$

To generate these values using our demand model, we must account for two complications. First, not every purchase was reviewed. Second, not every review was scraped by the data provider. We do this using the following framework. There are T dates over which consumers can make purchases and leave reviews. We assume that the decision to review a purchase is random, with the probability allowed to depend on drug type and equal to π_j^{review}. We

[25]For simplicity, we omit the city index c here. In practice, we sample agents from each market proportionally to the market size N_c and assume that each agent faces prices from the same city across all dates.

assume that the scraping process is also random, with the conditional probability of a given review being scraped equal to π_t^{scrape}. This probability is allowed to depend on time to account for potential imbalances in scraping over time.[26] The product of these numbers $\pi_{jt} = \pi_j^{review}\pi_t^{scrape}$ is the probability that a purchase yields a scraped review. Therefore, the probability of observing a review by user i for drug j on date t equals $\mathbb{P}(R_{ijt} = 1) = \pi_{jt}s_{ijt}$, where s_{ijt} is the predicted probability that consumer i purchases j on date t.

We can use this formula to find the moment values. First, to compute the numerator of the equation 6, we find the expected product of total reviews for consumer i:

$$\begin{aligned}\mathbb{E}\Big[R_{ij}R_{ik} \mid i\Big] &= \mathbb{E}\Big[\big(\sum_{t=1}^{T} R_{ijt}\big)\big(\sum_{t=1}^{T} R_{ikt}\big) \mid i\Big] = \sum_{t_1,t_2}\mathbb{E}\Big[R_{ijt_1}R_{ikt_2} \mid i\Big] \\ &= \sum_{t_1\neq t_2} \pi_{jt_1}\pi_{kt_2}s_{ijt_1}s_{ikt_2} + I(j=k)\sum_t \pi_{jt}s_{ijt}.\end{aligned} \tag{7}$$

Second, to compute the denominator of equation 6, we find the probability of selection into the observed sample, which equals to

$$\mathbb{P}\big(R_i > 0 \mid i\big) = 1 - \prod_{t=1}^{T}\Big(1 - \sum_{j=1}^{J}\pi_{jt}s_{ijt}\Big). \tag{8}$$

Finally, the probability of conversion into a review can be estimated as the ratio of reviews to total sales:

$$\hat{\pi}_{jt} = \frac{R_{jt}}{N \times s_{jt}}, \tag{9}$$

where R_{jt} is the total number of reviews observed for day t and type j, N is the market size, and s_{jt} is the market share of drug j on date t respectively.[27]

In practice, we observe listings for only 31 days, whereas reviews are available over a period of more than a year. To fully exploit the reviews data when constructing the moment conditions, we extrapolate the listings data to match the empirical moment values. Appendix C.2 provides details on how we apply Equations 7 and 8 in this setting.

One of the contributions of this paper is a novel method to estimate non-linear parameters in BLP-type models. Our approach exploits correlations in choices over time, with choices inferred from irregularly observed reviews. It can be particularly useful in the studies of online marketplaces, where review data can often be collected at relatively low cost. Our

[26] Scraping coverage fluctuated primarily because the data provider used a varying number of active scraping bots. See Section 2.4 for a discussion of our review data.

[27] By choosing π_{jt} this way, we guarantee that simpler moment conditions like $\mathbb{E}_i R_{ijt} = R_{jt}/N$ are satisfied, and our micro moments target not levels but *comovements* of observed reviews.

method is related to other studies that use micro-level data to identify non-linear parameters in BLP-type models (Chintagunta and Dubé, 2005; Bayer et al., 2007). It is most closely related to estimation based on second-choice data (Berry et al., 2004; Conlon et al., 2021; Conlon and Gortmaker, 2025), and provides a practical alternative in settings where such data is unavailable.

Procedure

We estimate our model in two stages. In the first stage, we estimate the non-linear parameters (Σ) using review data and the aggregate price-quantity data from listings. The non-linear parameters are identified by matching the observed micro-level moments with predicted moments. In the second stage, we estimate the linear parameters of the model (α, β) using IV restrictions and the aggregate price-quantity data.

We express indirect utility as $U_{ijct} = \delta_{jct} + \mu_{ijct} + \varepsilon_{ijct}$, where $\delta_{jt} = -\alpha p_{jct} + x_{jct}\beta + \xi_{jct}$ is the mean utility, which is common for all consumers in a particular market, and $\mu_{ijt} = \sum_{g \in G} \lambda_i^g I(j \in g)$, which is the consumer-specific component. We make the conventional assumption that ε_{ijct} are from the standard Gumbel distribution. For a fixed pair of δ_{jct} and μ_{ijct}, the probability that a consumer i purchases product j equals

$$s_{ijct} = \frac{\exp(\delta_{jct} + \mu_{ijct})}{1 + \sum_{k=1}^{J} \exp(\delta_{kct} + \mu_{ikct})}. \tag{10}$$

Each value of Σ defines a distribution $F(\mu|\Sigma)$ of idiosyncratic utilities. The predicted share of consumers in city c who purchase product j on date t equals

$$s_{jct}(\Sigma) = \int \frac{\exp(\delta_{jct} + \mu_{ijct})}{1 + \sum_{k=1}^{J} \exp(\delta_{kct} + \mu_{ikct})} dF(\mu|\Sigma) \tag{11}$$

and can be approximated by numerical integration. The system defined by Equation 11 can be inverted (Berry et al., 1995): the values of $\delta_{jct}(\Sigma)$ can be found such that predicted market shares match the observed market shares. We can then find the choice probabilities $s_{ijct}(\Sigma)$ for each simulated agent and calculate predicted moments given by Equation 5. Using gradient descent, we find non-linear parameters Σ such that predicted moments match the moments observed in the data. Our demand estimation procedure, outlined in Algorithm 1, is similar to the procedure described in Conlon and Gortmaker (2025) for survey-type micro moments. Our code is based on the PyBLP package (Conlon and Gortmaker, 2020).[28]

In Appendix Section C.1, we show that, compared to the standard BLP estimation

[28] We are extremely grateful to Jeff Gortmaker, who provided helpful suggestions about using PyBLP for our study.

Algorithm 1 Estimation of nested logit with micro moments.

Sample N agents with nodes ν_i. Iterate until convergence in Σ:

1. Calculate $\mu_{ijct}(\Sigma)$.
2. Find $\delta_{jct}(\Sigma)$ such that predicted market shares equal observed market shares.
3. Using $\delta_{jct}(\Sigma)$ and $\mu_{ijct}(\Sigma)$, compute predicted values $\mathbb{E}\big[R_{ij}R_{ik} \mid i\big]$ and $\mathbb{P}\big(R_i > 0 \mid i\big)$ for each agent i.
4. Estimate micro moments $g^M(\theta) = \Big(\big(\frac{1}{N}\sum_i \mathbb{E}\big[R_{ij}R_{ik} \mid i\big]\big)/\big(\frac{1}{N}\sum_i \mathbb{P}\big(R_i > 0 \mid i\big)\big) - \overline{R_{ij}R_{jk}}\Big)_{(j,k)\in P}$ for a set of product pairs P.
5. Update Σ by minimizing error function $g(\Sigma)'g(\Sigma)$.

Recover linear parameters (α, β) from regression of $\delta_{jct}(\Sigma)$ on x_{jct}, p_{jct} using instrumental variables Z.

procedure, our micro moments substantially improve estimation precision in test simulations. We use the optimal instruments for the second stage regression. We simulate $N = 100,000$ agents; the number of agents from each city is proportional to the corresponding market size. In Appendix Section C.3, we provide analytical expressions for gradients that enable a substantial reduction in estimation time. In the set of product pairs P for constructing our micro moments we include all pairs of drugs for which we have random coefficients. Thus, we have $K(K+1)/2$ moments, and the parameters of the model are exactly identified.[29]

We include several different variables in the set of instruments Z. First, we use distance to the nearest port, motivated by the fact that some drugs are available only from abroad and the cost of within-country transportation increases with distance from the point of entry (see the discussion in Section 2.3).[30] Because Saint Petersburg is a major port of entry for many drugs, we also include distance to Saint Petersburg as a separate instrument. Second, we use prices in other geographic markets in the same period (Hausman et al., 1994; Nevo, 2001). They capture price variation due to changes in costs common across locations. Third, we include measures of local market structure that affect pricing through competition, such as the number of drug types available and the number of shops operating in each market. We discuss these instruments in more detail and report results for alternative IV specifications in Appendix Section F.

Because we allow for an outside option, we need to define the total market size to calculate market shares. We set market size proportional to the population aged 18 to 45, motivated by Russian mortality data indicating that the majority of drug-related deaths occur within this age group. To map this to market size, we assume each person aged 18 to 45 consumes drugs

[29] Because we use a common dummy for hashish and marijuana, we structure our moments for cannabis in the same way, considering products of reviews for cannabis and reviews for other drugs in these moments.

[30] Hansen et al. (2023) find that legal seaborne trade flows increase availability and deaths from fentanyl.

at most once per month, with one consumption corresponding to one-third of a standard purchase.[31] Further details on the market size definition are provided in Appendix Section D. Appendix Section F describes robustness to different definitions of the market size.

4.2. Estimates

Table 5 presents point estimates and standard errors for the linear parameters. Columns (1) and (2) report main results for the random coefficient model. For comparison, columns (3) and (4) show estimates from the standard logit model. Most coefficients are precisely estimated and have the expected sign. As expected, we find a negative relationship between demand and price per dose, and we discuss the implied price elasticities below. Given the same price per dose, consumers prefer smaller dead-drops. This is consistent with the risks associated with purchasing larger quantities of drugs, as discussed in Section 2.4. It may also reflect buyers' liquidity constraints or the costs of holding larger inventories. In addition, we find that consumers value the hidden and magnet delivery methods more than dead-drops buried in the soil, which is the omitted category. This preference is likely driven by the greater risk and inconvenience associated with retrieving dead-drops from the soil. Consumers prefer drugs in crystal form relative to powder, which is often less pure and diluted with additives. The quality labels "very high quality" and "high quality" displayed on the platform indicated substance purity levels above 98% and 95%, respectively.[32] We find that consumers respond positively to the "very high quality" label but negatively to "high quality," suggesting that a quality label inferior to the best one may be interpreted as signaling low quality relative to no label at all. Other quality indicators, such as review sentiment and product and shop ratings, increase demand, with product ratings being around five times more important to consumers than shop ratings. The label of a trusted seller, which any shop could purchase after meeting a set of criteria, has a substantial positive effect on demand. Consumers also show a slight preference for younger shops.

We present estimates for non-linear parameters and the associated standard errors in Appendix Table E.1. To provide interpretation for these parameters, Figure 2 shows the estimated covariance matrix of the random coefficients. The covariances are precisely estimated, and we find that each random coefficient has substantial variance. This implies that many consumers experience strong taste shocks for specific drugs, consistent with the finding in Section 3.5 that consumers often review the same drug repeatedly across periods. The

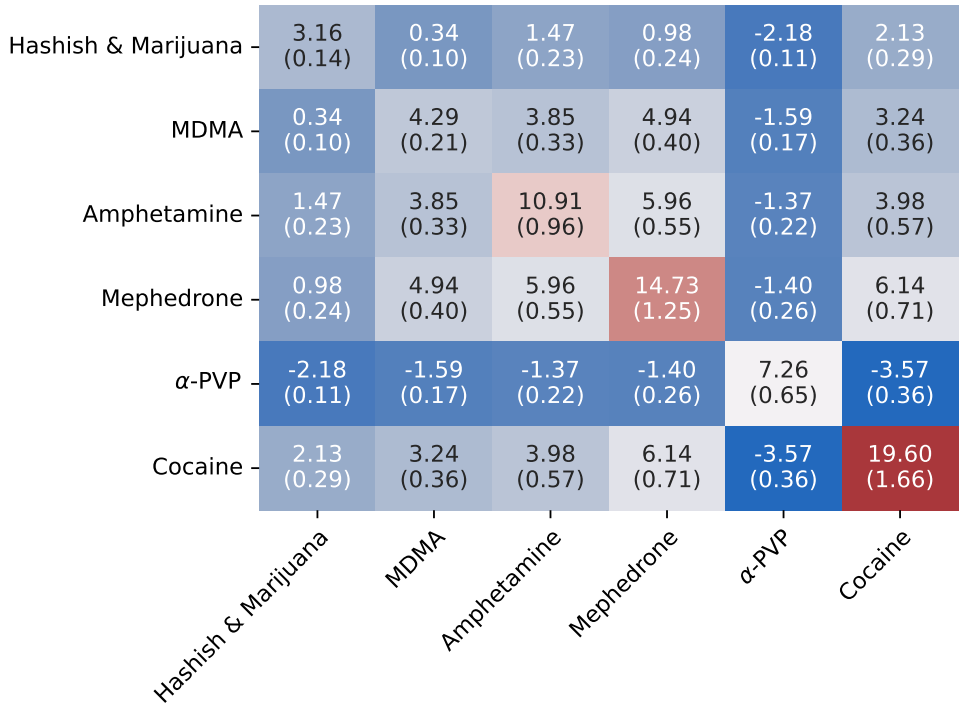
[31] This is similar to the definition used by Hollenbeck and Uetake (2021), who assume that each resident of a market can purchase 4 grams of legal marijuana per month.

[32] Although shops self-reported these labels, Hydra reportedly conducted random tests to verify compliance with these standards (Goonetilleke et al., 2023).

largest variance is observed for cocaine, which also has the highest dependence index among these drugs (see Table 1). Relatively high variance is also estimated for mephedrone and amphetamine, followed by α-PVP. In contrast, MDMA and cannabis exhibit lower variance, consistent with their lower dependence indices and the weaker attachment observed in the review data.

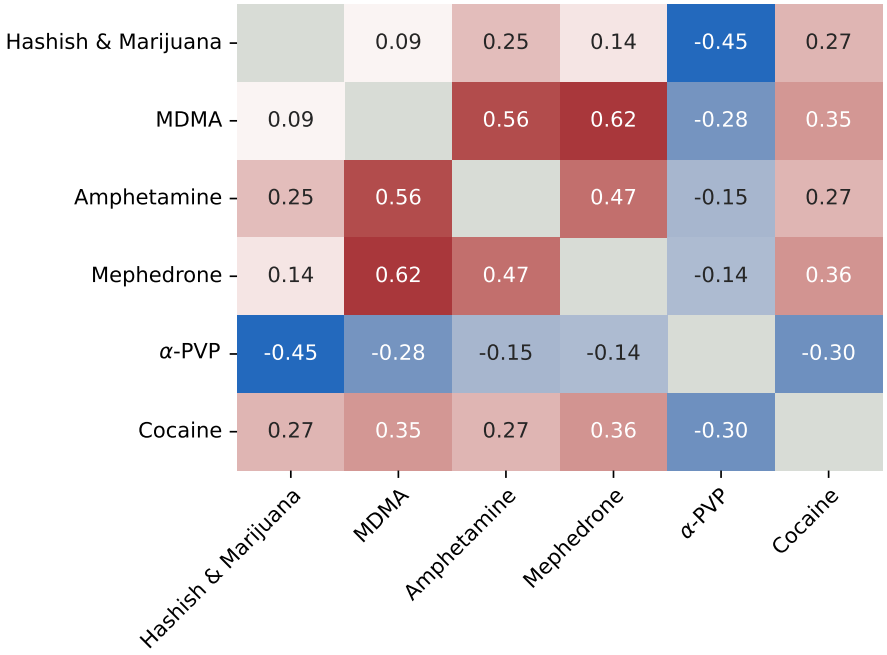
Figure 3 reports the estimated correlations between random coefficients. We find the highest correlation in taste shocks among the synthetic stimulants — amphetamine, MDMA, and mephedrone. This indicates that these three drugs are close substitutes, which could be driven by the similarity of their effect. In addition, they are all medium-risk stimulants commonly used as party drugs. At the same time, we observe a negative correlation between the random coefficient for $\alpha-$PVP and the random coefficients for all other drugs. This indicates that α-PVP lacks close substitutes despite its similarity to other medium-risk stimulants. More broadly, this finding suggests that observable drug characteristics alone do not fully explain substitution patterns across drugs, underscoring the need to model random tastes at the level of specific drug types.

Figure 2. Estimated covariances of random coefficients



Note: This figure presents the elements of $\hat{\Sigma}\hat{\Sigma}'$, the covariance matrix of the random coefficients. Standard errors in parentheses.

Figure 3. Estimated correlations of random coefficients

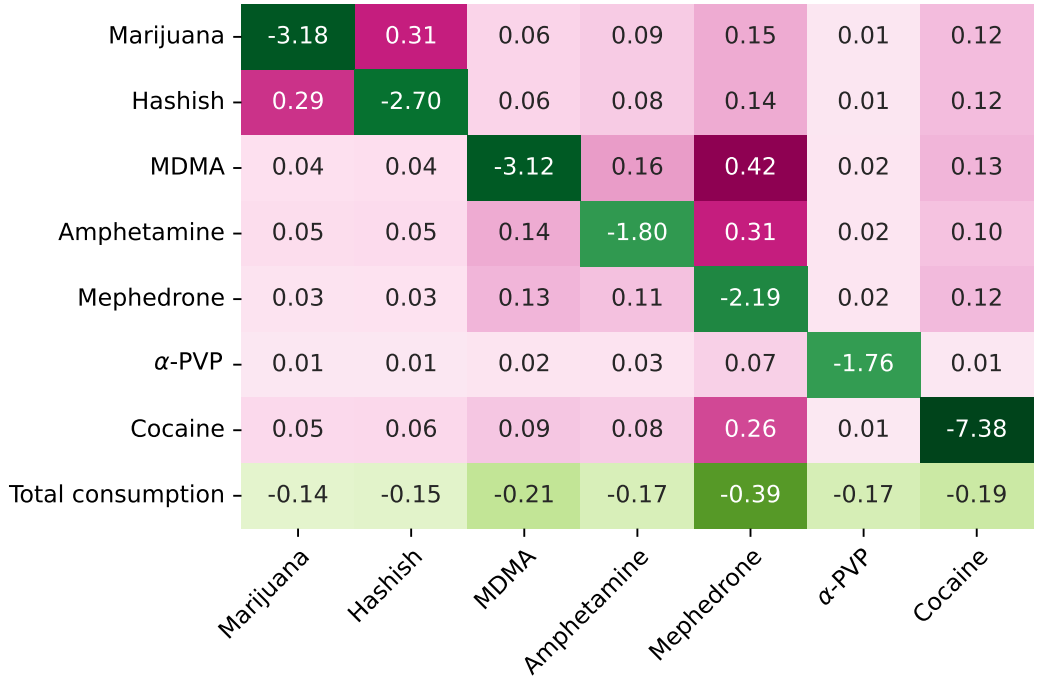


Note: This figure presents the estimated correlations between random coefficients.

Figure 4 presents median price elasticities across markets. The median own-price elasticity among all drug types is -3. Several factors determine the scale of elasticity. First, products with high attachment, captured by a high variance of the corresponding random coefficient, should have less elastic demand. Second, products with many close substitutes should have more elastic demand. Finally, more expensive products mechanically have higher elasticities as a percent change in price translates into a larger absolute price change. We find the lowest own-price elasticity for α-PVP. This likely reflects a combination of strong attachment, the absence of close substitutes, and the low price of this drug. Amphetamine and mephedrone also exhibit relatively low elasticities, consistent with the high attachment observed in the review data. Cocaine has the highest own-price elasticity, which is likely driven by its high price. Appendix Figure E.1 shows the distributions of own-price elasticities across markets and reveals substantial heterogeneity in price sensitivity.

Estimates of cross-price elasticities indicate heterogeneous substitution patterns. For example, an increase in the price of hashish has the largest effect on the demand for marijuana, with the effect on marijuana being five times larger than for the next most affected drug. Another strong substitution pattern is present for the stimulants amphetamine, MDMA, and mephedrone. A price increase for any of these drugs increases demand for the other

Figure 4. Median cross-price elasticities of demand



Note: This figure presents median price elasticities across all markets (c, t). Each element $\mathcal{E}_{j,k}$ of the matrix shows the elasticity of demand for product j with respect to the price of product k, $\varepsilon_{jkct} = \frac{p_{jct}}{s_{jct}} \frac{\partial s_{jct}}{\partial p_{kct}}$. The last row reports the elasticity of total drug demand with the respect to the price of product k.

two more than for any other drug. For example, a one percent increase in the price of mephedrone increases demand for MDMA and amphetamine by 0.4 and 0.3 percent, respectively. For comparison, Appendix Table E.2 reports elasticities from the standard logit model. As expected, the logit specification predicts unrealistic substitution patterns that ignore similarities between drugs. In addition, own-price elasticities are larger under logit, particularly for drug types with high variance in random coefficients. For example, the own-price elasticity for cocaine is 1.8 times larger in the logit model than in the random coefficients model. This difference reflects that the random coefficients model accounts for heterogeneity in attachment and allows some consumers to have low price sensitivity for cocaine.

Our estimated own-price elasticities are higher than most values reported in prior studies. The meta-analysis in Gallet (2014) finds a median price elasticity of drug demand of about -0.3, while the systematic review in Payne et al. (2020) reports an average elasticity of -0.9. One likely source of this discrepancy is differences in data quality and methodology. Differences in data sources effectively lead to studying different populations of drug users.

Many earlier studies rely on lower-quality price data and measure drug use through proxies such as emergency department visits or arrestee drug tests. These outcomes are likely to disproportionately capture heavy or addicted users, who are least responsive to price.[33] By contrast, our data reflect actual transactions — including prices and quantities — from a broad cross-section of marketplace consumers. Regarding the empirical methods, one example of differences is that many prior studies do not instrument for price, which is expected to bias the estimated price sensitivity toward zero. Consistent with this concern, when we do not instrument for price, the estimated median price elasticity is almost three times lower and equals -1.05. Our estimates closely match those from studies of legal addictive substances that similarly use high-quality, transaction-level data and structural demand models. Hollenbeck and Uetake (2021) estimate own-price elasticity of -2.8 to -3.7 for legal marijuana. For hard liquor, Miravete et al. (2018) and Conlon and Rao (2023) report elasticities of about -3.9 and -4.8, respectively. A second source of the discrepancy may be differences in setting. Drug users in Russia may be more price sensitive than those in the Western countries that have been studied in prior work, as average income is lower. Additionally, the online environment may further increase elasticity, as search costs are low, purchases are less impulsive due to the delay between ordering and retrieving dead-drops, and consumers do not face "take-it-or-leave-it" setting of street drug trade. We further validate our estimates for price sensitivity using the exogenous supply shock discussed in Section 4.3.

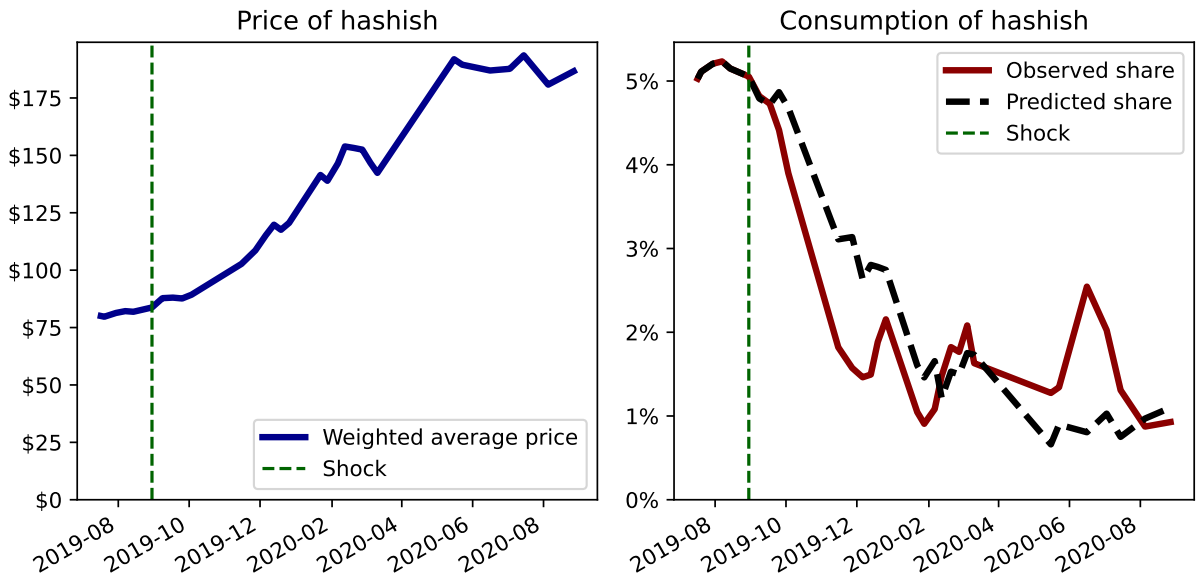
4.3. Validation: hashish shock

In 2019, increased enforcement targeting the production and trafficking of Moroccan hashish substantially reduced its supply in European markets (EMCDDA and Europol, 2020), and a major hashish seizure in Russia further disrupted supply domestically (TASS, 2019). These disruptions were followed by a significant increase in the price of hashish in the Russian drug market (FilterMag, 2020). Because this price increase was driven by exogenous supply shocks rather than unobserved shifts in demand, we expect that the equilibrium change in consumption can be explained by the price change alone.

We use this to validate our model estimates. Figure 5 shows predicted demand for hashish, given the observed prices, holding unobserved product characteristics ξ_{jct} fixed at their average value from the period preceding the shock. Our model closely predicts the decline in hashish consumption in the year following the price increase. This provides evidence that our estimated price sensitivity is consistent with consumer response to the

[33] Consistent with this, Payne et al. (2020) note that studies using experimental hypothetical drug-purchasing scenarios, which recruit a broader range of drug users, tend to find much larger elasticities than observational studies.

Figure 5. Actual and predicted consumption of hashish



Note: This figure presents the validation exercise. The left panel shows hashish prices during the enforcement shock, averaged across cities with weights proportional to market size and converted to USD at 74 RUB per USD. The right panel plots observed and model-predicted hashish market shares. Predicted shares are generated from the estimated model in Equation 2 using observed price changes, with ξ_{jct} held fixed at pre-shock means.

hashish shock.

5. Effects of Drug Policies

We use our model of the demand for illegal drugs to assess the effects of counterfactual drug policies while accounting for substitution between drug types.

5.1. Cannabis legalization

Cannabis legalization, one of the most discussed drug policies, has recently been adopted by various jurisdictions in the U.S. and around the world.[34] While legalization is motivated by several factors, including reducing incarceration and policing costs, one widely discussed

[34]The extent of legalization can vary; some jurisdictions have legalized only the medical use of marijuana, while others have also legalized recreational use. In the U.S., the first instance of medical use legalization was in California in 1996, while Colorado and Washington were the first states to legalize recreational marijuana in 2012. As of October 2023, recreational cannabis has been legalized in 23 U.S. states and the federal District of Columbia.

aspect is its potential to lower the use of riskier drugs. Because cannabis is considered low-risk on both dependence and harm measures (see Table 1), substitution away from other drugs would be risk-reducing.

Previous studies of the effect of marijuana legalization on the consumption of other drugs have primarily focused on the effect on opioid consumption, yielding mixed findings.[35] This aligns with our analysis of drug reviews in Section 3.5, which suggests that cannabis is unlikely to function as a substitute for opioids, and therefore legalization has a limited potential to decrease their use. In contrast, our findings indicate greater substitutability between cannabis and other drugs, particularly amphetamine, cocaine, and MDMA. We apply our model to measure the legalization-induced changes in both cannabis consumption and the consumption of other drugs and to quantify this trade-off.

We assume that legalization leads to the same substitution patterns as a reduction in the price of cannabis. This has two complementary interpretations. First, legalization was found to decrease cannabis prices in the U.S. (Anderson et al., 2013) and Canada (Hall et al., 2023). Legal marijuana can be produced at very low cost, and sellers avoid costs and risks associated with illegal production, transportation, and distribution (Caulkins, 2010). Second, legalization reduces the non-monetary costs of consumption such as the legal risk of purchase and the stigma associated with illegality (Jacobi and Sovinsky, 2016). If the reduction in these costs raises the indirect utility of cannabis consumption uniformly across consumers, it is equivalent in its effects to a price reduction.

In practice, policymakers often choose policies that limit the extent of the price reduction after legalization.[36] Governments could limit price decreases by setting higher taxes and decreasing the number of licenses granted. For this reason, we consider a range of counterfactual price reductions for marijuana and hashish. Table 6 shows predicted change in consumption of individual drug types and in total drug use.[37] Figure 6 presents predicted consumption change for cannabis and other drugs grouped by estimated risk using the harm index developed by Nutt et al. (2007).

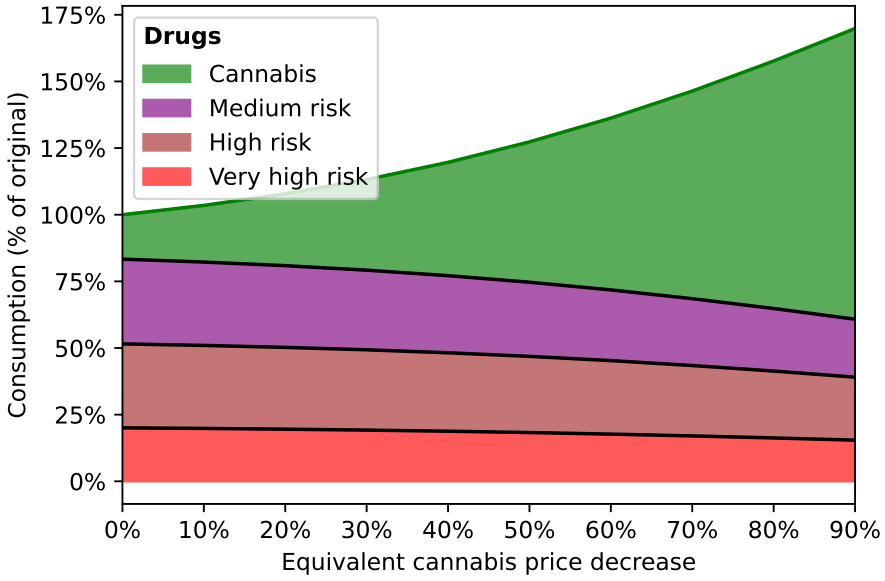
We find that legalization can enable the government to substantially reduce the consumption of more dangerous drugs. A 25% decline in the price of cannabis leads to a 4% reduction

[35] State-level event studies provide mixed evidence of the impact of legalization on opioid use. Bachhuber et al. (2014), Powell et al. (2018), and Chan et al. (2020) have reported that legalization has led to a reduction in opioid overdoses. However, Drake et al. (2021) found only a short-term effect, while Shover et al. (2019) argue that the association between legalization and opioid overdoses became positive over time.

[36] Hollenbeck and Uetake (2021) show that in Washington state, the low number of retail licenses resulted in high retail margins.

[37] In this and other counterfactual analyses, we simulate the change in consumption for all drugs, but we only report the effects on drugs that have random coefficients in the model because those drugs are the only ones for which we account for flexible substitution patterns. Collectively, they have 88% market share.

Figure 6. Cannabis legalization and predicted drug use



Note: This figure plots the predicted percent change in consumption by risk group when the price of cannabis (hashish and marijuana) decreases by x%. Drug groupings follow the harm index of Nutt et al. (2007); where a drug does not appear in that index, we assign risk categories based on state dependence in review data (Table 1). Medium-risk drugs include amphetamine, GHB, MDMA, LSD and other psychedelics, and sodium oxybate; high-risk drugs include mephedrone and other stimulants not otherwise listed; very high-risk drugs include $\alpha-$PVP, cocaine, and opioids. We include $\alpha-$PVP as very high-risk following Patocka et al. (2020) who document substantial overdose risk from this drug.

in the use of other drugs, while a 50% price decrease results in a 10% reduction (see columns (2) and (3) of Table 6). However, this benefit is accompanied by a substantial increase in cannabis consumption. As a result, total drug consumption increases: a 25% decrease in the price of cannabis raises total consumption by 10%, while a 50% decrease raises it by 27%.

Panel B of Table 6 shows that the relative change in drug use is fairly stable across a range of experiments. In particular, achieving a one-dose reduction in the consumption of other drugs would require 4.2 additional doses of cannabis consumption. This trade-off highlights a central policy question: whether one dose of other drugs imposes more social harm than 4.2 doses of cannabis.

Notably, substitution is not limited to other lower risk drugs: Figure 6 shows a decline in the use of drugs across all risk categories. Panel A of Table 6 indicates that legalization has the highest impact on demand for amphetamine, cocaine and MDMA. In particular, a 25% reduction in cannabis price results in 4-5% decline in consumption of each of these three drugs. While amphetamine and MDMA are medium risk drugs, cocaine is categorized as a very high risk drug, and both amphetamine and cocaine are more risky than cannabis across

all harm risk measures reported in Table 1.

This analysis has several limitations. First, as discussed by Jacobi and Sovinsky (2016), two key components of legalization are the removal of the stigma of illegality and the increase in accessibility. Treating legalization as equivalent to a reduction in the cannabis price therefore requires taste homogeneity across these dimensions. If individuals who did not consume drugs before legalization have a higher distaste for illegality, the utility from cannabis consumption will increase disproportionately more for them than for current drug consumers. Similarly, since non-users face substantially higher search costs than existing illegal market participants, legalization-induced reductions in search costs would affect them disproportionately as well.

Second, our model is static and therefore primarily captures short-run changes in consumption. In the presence of addiction, the long-run effects would likely be larger, with both the increase in cannabis use and the decline in the consumption of other drugs becoming more pronounced. However, if there is a stepping-stone effect, where greater cannabis use increases the likelihood of transitioning to more dangerous drugs, consumption of other drugs could rise over time. Taken together, these opposing mechanisms make the long-run effect on the use of other drugs ambiguous. Finally, this analysis is limited to the effect of legalization on drug consumption. The welfare analysis of legalization would need to account for other effects. For example, Gavrilova et al. (2019) show a reduction in violent crime in states bordering Mexico following the introduction of medical marijuana laws, while Adda et al. (2014) examines the impact of the reallocation of police resources following the decriminalization of cannabis possession.

5.2. Introduction of new drugs

Two popular drugs on Hydra are mephedrone and α-PVP, with market shares of 28% and 11%, respectively. Both belong to the class of synthetic cathinones, commonly known as "bath salts" (Soares et al., 2021). These substances emerged in the late 2000s and gained popularity not only in Russia but also in the U.K., the U.S., and several European countries.[38] They are part of the broader phenomenon of "legal highs," newly synthesized substances designed to mimic the effects of traditional drugs. These substances typically remained legal for several years before governments updated legislation to ban them.[39]

Bath salts account for a large share of the Russian drug market - about 39%. However,

[38] While mephedrone had been known to scientists since the late 1920s, it was rediscovered by underground chemists in the late 2000s and found its way to the black market soon thereafter.

[39] Another prominent category of legal highs is "synthetic cannabinoids," which are designed to replicate the effects of cannabis (Peacock et al., 2019).

this figure alone does not reveal the causal impact of their introduction, because the effect depends on the extent of substitution with other drugs. In one extreme case of perfect substitution, all consumers of bath salts would have used other drugs if bath salts had not been available, implying no change in total drug consumption. In the opposite extreme of no substitution, consumers of bath salts would not have used any drugs in the absence of these substances. Under this scenario, the introduction of bath salts increased total drug consumption by $1/(1-0.39)-1 \approx 64\%$. To estimate the actual effect, we simulate a counterfactual in which bath salts are removed from the market and compare the predicted outcomes to the observed market shares.

The estimates from Table 7 show that the introduction of bath salts has increased the total demand for illegal drugs by 36%. The large difference from the no-substitution estimate of 64% indicates substantial cannibalization of previously existing drug types. Nevertheless, the main conclusion remains: the introduction of bath salts significantly expanded the overall drug use. This could be driven by the unique characteristics of bath salts that appeal to users who were not previously active in the market. As discussed in Section 4.2, $\alpha-$PVP does not have close substitutes and is among the cheapest drugs available. Although mephedrone has closer substitutes, the large variance of its random coefficient indicates strong attachment among its users. Consistent with this interpretation, Section 3.5 shows that users of both $\alpha-$PVP and mephedrone rarely review other drug types in other periods.

Our model also allows us to estimate how the introduction of bath salts has affected the demand for specific preexisting drugs. Table 7 shows the largest declines for MDMA and amphetamine, which are the closest substitutes for mephedrone. Their consumption is estimated to be 27% and 20% lower relative to the counterfactual scenario without competition from bath salts, indicating a substantial shift in demand away from these drugs. In contrast, hashish and marijuana are the least affected, with declines of 9% and 11%, respectively.

Forecasting how illegal drug consumption would respond to the potential future introduction of new synthetic substances is inherently difficult, as the overall effect depends on both the price of the new drugs and the degree of substitution between them and existing drug types. At the same time, studying past introductions is challenging because it requires detailed data and advanced methods. To our knowledge, this paper provides the first estimate of the effect of emerging drugs on total drug use. Our results for the case of bath salts in Russia show that the emergence of new substances can substantially expand overall drug consumption. These findings have important policy implications, highlighting the value of allocating resources to limit the discovery, production, or adoption of new illegal drugs. For example, governments could benefit from faster legislative responses to ban new drugs or from stricter regulations governing research of new substances.

5.3. Enforcement and revenue

Drug enforcement may unintentionally increase the total revenue of black markets. The model developed in Becker et al. (2006) shows that this outcome critically depends on price elasticities. Supply-side interventions, such as seizures or crop eradication, raise the price of the targeted drug. When demand is inelastic, the resulting reduction in consumption is smaller than the increase in price, causing the total revenue in the drug market to rise. Higher revenues can expand the resources available for drug smuggling and strengthen incentives to fight for control over the drug trade (Becker et al., 2006; Castillo et al., 2020). As a result, even if enforcement reduces consumption, it may simultaneously increase the scale of associated illegal activities, including gang violence, corruption, and attacks on journalists and civil society.

The elasticity of revenue of product j with respect to its price p_j equals $1+\varepsilon_{jj}$, where ε_{jj} is its own-price elasticity. This relationship motivates a common approach in the literature on illegal drug markets, where researchers estimate the demand elasticity for a given drug and compare it to -1 to infer the effect of enforcement on drug revenue (see Gallet, 2014 for a review). However, this approach ignores substitution across drugs. Some consumers who stop using the targeted drug switch to other drugs rather than exit the market, increasing revenue from those other drugs. Therefore, the relevant object is the elasticity of the total revenue of all drugs with respect to the price of drug j, which equals

$$\frac{p_j}{\sum_{k=1}^{J} p_k s_k} \frac{\partial \sum_{k=1}^{J} p_k s_k}{\partial p_j} = s_j^r + \sum_{k=1}^{J} s_k^r \varepsilon_{kj} = s_j^r \underbrace{\left(1+\varepsilon_{jj}\right)}_{\text{Own revenue}} + \underbrace{\sum_{k \neq j}^{J} s_k^r \varepsilon_{kj}}_{\text{Substitution}}, \tag{12}$$

where $s_j^r = p_j s_j / \left(\sum_{k=1}^{J} p_k s_k\right)$ is the revenue share of product j. Thus, even if the own-price elasticity ε_{jj} is below -1, enforcement can still increase total market revenue due to substitution. Assessing this possibility therefore requires estimates not only of own-price elasticities but also of cross-price elasticities, parameters that are rarely available in the existing literature.

We use our model estimates to evaluate how drug-specific enforcement affects total black-market revenue. Specifically, we weigh the elasticities across all markets to compute the elasticity of total drug revenue in all city-dates with respect to the price of each drug. Table 8 reports the revenue elasticities for the most popular drug types. Column (1) reports the own-revenue elasticity for each drug, which is the measure typically used in studies that estimate demand for a single drug type. Column (2) illustrates the role of substitution by reporting the elasticity of total revenue under the assumption of no substitution across drugs.

This corresponds to reporting only the first term of equation 12. Column (3) reports our main estimates of the elasticity of total revenue, which incorporate substitution across drug types.

We find that enforcement targeting amphetamine increases total drug revenue. This result is consistent with the observed substitution patterns: amphetamine has two close substitutes, MDMA and mephedrone, and mephedrone in particular has the largest market share in the market. As a result, higher amphetamine prices shift demand toward these alternatives rather than substantially reducing overall spending. The magnitude of the effect is modest, with 10% increase in the price of amphetamine raising total drug revenue by about 0.3%. Nevertheless, the result highlights a potential unintended consequence of enforcement policies: by redirecting demand toward substitute drugs, enforcement can increase black market revenues and potentially support other illegal activities.

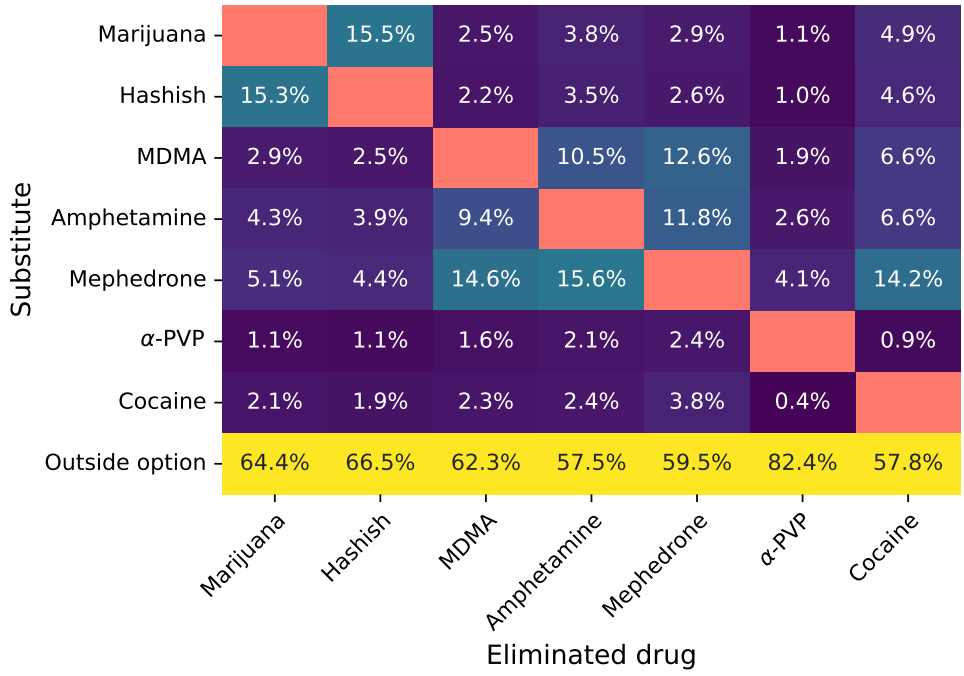
A second finding is that accounting for substitution substantially changes the predicted effects of enforcement on revenue, even when the effect remains negative. With the exception of cocaine, which has the largest impact on total revenue, the estimated elasticities for other drugs are about 2.5 times smaller once substitution is taken into account. This suggests that analysis that ignores substitution may substantially overestimate the effectiveness of enforcement in reducing drug market revenues.

5.4. Drug elimination

Supply-side interventions that restrict the availability of a particular drug increase the consumption of other drugs that serve as substitutes. Manski et al. (2001) hypothesized that such substitution could offset the benefits of reducing access to the targeted drug. In some cases, substitution may even shift consumption toward more harmful substances. For example, Alpert et al. (2018) and Evans et al. (2019) show that heroin-related mortality increased sharply after a supply-side intervention changed the formulation of OxyContin, as individuals addicted to Oxycontin switched to heroin. These findings raise the question: What are the overall effects of drug reduction policies given potential substitutions between drugs? To address this question, we examine how the demand for illegal drugs would change if a particular drug were eliminated from the market. We interpret this scenario as an extreme case of a successful targeted government intervention. In practice, some interventions may come close to eliminating a drug, at least in the short run, as illustrated by crackdowns on heroin in Australia (Moore and Schnepel, 2021) and on methamphetamine in the United States (Dobkin and Nicosia, 2009).

Figure 7 reports diversion ratios resulting from the elimination of each drug. For a

Figure 7. Diversion ratios for most popular drug types



Note: This figure presents the percent change in the consumption of drug j following the complete elimination of drug k. Diversion ratios are defined as $D_{jk} = (s_j^{-k} - s_j)/s_k$, where s_j^{-k} is the counterfactual market share of product j when product k is removed from the choice set.

given drug, these ratios show how its former consumption would shift to other drugs or to the outside option. The results reveal substantial heterogeneity in substitution patterns. For example, if mephedrone were eliminated, around 24% of its consumption would shift to amphetamine or MDMA, while only around 1% would move to opioids and roughly 3% each to hashish and marijuana. More broadly, the figure highlights clusters of drugs with strong substitution, consistent with the patterns documented in Section 3.5 and Section 4.2. In particular, amphetamine, MDMA, and mephedrone form a closely connected group: eliminating any one of these drugs leads many users to shift toward the remaining two. A similar pattern appears for cannabis products, where the elimination of hashish leads its consumers to switch to marijuana more than to any other drug, and vice versa.

Figure 7 also reveals substantial variation in the effect on the total drug use among consumers of each eliminated substance. For example, after the removal of $\alpha-$PVP, 82% of its consumption is predicted to be eliminated. In contrast, targeting amphetamine would result in only 58% of its consumption shifting to the outside option. This does not imply that 58% of amphetamine consumers would leave the drug market altogether, since many users consume multiple drugs: around half of them review other drugs in different periods,

as shown in Figure 1. More broadly, the lowest declines in total drug use occur for drugs with many close substitutes, such as amphetamine, cocaine, mephedrone, and MDMA. In contrast, diversion to the outside option is the largest for $\alpha-$PVP, a substance with few close substitutes.

These findings have implications for the prioritization of enforcement policies. Our results are most informative about short-run effects, since complete elimination of a drug is plausible only in the short term and our static model is most suitable to predict short-term substitution responses. If drugs posed similar health and social risks, targeting those with few close substitutes would not only generate the largest reductions in total drug use but also be the most effective strategy overall. Taking health risks into account, the recommendation would likely still prioritize targeting $\alpha-$PVP, which both exhibits high diversion to the outside option and is considered a very high-risk drug. The policy implications are more nuanced for other substances. For example, three drugs with the lowest diversion to the outside option, amphetamine, cocaine, and mephedrone, all have elimination shares in the range of 58-60%. However, they would not necessarily be equally ineffective to target. Since cocaine is considered a very high-risk drug, it is likely the most effective target among these three drugs from a public health perspective. The welfare consequences of targeting specific drugs ultimately depend on how policymakers value health, crime and other social harms of using each individual drug, not using drugs as well as the costs of enforcement. Our results provide one input into this policy evaluation.

Discussion

We examine the robustness of our results to assumptions about market size and the choice of instruments. Appendix Section F presents these exercises and discusses the results in detail. First, our findings are robust to the market size definition, which is achieved by our random coefficient model effectively isolating a subset of active drug users in markets of different sizes. Second, the effects of counterfactual policies are also stable across IV specifications.

One limitation of our analysis is that we model preferences as static. While our model incorporates addiction stock through the variance of random coefficient, it does not allow addiction to evolve over time. As a result, our counterfactual predictions are most informative about short-run responses. In the longer run, increases in drug consumption may accumulate as users become more addicted, and vice versa. This limitation affects the interpretation of several counterfactual exercises. Studying the introduction of bath salts, we may overstate the increase in total drug use because we underestimate the extent of long-run substitution

away from pre-existing drugs. For revenue elasticities, the difference between short-run and long-run effects is ambiguous. While both own-price and cross-price elasticities are likely to be larger in the long run, they affect revenue elasticity in opposite directions. For drug elimination, it implies that we may underestimate substitution toward other drugs and therefore overestimate the reduction in total consumption. We discuss limitations of studying cannabis legalization in Section 5.1.

6. Conclusion

We analyze the market for illegal drugs utilizing data scraped from Hydra, the world's largest darknet marketplace to date. This dataset enabled us to estimate a model of demand for a wide range of illegal drugs and study substitution between them. To identify consumer preferences, we employed a novel approach based on micro-level moment conditions that capture inter-temporal correlations in individual choices. Our findings reveal significant variation in the level of attachment to different drugs and substitutability between them. Several groups of substances are close substitutes: the three medium-risk stimulants and the two types of cannabis. We employ our model to evaluate the effects of key drug policies that affect the supply of illegal drugs. First, the legalization of cannabis can achieve a decrease in the use of riskier drugs, but such a decrease will be accompanied by a substantial increase in cannabis consumption. Second, governments should proactively seek to prevent the introduction of new drugs into the market because recent introduction of bath salts have had pronounced effects on overall drug consumption. Finally, drug enforcement is likely to be more successful when it targets drugs with few substitutes.

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Table 5: Coefficient estimates with standard errors

	Random coef.		Logit	
	Coef.	S.E.	Coef.	S.E.
	(1)	(2)	(3)	(4)
Price per dose	-0.187	0.008	-0.194	0.008
2 doses	-0.735	0.144	-0.951	0.135
3 doses	-1.197	0.173	-1.359	0.165
4 doses	-1.334	0.150	-1.545	0.141
Magnet	0.647	0.109	1.280	0.100
Hidden	0.881	0.079	0.830	0.072
Crystal form	1.045	0.198	0.686	0.158
Very high quality	0.531	0.090	0.472	0.084
High quality	-0.247	0.088	-0.258	0.082
Product rating	0.154	0.030	0.111	0.028
Reviews sentiment	0.062	0.029	0.052	0.028
Shop age	-0.017	0.003	-0.019	0.003
Shop rating	0.029	0.018	0.025	0.017
"Trusted seller"	0.663	0.065	0.620	0.061
FE	Date		Date	
Markets	1,054		1,054	
Obs.	12,203		12,203	

Note: This table presents the results of the demand estimation for the linear parameters. Columns (1) and (2) report the main results from the mixed logit model. Columns (3) and (4) provide the standard logit estimates for comparison. Price per dose is in USD (exchange rate for Dec 2021, 1 dollar = 74 rubles). "Magnet" and "hidden" refer to types of dead drops, with "dug in soil or snow" serving as the omitted category. The quality labels "very high quality" and "high quality" were displayed on the platform if the self-reported substance purity level was above 98% and 95% respectively. The "trusted seller" label was displayed for shops that both paid for it and that met quality criteria required by the platform. The construction of the "reviews sentiment" variable is described in Section 3.4. Standard errors are heteroskedasticity-robust and adjusted for variance in the first stage (see Appendix Section C.4 for details). Due to space limitations, drug-type dummies are not reported, see Appendix Table E.2 for a full set of linear parameters.

Table 6: Cannabis legalization and predicted consumption change

	10.0% reduction (1)	25.0% reduction (2)	50.0% reduction (3)	75.0% reduction (4)
Panel A: Change in use				
Marijuana	32.0%	96.6%	260.4%	504.1%
Hashish	23.2%	67.7%	173.7%	323.1%
MDMA	-1.5%	-4.4%	-11.8%	-22.6%
Amphetamine	-1.5%	-4.6%	-12.2%	-23.1%
Mephedrone	-1.0%	-3.1%	-8.4%	-16.9%
α-PVP	-0.6%	-1.8%	-5.0%	-10.6%
Cocaine	-1.7%	-5.1%	-12.9%	-23.7%
Non-cannabis use	-1.3%	-3.9%	-10.4%	-19.9%
Cannabis use	27.4%	81.7%	215.8%	410.9%
Total use	3.5%	10.4%	27.3%	51.9%
Panel B: Change per 1 dose decrease in use of non-cannabis drugs				
Cannabis use	4.2 doses	4.2 doses	4.2 doses	4.1 doses
Total use	3.2 doses	3.2 doses	3.2 doses	3.1 doses

Note: This table reports the percent change in predicted drug consumption across all city-dates when the price of cannabis (hashish and marijuana) in each city-date decreases by x%. Panel A shows percent change in consumption of individual drug types as well as total use. Panel B reports additional doses of cannabis or all drugs used per one less dose of non-cannabis drugs consumed under each price decline.

Table 7: Effect of bath salts' introduction on drug demand

Drug type	Estimated effect
Amphetamine	-19.5%
Cocaine	-15.7%
Hashish	-9.1%
LSD	-12.3%
Marijuana	-10.6%
MDMA	-26.7%
Opioids	-14.7%
Other cannabis	-14.6%
Other stimulants	-14.2%
Other psychedelics	-13.6%
Total (with bath salts)	36.3%

Note: This table reports the predicted percent change in drug consumption following the introduction of bath salts mephedrone and α-PVP. We compare a counterfactual with bath salts removed from the choice set to the observed market.

Table 8: Elasticity of revenue with respect to drug prices

	Own revenue (1)	Total revenue (w/o substitution) (2)	Total revenue (with substitution) (3)
Marijuana	-2.302	-0.169	-0.085
Hashish	-1.842	-0.114	-0.044
MDMA	-1.854	-0.168	-0.059
Amphetamine	-0.684	-0.076	0.028
Mephedrone	-0.898	-0.267	-0.077
α-PVP	-0.737	-0.053	-0.022
Cocaine	-5.332	-0.982	-0.846

Note: Column (1) reports the elasticity of own revenue with respect to the price of each product, which is equal to one plus own-price elasticity. Column (2) shows the implied elasticity of total drug revenue without accounting for substitution, obtained by scaling the own-revenue elasticity by the market share of each product. Column (3) presents the elasticity of total revenue with respect to each product price, as defined in equation 12.

Appendices

A. Data

A.1. Scraping of Hydra

The scraping process was done by running a program on a personal computer.[40] The computer operated on OS Windows 10 and had an AMD processor and 4GB of RAM. The process was organized in two stages. In the first stage, the program scraped all pages with the output of the search in 62 categories of the Hydra website to obtain URLs of all products within each category.[41] After that, the program iterated over all obtained product URLs and scraped each product-specific page to collect information on the listings available for the product.

Table A.1: List of dates when scrapes of Hydra are available

Date	Day of week	Week #	Listings	Date	Day of week	Week #	Listings
Jul 17, 2019	Wed	29	73,313	Jan 22, 2020	Wed	4	94,859
Jul 20, 2019	Sat	29	73,448	Jan 28, 2020	Tue	5	95,634
Jul 30, 2019	Tue	31	77,652	Feb 06, 2020	Thu	6	106,351
Aug 07, 2019	Wed	32	77,898	Feb 12, 2020	Wed	7	107,449
Aug 14, 2019	Wed	33	80,911	Feb 20, 2020	Thu	8	112,504
Aug 30, 2019	Fri	35	87,357	Feb 27, 2020	Thu	9	110,864
Sep 08, 2019	Sun	36	84,934	Mar 05, 2020	Thu	10	118,579
Sep 17, 2019	Tue	38	84,511	Mar 11, 2020	Wed	11	114,769
Sep 25, 2019	Wed	39	88,750	May 16, 2020	Sat	20	119,769
Oct 03, 2019	Thu	40	91,293	May 23, 2020	Sat	21	126,192
Nov 15, 2019	Fri	46	89,510	Jun 16, 2020	Tue	25	138,312
Nov 27, 2019	Wed	48	93,188	Jul 03, 2020	Fri	27	153,464
Dec 06, 2019	Fri	49	96,817	Jul 15, 2020	Wed	29	156,465
Dec 13, 2019	Fri	50	103,550	Aug 05, 2020	Wed	32	167,312
Dec 19, 2019	Thu	51	101,335	Aug 27, 2020	Thu	35	168,508
Dec 26, 2019	Thu	52	105,832				

Available dates. The script was run on 33 days from July 17, 2019 to Aug 27, 2020. On two days, November 21 of 2019 and September 9 of 2020, the program failed to complete

[40] The code is available upon request.

[41] For example, ⋆.onion/catalog/3?page=1 was the first page listing marijuana products.

scraping due to a technical error. We exclude these days from the sample. The list of days and the total number of listings scraped are provided in Table A.1.

A.2. Data cleaning

To remove listings that are intended for redistribution rather than personal consumption, we drop all listings that contain more than 5 doses.[42] We also drop all listings with a price per dose greater than three times the median price per dose of the same drug type. This is necessary because shops on Hydra sometimes set prohibitively high prices instead of deleting a listing when they were out of stock.[43] We also observe several shops with many thousands of listings and a much smaller cumulative number of fulfilled orders. A common feature of such shops is that they operated in more cities than even the largest shops on the platform. This seems to be inconsistent with the normal operation of shops on Hydra. One potential explanation is that this is a form of drop shipping: these shops copy the listings of other shops and sell those listings at a premium. Because drop-shipping merchants copy the listings of other shops, including their listings would lead to a double-counting of dead drops. We remove all shops for which there are more listings than total sales from our data.

We exclude all reviews of job postings or non-drug products sold on Hydra. We also remove duplicates if we observe several reviews with the exact same text left for the same product by the same user. We only use reviews for the period when we have listings from the marketplace.

A.3. Dose definition

Table A.2 displays the distribution of different quantities for each drug type. To account for potential differences in potency between various drug types and substance forms, we normalize the listed amounts by dividing them by a drug-specific quantity, which we refer to as the "standard amount" or "dose." Intuitively, the standard amount represents the first frequently used quantity in the distribution of listed amounts. We define a dose for each drug type as an amount with a frequency of at least 15% of total listings and at least 40% of listings of any other higher amount.

Our interpretation of this definition is that the first popular amount in the distribution of quantities corresponds to the "minimal suitable quantity." While the distribution of purchased amounts could be endogenous and dependent on the price and other factors, it is plausible that for each drug type, there exists a subset of constrained consumers who will

[42] See A.3 for our definition of a dose.

[43] Sellers use such strategies on legal online platforms as well, e.g., on Airbnb (Culotta et al., 2022).

only purchase this minimal suitable quantity. Our strategy aims to identify this specific quantity and use it for normalization.

Table A.2: Shares of different amounts for each drug type

	0.1	0.25	0.5	1	2	3	Other	Total
2c	**63.5**	7.7	0.8	0.0	0.0	0.0	28.0	100.0
α-PVP	0.1	1.2	**33.1**	34.5	15.8	0.0	15.3	100.0
Amphetamine	0.0	0.0	5.6	**32.0**	27.1	18.4	16.8	100.0
Marijuana (buds)	0.0	0.0	4.3	**39.6**	25.3	16.0	14.7	100.0
Cannabinoids	0.0	0.0	**20.5**	43.2	35.6	0.0	0.8	100.0
Cannafood	0.0	0.0	0.7	**24.2**	46.2	10.9	18.0	100.0
Cocaine	0.3	3.3	**31.3**	40.6	13.9	0.0	10.6	100.0
Dissociatives	0.0	2.7	**33.6**	37.3	9.9	0.0	16.4	100.0
DMT	**16.0**	23.8	39.6	0.0	0.0	0.0	20.7	100.0
GHB	0.7	16.3	**64.5**	7.8	0.0	0.0	10.6	100.0
Hashish oil	1.3	**13.7**	23.3	46.6	0.0	0.0	15.1	100.0
Hashish	0.0	0.1	5.1	**32.9**	27.4	17.5	17.1	100.0
Heroin	1.4	**14.5**	34.0	37.7	0.0	0.0	12.4	100.0
Marijuana (leaves)	0.0	0.0	0.8	**17.2**	25.1	26.1	30.9	100.0
LSD	0.0	0.0	0.0	10.0	**34.8**	18.4	36.9	100.0
MDMA (pill)	0.0	0.0	0.0	8.2	**27.2**	24.0	40.6	100.0
MDMA (crystal)	0.0	2.2	**27.9**	41.5	21.0	0.0	7.4	100.0
MDPV	0.0	1.3	**28.7**	43.2	25.7	0.0	1.0	100.0
Mephedrone	0.0	0.3	9.2	**36.0**	24.5	15.9	14.0	100.0
Methadone	4.6	**20.8**	33.8	23.8	0.0	0.0	17.1	100.0
Methamphetamine	0.0	1.6	**19.4**	42.5	29.7	0.0	6.7	100.0
Mushrooms	0.0	0.0	0.0	**19.3**	9.1	40.2	31.4	100.0
NBOME	0.0	0.0	0.0	11.6	**25.1**	23.3	39.9	100.0
Opioids	1.0	5.1	**36.4**	28.6	17.8	0.0	11.1	100.0
Psychedelics	0.0	0.0	0.9	3.5	**20.8**	29.0	45.8	100.0
Synthetic cannabinoids	0.0	0.0	2.8	**27.2**	27.4	20.9	21.7	100.0
Total	0.2	1.2	13.0	32.3	22.8	12.9	17.6	100.0

Note: Each column shows shares of a corresponding amount for each drug type. For MDMA (pills) and LSD, the amount is in counts. For all other drug types, the amount is in grams. The standard amount for each drug type is highlighted in bold and defined as an amount with a frequency of at least 15% and a frequency that is at least 40% of the frequency of any other higher amount.

A.4. Descriptive statistics

Table A.3: Summary statistics: properties of shops on Hydra

	Mean	Median	Std	Min	Max
Products offered	7.61	6	5.83	1	60
Drug types offered	3.35	3	2.25	1	14
Cities present	3.36	2	4.61	1	33
Daily listings	37.53	20	77.69	1	2,315
Age (months)	17.71	15.10	11.42	0	44.50
Total sales	13,830	4,500	39,333	3	800,000
Rating	4.90	4.93	0.11	2.65	5
Trusted Seller	0.17	–	–	–	–

Table A.4: Summary statistics for reviews data

Panel A: Available data					
Reviews	Total				197,177
	By users with 1 review				81,254
	By users with > 1 reviews				115,923
Users	Total				122,021
	With 1 review				81,254
	With > 1 reviews				40,767
	With > 1 purchased types				19,515
Shops	Total				753
Panel B: Descriptive statistics					
	Mean	Median	Std	Min	Max
Rating	9.55	10	1.91	0	10
Number of words	16.54	8	27.02	0	1596
Reviews per nickname	1.62	1	1.14	1	8
Days between reviews	63.16	16	102.16	0	441

Note: Days between reviews are calculated for reviews such that a review left by the same user at a later day is present in the sample.

A.5. Proxies for sales

The assumption that listings are proportional to transactions could be violated for several reasons. First, it is possible that it took several days for a particular listing to be sold.

Table A.5: Shares of drug types in all listings and reviews

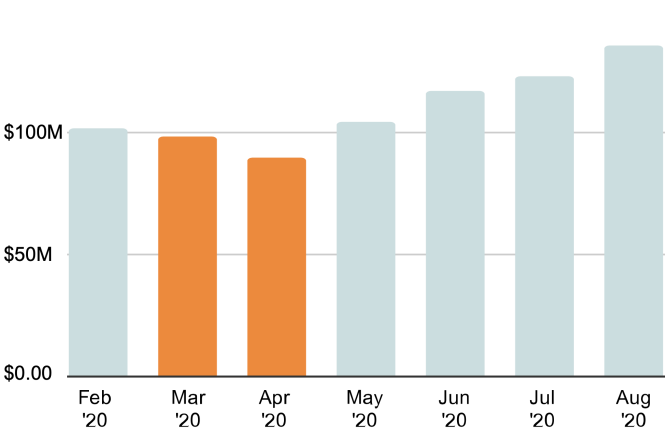
Drug type	Share of listings	Share of reviews	Drug type	Share of listings	Share of reviews
Mephedrone	29.6%	26.3%	Heroin	0.8%	1.4%
Amphetamine	13.9%	12.8%	Marijuana (leaves)	0.7%	0.6%
α-PVP	12.5%	8.6%	NBOME	0.7%	0.7%
MDMA	10.8%	12.4%	Synthetic cannabinoids	0.7%	1.1%
Marijuana (buds)	7.9%	10.4%	Mushrooms	0.4%	0.9%
Hashish	7.8%	7.7%	Hashish oil	0.3%	0.5%
Cocaine	7.1%	9.0%	Dissociatives	0.3%	0.5%
LSD	3.1%	2.6%	DMT	0.2%	0.2%
Methadone	2.0%	2.7%	Cannafood	0.1%	0.3%
Methamphetamine	0.9%	0.9%	2C-B	0.1%	0.3%

Second, a particular dead-drop could remain unsold, resulting in no transactions. Third, shops could list one dead-drop under several adjacent neighborhoods to maximize their presence in search results. Finally, some transactions on the platform were conducted via pre-orders.

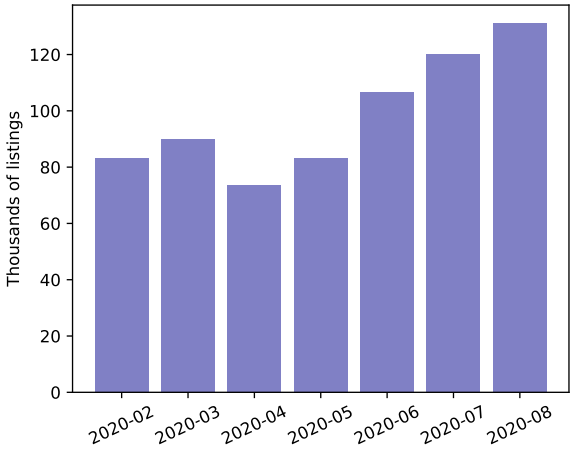
Shares of drugs. The assumption could also be violated if the ratio of listings to dead drops is different across drug types. For example, it could be the case that, first, several dead-drops of the same weight and hiding type are hidden in the same neighborhood and, second, that this is most common for the more popular drug types. In this case, listings could disproportionately underestimate transactions for more popular drugs. Table A.5 shows market shares of different drug types defined through listings and reviews. While we do not observe actual transactions, we can compare the two proxies for transactions on the aggregate level to test their validity. We find that these two measures are close to each other. Moreover, we do not find a pattern of listings underestimating the market shares relative to reviews for popular drug types.

Listings and cryptocurrency inflows. Figure A.1 shows the monthly estimates of Hydra revenue provided in Flashpoint, Chainanalysis (2021)[p. 5] and the average daily number of listings in our data during the same period. Our results indicate a strong correlation between cryptocurrency inflows to Hydra and the number of listings across time.

Figure A.1. Estimated revenue and listings on Hydra over time



(a) Estimated monthly revenue from Flashpoint, Chainanalysis (2021)



(b) Mean daily number of listings in our data

Note: Panel (a) plot is obtained from Flashpoint, Chainanalysis (2021)[p. 5]. Panel (b) plots the mean daily number of listings by month using our listings data. To calculate mean listings for April 2020, we use supplementary dataset, which was purchased from an independent data collector for this particular month and was also used by Goonetilleke et al. (2023). This supplementary data is not used for demand estimation.

B. Constructing Review Sentiment

We apply two approaches to extract the sentiment of reviews: the lexicon approach and LLM embeddings. In the first approach, we start by constructing a balanced sample of reviews with positive and negative ratings. We label a review as positive if it has a rating of 10/10. We label a review as negative if it has a rating below 6/10. We obtain a total of 14,000 negative reviews. We randomly select the same number of positive reviews. We then apply lemmatization to words and drop all "stopwords," for example, prepositions and pronouns. We find in the corpus of processed reviews the 200 most frequently used terms. We use the frequencies of these terms to generate a vector of 200 elements for each review. We standardize these variables and include the length of a review as an additional predictor. This gives us a vector representation $\mathbb{X}_i$ for each review i in the sample. We then run a logistic regression to estimate the model

$$\mathbb{P}(\text{review } i \text{ is positive}) = \text{logit}(\mathbb{X}_i'\beta).$$

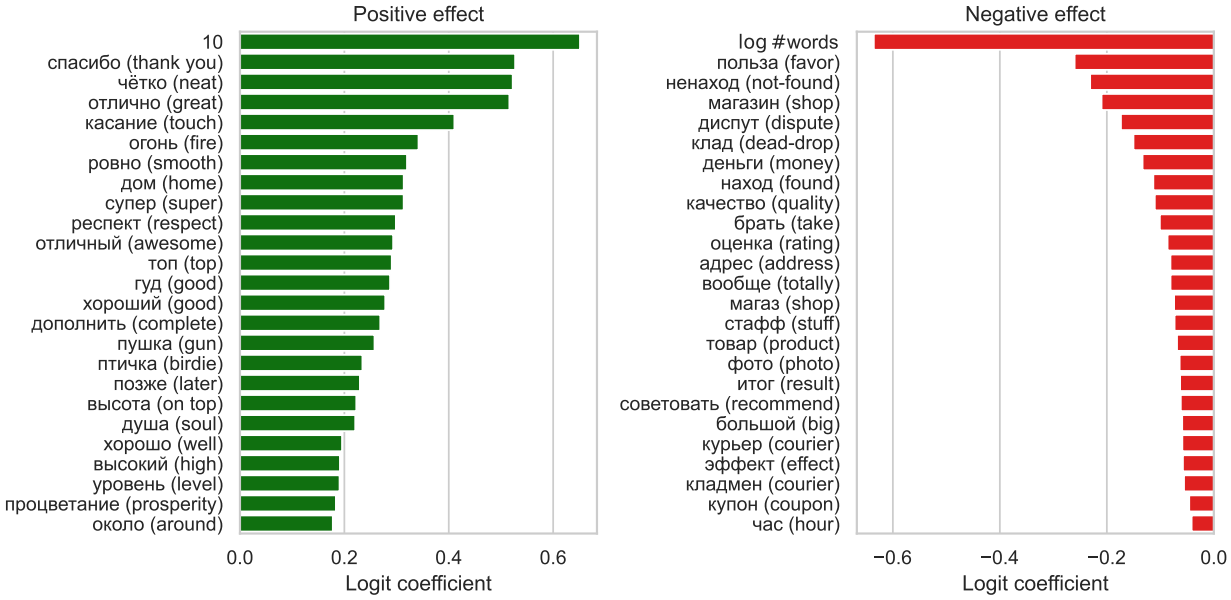
We obtain an out-of-sample accuracy of 85% with this algorithm. We use $\mathbb{X}_i'\hat{\beta}$ as our measure of the (positive) sentiment of the review.

The intuition behind this method is the following. From rating-based labels of reviews, the algorithm learns which words have good and bad connotations. Then, weighting these words allows us to distinguish differences in the sentiment even within the 96% of reviews that have the highest possible rating. Figure B.1 describes the words that have the largest power for predicting positive or negative labels. The most predictive signal for positive feedback is "10": reviewers type numerical ratings to express satisfaction. The length of the review is a strong predictor of negative feedback. Most of the words we find predictive for positive feedback describe general satisfaction with the purchase, for example, "thank you" or "super." Many words are related to the delivery process. For example, "not-found" describes the common problem of not being able to find the purchased dead-drop; "touch" is a colloquial way to explain that the drug was picked up quickly; and "photo" is often used to complain about the quality of the photo of the dead-drop location. Some words seem to be used to describe the substance, e.g., "quality" and "stuff." Others describe the process of disputes, e.g., "favor," "dispute," or "coupon."

However, this method does not take into account many properties of language – for example, the difference between "recommend" and "not recommend." For this reason, we also use modern developments in large language models for our sentiment analysis. For each review R, we obtain a vector embedding $e(R) \in \mathbb{R}^{1536}$ using the API from OpenAI.[44]. We

[44]See Neelakantan et al. (2022) for more details.

Figure B.1. Most predictive words for positive and negative reviews



then manually choose a small sample[45] of positive and negative reviews, with 25 reviews in each group. We define our measure of positive sentiment as the difference between average cosine similarity to good reviews and average cosine similarity to bad reviews. That is,

$$sentiment(R) = \frac{1}{\#G}\sum_{X\in G} D_C\big(e(R), e(X)\big) - \frac{1}{\#B}\sum_{X\in B} D_C\big(e(R), e(X)\big),$$

where G is the set of good reviews, B is the set of bad reviews, and cosine similarity is given by

$$D_C(X, Y) = 1 - \frac{X \cdot Y}{\|X\|\|Y\|}.$$

The two obtained measures are highly correlated, with a correlation coefficient of 0.67. We use the first principal component of these two measures to obtain our final estimate of review sentiment. Given the varying number of reviews across shops in our sample, we employ empirical Bayes to regularize the obtained shop-level average sentiment.

[45] To minimize the computational costs associated with including every additional review in this sample, we manually selected reviews that encompass a variety of scenarios reflecting both satisfaction and dissatisfaction.

Table B.1: Examples of reviews with highest rating and negative sentiment

Date	Drug	Translation	Original	Rating
2020-06-04	Amphetamine	Fast collection, respect to the courier. But the quality is below average, I expected a lot more. Did not get any pleasure or feelings from it.	В касание, минеру респект. Но качество ниже среднего, я ожидал на много большего, а не получил от этого ни удовольствия ни ощущений	10
2020-06-09	Heroin	Fast collection, the product is damp. Brothers, do not even think to buy heroin from here, the dead-drops are from the winter, and the product does not work well.	Забрал в касание, товар отсырел, братчанин, не вздумай тут покупать хмурый, зимние адреса, товар прёт ну точно не 777	10
2019-06-06	Mephedrone	Did not find the dead-drop, but I can only blame myself. Also, do not want to start a dispute because of just 0.5 grams. I guess I will not buy dug dead-drops for a while.	Сокровище не нашёл, но тут скорее могу винить только себя, да и из-за 0.5 диспут открывать не хочется.. Пожалуй, не буду больше пока брать прикопы)	10
2020-08-01	Amphetamine	Fast collection, also an interesting experience. But the quality is quite bad... No offense guys. Rating 10/10/10, will not lower it.	В касание! Интересный опыт по касашке... Но качество чёт подводит.... Без обид, пацаны. Оценка 10.10.10 понижать не буду	10
2020-05-26	Mephedrone	We found everything but with lots of complications. The product was around the specified location.	Все нашли но с большими трудностями товар был рядом с указанным местом	10
2019-02-15	MDMA	In general it was good, but some of the pills were broken. The courier confuses left and right. Liked the quality.	В целом всё в порядке, но таблы оказались поломанные. И кладмен путает лево и право. Качество понравилось	10
2020-04-03	Marijuana buds	Good buds but not dried enough. Thus, the quantity actually is smaller than specified	Хорошие шишки, только недосушены, соответсвенно количество меньше чем заявлено	10
2020-05-20	Hashish	Did not find the dead-drop, it was hidden badly and the location was marked badly. When you pay 2800 rubles per 1 gram you expect a good dead-drop. The support responses slower than once per day. In the end, they gave me a coupon. Overall, not satisfied with the shop.	Был ненаход, откровенно говоря плохо спрятали и плохо метку поставили, когда 2800 за 1г. отдаешь рассчитываешь на нормальную закладку, поддержка у магазина отвечат даже не раз в сутки, в итоге разошлись купоном, всем магазином в целом не доволен.	10

Note: Table sourced from Goonetilleke et al. (2023).

C. Micro Moments

Here we provide a more detailed discussion of our micro-level moment conditions. We start by showing how micro moments can facilitate demand estimation in a simulated dataset.

C.1. Simulated example

We generate simulated data in which consumers have correlated taste shocks for two products. This is a simplified version of the demand model presented in Section 4. Specifically, there are products $j = 1, \ldots, 5$ sold by 5 different firms. Consumer preferences are given by

$$U_{ijt} = \alpha p_{jt} + \beta^0 + \sum_{n=1}^{3} \beta^n x_{jt}^n + \lambda_i^0 + \lambda_i^1 I(j=1) + \lambda_i^2 I(j=2) + \xi_{jt} + \varepsilon_{ijt}. \tag{13}$$

The linear parameters of demand are $\alpha = -5$, $\beta = (5, 1, 1, 1)$. Consumers have correlated random coefficients λ for the constant term and the dummies for products 1 and 2:

$$\begin{pmatrix} \lambda_i^0 \\ \lambda_i^1 \\ \lambda_i^2 \end{pmatrix} = \Sigma \nu_i, \;\; \nu_i \sim \mathcal{N}(0, I_3), \;\; \Sigma = \begin{pmatrix} 2 & 0 & 0 \\ 1 & 2 & 0 \\ 1 & 2 & 2 \end{pmatrix}. \tag{14}$$

Intuitively, consumers who like product 1 (2) are more inclined to like product 2 (1) and less inclined to choose the outside option. Prices are given by the Bertrand-Nash equilibrium where producers maximize total profits $(p_{jt} - MC_{jt})s_{jt}$ and face marginal costs that are given by

$$MC_{jt} = 1 + 0.1 \sum_{n=1}^{3} x_{jt}^n + 0.1 \sum_{n=1}^{7} z_{jt}^n + \omega_{jt}, \tag{15}$$

where z^n are observed cost shifters, x^n are observed product characteristics, and ω is an unobserved product characteristic. We simulate $T = 100$ markets with 500 Monte Carlo agent draws. Variables x, z are all iid from $\mathcal{N}(0, 1)$, and $\omega, \xi \sim \mathcal{N}(0, 1)$ with $corr(\omega, \xi) = 0.5$.

We then obtain an analog of our review moments. We simulate 100,000 agents in this economy who keep the same draws ν_i across all markets. To make our setting closer to the empirical setting in the paper, we consider a theoretical counterpart of reviews: for each agent-period pair, if at period t agent i chooses product $j = j(i, t)$, this choice is observed with probability $\pi = 0.1$ and added to R_{ij}. Because the econometrician can only observe consumers with at least one review, we calculate averages $\overline{R_{ij}R_{ik}}$ over agents i such that $R_i > 0$. Table C.1 shows that our inter-temporal micro moments reflect the assumptions

about correlations for products 1 and 2: consumers are more likely to purchase 1 and 2 together. The assumed correlation between λ_i^1 and λ_i^2 also implies that reviews for products 3 to 5 are correlated as well. Intuitively, the agents who buy these products are the agents who do not like products 1 and 2.

Table C.1: Moment values $\overline{R_{ij}R_{ik}}$ in simulated data

	R_1	R_2	R_3	R_4	R_5
R_1	3.17	2.56	1.38	1.52	1.52
R_2	2.56	7.82	2.00	2.15	2.10
R_3	1.38	2.00	3.23	2.16	2.24
R_4	1.52	2.15	2.16	3.74	2.44
R_5	1.52	2.10	2.24	2.44	3.97

We then estimate the model using the simulated data. To make the exercise closer to the setting of the paper, we only estimate the demand parameters of the model and do not rely on supply-side moment conditions. We use the observable cost shifters z^n and the differentiation IVs of Gandhi and Houde (2019) as the instrumental variables. First, we apply the standard BLP procedure, which uses the aggregate price-quantity data only, and obtain estimates $\hat{\Sigma}^{BLP}, \hat{\alpha}^{BLP}, \hat{\beta}^{BLP}$. Then, we estimate the parameters by fitting the predicted micro moments to estimated micro moments, as described in Sections 4.1 and 4.1, and obtain estimates $\hat{\Sigma}^{Micro}, \hat{\alpha}^{Micro}, \hat{\beta}^{Micro}$. Our results are provided below:

$$\hat{\Sigma}^{BLP} = \begin{pmatrix} 1.35 & 0.00 & 0.00 \\ 1.39 & 1.26 & 0.00 \\ -0.49 & 2.54 & 2.87 \end{pmatrix}, \quad \hat{\Sigma}^{Micro} = \begin{pmatrix} 1.97 & 0.00 & 0.00 \\ 1.27 & 1.96 & 0.00 \\ 1.16 & 1.97 & 1.97 \end{pmatrix},$$

$$\hat{\alpha}^{BLP} = -4.70, \ \hat{\alpha}^{Micro} = -4.44,$$

$$\hat{\beta}^{BLP} = (3.83, 1.07, 1.09, 0.96), \ \hat{\beta}^{Micro} = (4.02, 1.02, 0.96, 1.01).$$

We find that micro moments substantially improved precision of estimates for Σ.

C.2. Definition of periods

In this section, we describe how we apply our micro moments from Section 4.1 to the case where price-quantity data is only available for a subset of days compared to reviews data. Suppose that reviews can be observed over days $t = 1, \ldots, T$. However, quantities and prices can only be observed for several specific days $\tau_1, \ldots, \tau_n$, where $1 \leqslant \tau_k \leqslant T$. In our case, reviews can be observed for $T = 423$ days, but we only have listings data for $n = 31$ days.

In principle, we could keep reviews for days τ_k only and use the expressions from Section 4.1 directly. However, that would imply not utilizing most of the review data.

The expected value of $R_{ij}R_{ik}$ among all agents who left at least one observed review is

$$\mathbb{E}\Big[R_{ij}R_{ik} \mid R_i > 0\Big] = \frac{\mathbb{E}R_{ij}R_{ik}}{\mathbb{P}\big(R_i > 0\big)}, \tag{5}$$

where we approximate the denominator and the numerator by averages $\frac{1}{N}\sum_i \mathbb{E}\big[R_{ij}R_{ik} \mid i\big]$ and $\frac{1}{N}\sum_i \mathbb{P}\big(R_i > 0 \mid i\big)$, respectively. Including reviews for all days $t = 1, \dots, T$, the expected value of the product term for consumer i is

$$\mathbb{E}\Big[R_{ij}R_{ik} \mid i\Big] = \sum_{t_1 \neq t_2} \pi_{jt_1}\pi_{kt_2}s_{ijt_1}s_{ikt_2} + I(j=k)\sum_{t=1}^{T}\pi_{jt}s_{ijt}, \tag{16}$$

where $\pi_{jt} = \pi_j^{review}\pi_t^{scrape}$ is the probability that a purchase is converted into a scraped review and s_{ijt} is the predicted probability that consumer i purchases j on date t. Because we do not observe prices and quantities for other days, we approximate s_{ikt} by finding the closest day $\tau(t)$ when we observe listings for each t and using $s_{ik\tau}$ instead:

$$\begin{aligned}
\mathbb{E}\Big[R_{ij}R_{ik} \mid i\Big] &\approx \sum_{t_1 \neq t_2} \pi_{jt_1}\pi_{kt_2}s_{ij\tau(t_1)}s_{ik\tau(t_2)} + I(j=k)\sum_{t}\pi_{jt}s_{ij\tau(t)} \\
&= \sum_{\tau_1,\tau_2}\Big(\sum_{\tau(t)=\tau_1}\pi_{jt}\Big)\Big(\sum_{\tau(t)=\tau_2}\pi_{kt}\Big)s_{ij\tau_1}s_{ik\tau_2} \\
&+ I(j=k)\sum_{\tau}\Big(\sum_{\tau(t)=\tau}\pi_{jt}\Big)s_{ij\tau} \\
&- \sum_{\tau}\Big(\sum_{\tau(t)=\tau}\pi_{jt}\pi_{kt}\Big)s_{ij\tau}s_{ik\tau}.
\end{aligned} \tag{17}$$

We find that terms $\sum_{\tau(t)=\tau}\pi_{jt}\pi_{kt}$ are two orders of magnitude smaller compared to terms $\sum_{\tau(t)=\tau}\pi_{jt}$ and are one order of magnitude smaller than the terms $\big(\sum_{\tau(t)=\tau_1}\pi_{jt}\big)\big(\sum_{\tau(t)=\tau_2}\pi_{kt}\big)$.[46] Therefore, we can further approximate

$$\mathbb{E}\Big[R_{ij}R_{ik} \mid i\Big] \approx \sum_{\tau_1,\tau_2}\tilde{\pi}_{j\tau_1}\tilde{\pi}_{j\tau_2}s_{ij\tau_1}s_{ik\tau_2} + I(j=k)\sum_{\tau}\tilde{\pi}_{j\tau}s_{ij\tau}, \tag{18}$$

where $\tilde{\pi}_{j\tau} = \sum_{\tau(t)=\tau}\pi_{jt}$ is the sum of probabilities of conversion into observed review over all days t attributed to τ.

[46] Intuitively, the last term in Equation 17 corrects for the fact that consumers cannot purchase j and k on the same day. This possibility has a relatively negligible role in $R_{ij}R_{ik}$ if reviews are observed rarely (π_{jt} are small) or T is large and cross-period combinations dominate. Both apply in our setting.

If we apply the approximation by the closest observed day to the equation describing the connection between reviews and sales, we obtain

$$\sum_{\tau(t)=\tau} R_{jt} = N \sum_{\tau(t)=\tau} \pi_{jt} s_{jt} \approx N \sum_{\tau(t)=\tau} \pi_{jt} s_{j\tau} = N \tilde{\pi}_{j\tau} s_{j\tau}. \tag{19}$$

Thus, we can estimate $\tilde{\pi}_{j\tau}$ as the ratio of reviews over the larger period $\{t : \tau(t) = \tau\}$ to $N s_{j\tau}$, as is done in Equation 9.

Finally, we can also approximate the selection probability in a similar way:

$$\begin{aligned} \mathbb{P}\big(R_i > 0 \mid i\big) &= 1 - \prod_{t=1}^{T} \Big(1 - \pi_{jt} \sum_{j=1}^{J} s_{ijt}\Big) \\ &\approx 1 - \prod_{t=1}^{T} \Big(1 - \pi_{jt} \sum_{j=1}^{J} s_{ij\tau(t)}\Big) \\ &\approx 1 - \prod_{\tau} \Big(1 - \tilde{\pi}_{j\tau} \sum_{j=1}^{J} s_{ij\tau(t)}\Big). \end{aligned} \tag{20}$$

Table C.2 shows the assignment of dates in our review data to dates $\tau(t)$ in our listings data and the number of reviews for each τ.

Table C.2: Attribution of reviews to dates where listings were scraped

Scrape date	Period start	Period end	Length	Reviews	Scrape date	Period start	Period end	Length	Reviews
Jul 17, 2019	Jul 01, 2019	Jul 18, 2019	17	1,613	Jan 22, 2020	Jan 09, 2020	Jan 25, 2020	30	1,785
Jul 20, 2019	Jul 19, 2019	Jul 25, 2019	8	4,415	Jan 28, 2020	Jan 26, 2020	Feb 01, 2020	10	1,525
Jul 30, 2019	Jul 26, 2019	Aug 03, 2019	14	5,651	Feb 06, 2020	Feb 02, 2020	Feb 09, 2020	12	7,683
Aug 07, 2019	Aug 04, 2019	Aug 10, 2019	11	965	Feb 12, 2020	Feb 10, 2020	Feb 16, 2020	10	4,529
Aug 14, 2019	Aug 11, 2019	Aug 22, 2019	15	4,967	Feb 20, 2020	Feb 17, 2020	Feb 23, 2020	11	2,517
Aug 30, 2019	Aug 23, 2019	Sep 03, 2019	20	1,779	Feb 27, 2020	Feb 24, 2020	Mar 01, 2020	10	391
Sep 08, 2019	Sep 04, 2019	Sep 12, 2019	13	926	Mar 05, 2020	Mar 02, 2020	Mar 08, 2020	10	499
Sep 17, 2019	Sep 13, 2019	Sep 21, 2019	13	1,147	Mar 11, 2020	Mar 09, 2020	Apr 13, 2020	39	13,080
Sep 25, 2019	Sep 22, 2019	Sep 29, 2019	12	89	May 16, 2020	Apr 14, 2020	May 19, 2020	69	21,407
Oct 03, 2019	Sep 30, 2019	Oct 24, 2019	29	520	May 23, 2020	May 20, 2020	Jun 04, 2020	19	29,901
Nov 15, 2019	Oct 25, 2019	Nov 21, 2019	49	619	Jun 16, 2020	Jun 05, 2020	Jun 24, 2020	32	15,692
Nov 27, 2019	Nov 22, 2019	Dec 01, 2019	16	301	Jul 03, 2020	Jun 25, 2020	Jul 09, 2020	23	9,389
Dec 06, 2019	Dec 02, 2019	Dec 09, 2019	12	230	Jul 15, 2020	Jul 10, 2020	Jul 25, 2020	22	13,210
Dec 13, 2019	Dec 10, 2019	Dec 16, 2019	10	226	Aug 05, 2020	Jul 26, 2020	Aug 16, 2020	32	29,420
Dec 19, 2019	Dec 17, 2019	Dec 22, 2019	9	249	Aug 27, 2020	Aug 17, 2020	Sep 15, 2020	41	21,300
Dec 26, 2019	Dec 23, 2019	Jan 08, 2020	20	1,152					

C.3. Gradients

To facilitate stability and speed of convergence, we use analytical gradients for the estimation procedure that is outlined in Section 4.1. We provide our derivations here. To simplify notation, we omit the city index because all expressions stay the same. We consider the more general case with demographic variables D in random coefficients, where idiosyncratic utilities are $\mu_{ijt} = X_{ijt}\big(\Pi D_i + \Sigma\nu_i\big)$, and the non-linear parameters of the model are $\theta = \big(\Sigma, \Pi\big)$. The choice probabilities for consumer i are given by

$$s_{ijt} = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J}(\delta_{jkt} + \mu_{ikt})}, \tag{21}$$

and the standard multinomial logit derivatives are

$$\frac{\partial}{\partial\delta_{kt}}s_{ijt} = \frac{\partial}{\partial\mu_{ikt}}s_{ijt} = \begin{cases} s_{ijt}\big(1 - s_{ijt}\big), & j = k \\ -s_{ijt}s_{ikt}, & j \neq k. \end{cases} \tag{22}$$

For δ_{jt} and μ_{ijt} defined by θ, we have

$$\begin{aligned} \frac{\partial}{\partial\theta}s_{ijt}(\theta) &= \sum_{k=1}^{J}\Big[\frac{\partial s_{ijt}}{\partial\delta_{kt}}\frac{\partial\delta_{kt}}{\partial\theta} + \frac{\partial s_{ijt}}{\partial\mu_{ikt}}\frac{\partial\mu_{ikt}}{\partial\theta}\Big] \\ &= -s_{ijt}\sum_{k} s_{ikt}\Big[\frac{\partial\delta_{kt}}{\partial\theta} + \frac{\partial\mu_{ikt}}{\partial\theta}\Big] + s_{ijt}\Big[\frac{\partial\delta_{jt}}{\partial\theta} + \frac{\partial\mu_{ijt}}{\partial\theta}\Big]. \end{aligned} \tag{23}$$

As

$$\frac{\partial}{\partial\Pi}\mu_{ijt} = X_{ijt}D_i', \frac{\partial}{\partial\Sigma}\mu_{ijt} = X_{ijt}\nu_i', \tag{24}$$

we obtain

$$\frac{\partial}{\partial\Pi}s_{ijt}(\theta) = -s_{ijt}\sum_{k} s_{ikt}\Big(\frac{\partial\delta_{kt}}{\partial\Pi} + X_{ikt}D_i'\Big) + s_{ijt}\Big(\frac{\partial\delta_{jt}}{\partial\Pi} + X_{ijt}D_i'\Big), \tag{25}$$

and

$$\frac{\partial}{\partial\Sigma}s_{ijt}(\theta) = -s_{ijt}\sum_{k} s_{ikt}\Big(\frac{\partial\delta_{kt}}{\partial\Sigma} + X_{ikt}\nu_i'\Big) + s_{ijt}\Big(\frac{\partial\delta_{jt}}{\partial\Sigma} + X_{ijt}\nu_i'\Big). \tag{26}$$

We can apply these expressions[47] to calculate the gradient for our moments

$$m_{jk}(\theta) = \mathbb{E}\Big[R_{ij}R_{ik} \mid R_i > 0\Big] = \frac{\mathbb{E}R_{ij}R_{ik}}{\mathbb{P}\big(R_i > 0\big)}, \tag{27}$$

[47] PyBLP package reports $\frac{\partial\delta_{kt}}{\partial\theta}$.

which equals

$$\frac{\partial}{\partial\theta}m_{jk}(\theta)=\frac{1}{\mathbb{P}\big(R_i>0\big)^2}\left(\mathbb{P}\big(R_i>0\big)\frac{\partial\mathbb{E}\big[R_{ij}R_{ik}\big]}{\partial\theta}-\mathbb{E}\big[R_{ij}R_{ik}\big]\frac{\partial\mathbb{P}\big(R_i>0\big)}{\partial\theta}\right). \tag{28}$$

The terms in this expression can be approximated with averages taken over random draws of agents. In particular,

$$\frac{\partial\mathbb{E}\big[R_{ij}R_{ik}\big]}{\partial\theta}\approx\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\mathbb{E}\Big[R_{ij}R_{ik}\mid i\Big], \tag{29}$$

$$\frac{\partial\mathbb{P}\big(R_i>0\big)}{\partial\theta}\approx\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\mathbb{P}\big(R_i>0\mid i\big). \tag{30}$$

The gradients for the individual product terms are given by

$$\begin{aligned}\frac{\partial}{\partial\theta}\mathbb{E}\Big[R_{ij}R_{ik}\mid i\Big]&=\frac{\partial}{\partial\theta}\Big[\sum_{t_1\neq t_2}\pi_{jt_1}\pi_{kt_2}s_{ijt_1}(\theta)s_{ikt_2}(\theta)+I(j=k)\sum_t\pi_{jt}s_{ijt}(\theta)\Big]\\&=\sum_{t_1\neq t_2}\pi_{jt_1}\pi_{kt_2}\big[s_{ijt_1}(\theta)\frac{\partial}{\partial\theta}s_{ikt_2}(\theta)+s_{ikt_2}(\theta)\frac{\partial}{\partial\theta}s_{ijt_1}(\theta)\big]\\&+I(j=k)\sum_t\pi_{jt}\frac{\partial}{\partial\theta}s_{ijt}(\theta).\end{aligned} \tag{31}$$

For the probability of observing at least one review by consumer i in the data, which equals

$$\mathbb{P}\big(R_i>0\mid i\big)=1-\prod_{t=1}^{T}\Big(1-\sum_{j=1}^{J}\pi_{jt}s_{ijt}(\theta)\Big), \tag{8}$$

we obtain

$$\frac{\partial}{\partial\theta}\mathbb{P}\big(R_i>0\mid i\big)=\sum_{t=1}^{T}\Big[\prod_{t'\neq t}^{T}\big(1-\sum_{j=1}^{J}\pi_{jt'}s_{ijt'}(\theta)\big)\Big]\sum_{j=1}^{J}\pi_{jt}\frac{\partial}{\partial\theta}s_{ijt}(\theta). \tag{32}$$

C.4. Asymptotic variance

We start with deriving the asymptotic variance of $\hat{\theta}$, our estimator for the non-linear parameters. Then, we derive the asymptotic variance of $\hat{\beta}=\hat{\beta}(\hat{\theta})$, which will be equal to the variance of 2SLS adjusted for the noise in $\hat{\theta}$.

First-stage variance. We use the results on minimal distance estimators from Newey and McFadden (1994), in particular, their Theorem 3.2. In their notation, we have

$$\hat{g}_M(\theta) = \left(\mathbb{E}\Big[R_{ij}R_{ik} \mid R_i > 0\Big] - \overline{R_{ij}R_{jk}}\right)_{(j,k)\in P}. \tag{33}$$

Similarly to Conlon and Gortmaker (2025), we assume that the conditions of the theorem are satisfied. In particular, we assume

$$\sqrt{n}\hat{g}_M(\theta_0) \to \mathcal{N}(0, \Omega_M) \tag{34}$$

and

$$\sup_{\theta\in U} \|\nabla_\theta \hat{g}_M(\theta) - G_M(\theta)\| \xrightarrow{p} 0. \tag{35}$$

In the above, $n = T \times C \times J$ is the sample size, the total number of market-product combinations. Our interpretation for this is that the size of the review data is going up with the number of markets and allows to estimate the micro-level moment conditions more precisely. Applying Theorem 3.2, we obtain $\sqrt{n}(\hat{\theta} - \theta_0) \to \mathcal{N}\big(0, \mathbb{V}(\hat{\theta})\big)$, where

$$\mathbb{V}(\hat{\theta}) = \big(G_M' W_M G_M\big)^{-1} G_M' W_M \Omega_M W_M G_M \big(G_M' W_M G_M\big)^{-1} \tag{36}$$

and $G_M = G_M(\theta_0)$. Because in our first stage we have the same number of parameters as moment conditions, all matrices are quadratic, and the sandwich expression simplifies to

$$\mathbb{V}(\hat{\theta}) = G_M^{-1} \Omega_M G_M^{-1\prime}. \tag{37}$$

We approximate Ω_M using the bootstrap distribution of $\hat{g}_M(\hat{\theta})$. For this, we re-draw the users in our data with replacement, recalculating the moment targets and the estimated probabilities of conversion $\hat{\pi}_{jt}$ for each bootstrap sample. We approximate $\hat{G}_M = \dfrac{\partial \hat{g}_M}{\partial \theta}(\hat{\theta})$.

Second-stage variance. Our second-stage estimates are given by 2SLS with weighting matrix W:

$$\hat{\beta}(\hat{\theta}) = (X'ZWZ'X)^{-1} X'ZWZ'\delta(\hat{\theta}). \tag{38}$$

We decompose the asymptotic error as

$$\sqrt{n}\big(\hat{\beta}(\hat{\theta}) - \beta_0\big) = \sqrt{n}\big(\hat{\beta}(\theta_0) - \beta_0\big) + \sqrt{n}\big(\hat{\beta}(\hat{\theta}) - \hat{\beta}(\theta_0)\big) = \tag{39}$$

$$\sqrt{n}\big(\hat{\beta}(\theta_0) - \beta_0\big) + \sqrt{n}(X'ZWZ'X)^{-1}(X'ZWZ')\big(\delta(\hat{\theta}) - \delta(\theta_0)\big) \approx \tag{40}$$

$$\sqrt{n}\big(\hat{\beta}(\theta_0) - \beta_0\big) + (X'ZWZ'X)^{-1}(X'ZWZ')\frac{\partial \delta}{\partial \theta}(\theta_0)\sqrt{n}\big(\hat{\theta} - \theta_0\big). \tag{41}$$

The first summand in Equation 41 is the standard 2SLS variance. The second component accounts for the noise from the first stage. Because the two stages are estimated from two different datasets, we assume that the two terms are asymptotically uncorrelated. Therefore, we obtain $\sqrt{n}(\hat{\beta} - \beta_0) \to \mathcal{N}\big(0, \mathbb{V}(\hat{\beta})\big)$, where

$$\begin{aligned}\mathbb{V}(\hat{\beta}) = &(X'ZWZ'X)^{-1}(X'ZW\Omega WZ'X)(X'ZWZ'X)^{-1} \\ &+ (X'ZWZ'X)^{-1}(X'ZWZ')\frac{\partial \delta}{\partial \theta}(\theta_0)\mathbb{V}(\hat{\theta})\frac{\partial \delta'}{\partial \theta}(\theta_0)(ZWZ'X)(X'ZWZ'X)^{-1}.\end{aligned} \tag{42}$$

In the above, $\Omega = \mathbb{E}\big[\xi_i^2 z_i z_i'\big]$ for residuals ξ_i and instruments z_i. We use heteroskedasticity-robust SEs for 2SLS and approximate

$$\hat{\Omega} = \frac{1}{n}\sum_{i=1}^{n}(z_i\hat{\xi}_i)(z_i\hat{\xi}_i)'.$$

Finally, we approximate $\dfrac{\partial \delta}{\partial \theta}(\theta_0)$ with $\dfrac{\partial \delta}{\partial \theta}(\hat{\theta})$.

D. Market Size

As discussed in Section 3.3, we assume that the number of transactions is proportional to the number of listings with the same characteristics. To estimate the market size and the share of the outside option, we need to estimate the corresponding multiplier. There are two important mechanisms that can make the multiplier not equal to 1. First, because deposited dead-drops can stay unsold for several days, a listing observed on a particular day does not necessarily correspond to a transaction on that day. Second, there can be several dead-drops behind one listing. We address this using the following simple framework. Suppose there are L_t listings on the website on day t, among which L_t^{new} are added on that day. Suppose that S_t is the number of sales made on day t. We assume that each listing exists for ω days and there are κ dead-drops behind each listing. For a large T, we can approximate

$$\sum_{t=1}^{T} L_t \approx \omega \sum_{t=1}^{T} L_t^{new}, \tag{43}$$

$$\sum_{t=1}^{T} S_t \approx \kappa \sum_{t=1}^{T} L_t^{new}. \tag{44}$$

We do not observe L_t^{new}, but we can express

$$\frac{\kappa}{\omega} \approx \frac{\sum_{t=1}^{T} S_t}{\sum_{t=1}^{T} L_t} \approx \frac{\sum_{t=1}^{T} S_t}{\sum_{t=1}^{T} L_{\tau(t)}},$$

where we approximate listings on day t by listings on the closest day where scraped data is available. We approximate the numerator by the sum of differences in total sales across all shops over the observed period and obtain $\kappa/\omega \approx 0.7$.

In the Russian mortality data, the majority of deaths associated with drug use occur among individuals aged between 18 and 45. Motivated by this fact, we focus on this age group and assume that each person between 18 and 45 can consume drugs 1 time per month. We assume that 1 standard amount is enough to consume drugs 3 times. Thus,

$$N_c = \frac{\omega}{\kappa} \frac{\text{Population between 18 and 45 in } c}{30 \times 3} \approx \frac{\text{Population between 18 and 45 in } c}{65}.$$

Under this assumption, the median market share of the outside option across markets is around 70%.

E. Estimates

Table E.1: Estimated non-linear parameters and associated standard errors

Matrix	Value					
$\hat{\Sigma}$	1.7784	0.0000	0.0000	0.0000	0.0000	0.0000
	0.1926	2.0621	0.0000	0.0000	0.0000	0.0000
	0.8288	1.7914	2.6489	0.0000	0.0000	0.0000
	0.5528	2.3436	0.4917	2.9483	0.0000	0.0000
	−1.2237	−0.6563	0.3091	0.2248	2.2776	0.0000
	1.1972	1.4586	0.1427	0.6756	−0.5880	3.9014
$SE\left(\hat{\Sigma}\right)$	0.0385	0.0000	0.0000	0.0000	0.0000	0.0000
	0.0523	0.0496	0.0000	0.0000	0.0000	0.0000
	0.1266	0.1341	0.0728	0.0000	0.0000	0.0000
	0.1337	0.1651	0.0679	0.0691	0.0000	0.0000
	0.0669	0.0858	0.1354	0.1252	0.1658	0.0000
	0.1628	0.1519	0.1029	0.0880	0.2016	0.1394

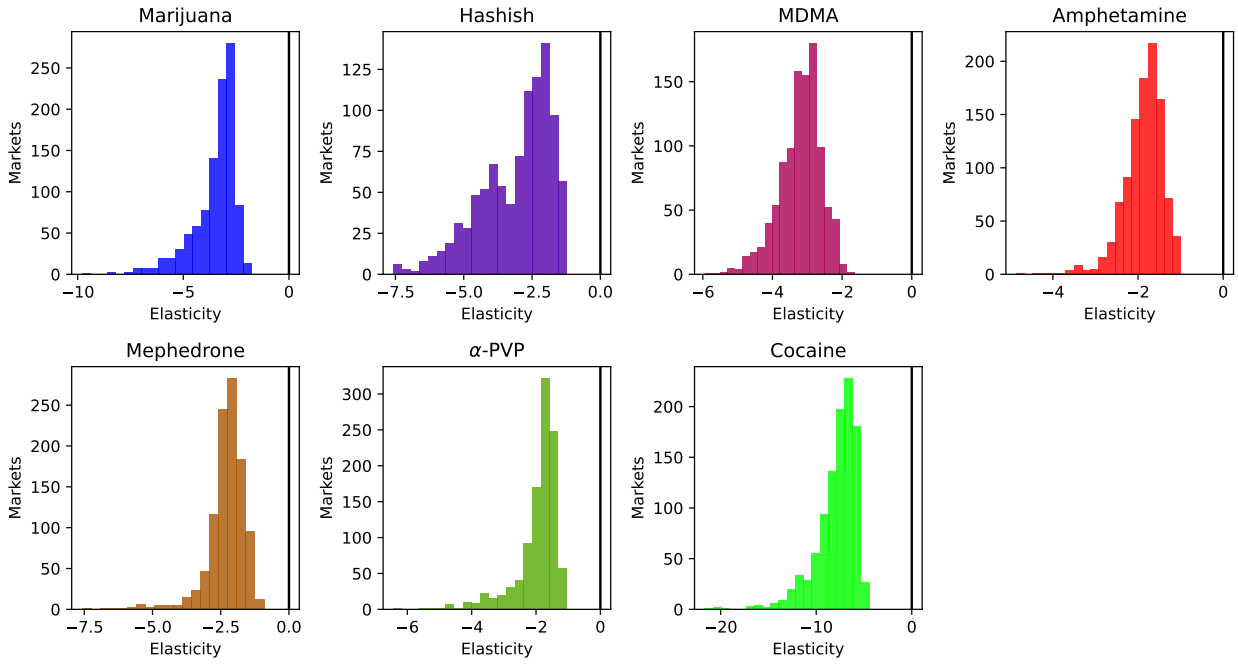
Note: Σ is the Cholesky root of the covariance matrix $\Sigma\Sigma'$ of random coefficients λ_i. The order of coefficients is as follows: cannabis, MDMA, amphetamine, mephedrone, α-PVP, cocaine.

Table E.2: Coefficient estimates with standard errors

	Random coef.		Logit	
	Coef.	S.E.	Coef.	S.E.
	(1)	(2)	(3)	(4)
Price per dose	-0.187	0.008	-0.194	0.008
2 doses	-0.735	0.144	-0.951	0.135
3 doses	-1.197	0.173	-1.359	0.165
4 doses	-1.334	0.150	-1.545	0.141
Magnet	0.647	0.109	1.280	0.100
Hidden	0.881	0.079	0.830	0.072
Crystal form	1.045	0.198	0.686	0.158
Very high quality	0.531	0.090	0.472	0.084
High quality	-0.247	0.088	-0.258	0.082
Product rating	0.154	0.030	0.111	0.028
Reviews sentiment	0.062	0.029	0.052	0.028
Shop age	-0.017	0.003	-0.019	0.003
Shop rating	0.029	0.018	0.025	0.017
"Trusted seller"	0.663	0.065	0.620	0.061
Amphetamine	1.268	0.369	1.353	0.145
Marijuana	3.198	0.276	1.375	0.165
Cocaine	6.691	0.647	10.216	0.444
Hashish	3.068	0.269	1.175	0.154
LSD	4.686	0.288	1.649	0.179
MDMA	3.019	0.246	1.470	0.111
Mephedrone	2.279	0.325	2.948	0.109
Opioids	4.298	0.278	1.350	0.165
Other Cannabis	1.951	0.265	-1.082	0.148
Other Psychedelics	2.535	0.270	-0.503	0.156
Other Stimulants	3.032	0.280	0.137	0.170
Sodium Oxybate	0.613	0.273	-2.377	0.160
FE	Date		Date	
Markets	1,054		1,054	
Obs.	12,203		12,203	

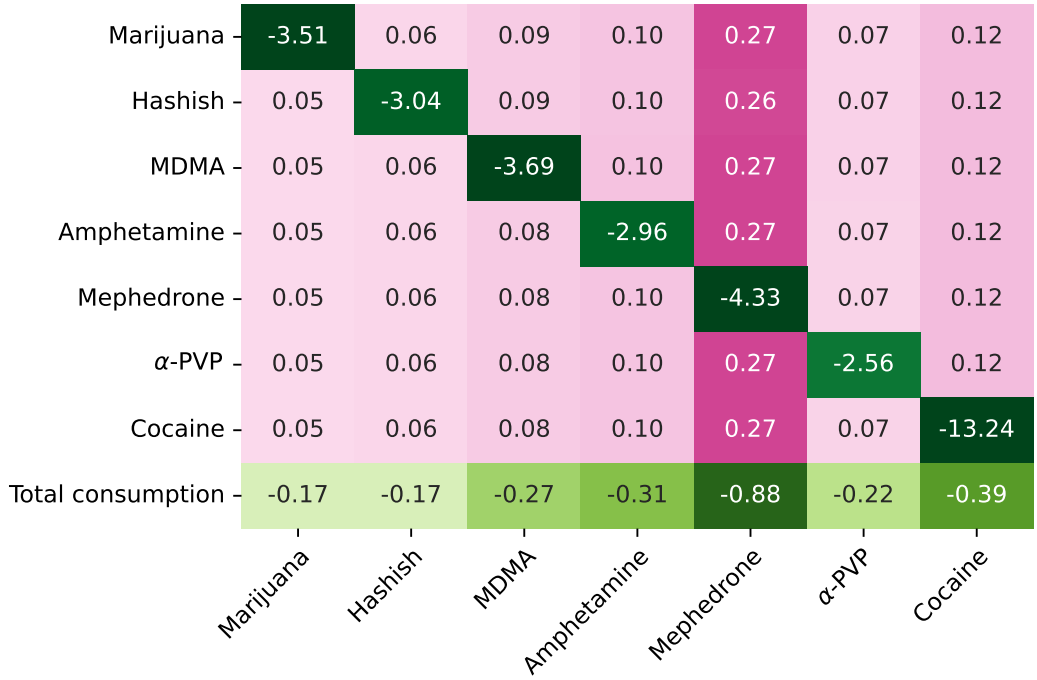
Note: All linear coefficients are reported. See notes for Table 5 for details.

Figure E.1. Distribution of own-price elasticities of demand



Note: The figure shows the distribution of own-price elasticity across markets for each of the eight most popular drug types.

Figure E.2. Median cross-price elasticities of demand: logit model



Note: This figure presents median price elasticities predicted by the logit model, where the median is across all markets (c, t). Each element $\mathcal{E}_{j,k}$ of the matrix shows the elasticity of demand for product j with respect to the price of product k, $\varepsilon_{jkct} = \frac{p_{jct}}{s_{jct}} \frac{\partial s_{jct}}{\partial p_{kct}}$. The last row reports the elasticity of total drug demand with the respect to the price of product k.

F. Robustness

This section describes robustness of our results to market size definition and IV specification.

First, we explore robustness to the definition of market size. In the main analysis, we assume that market size is proportional to the population aged 18 to 45 and each person in this age group can consume one-third of a standard purchase per month. We consider reducing the market size to 70% of the original and increasing to 150% and 200%, and we report our main results for comparison.[48] Appendix Table F.1 reports linear coefficients under each assumption on the market size. We find that linear parameters are very similar across definitions.

Appendix Table F.2 reports results for counterfactual policies for each market size assumption and shows that our main findings are robust. The results for the 70% specification

[48]For the market size of 70% of the original, we remove markets for which the market share of the outside option is less than 10%.

are somewhat less robust than those for 150% and 200% of the baseline. This may reflect the fact that, at smaller market sizes, total consumption approaches market size, leaving limited scope for substitution to the outside option. The median own-price elasticity is nearly unchanged across the baseline, 150%, and 200% specifications, ranging from -2.95 to -2.98, while it is somewhat larger under the 70% specification, at -3.24. For the cannabis legalization counterfactual, we report the ratio of additional cannabis doses to one fewer dose of other drugs under a 25% price reduction. This ratio is similar for the market sizes from 100% to 200% of the baseline, varying from 4.2 to 4.62. It is notably lower under the 70% specification, at 3.39, which may reflect that the market is too small to attract a substantial number of new users. The estimated effect of the introduction of bath salts on total drug consumption is also stable, ranging from 32% to 36%. We provide the range of the total revenue elasticity for different drugs and find that under each scenario total revenue elasticity is positive for amphetamine. For the drug elimination policy, we report the range of diversion ratios to the outside option for different drugs and find that the results are relatively stable.

This robustness is largely due to inclusion of random coefficients in the utility model. Appendix Table F.3 reports the estimated standard deviations of random coefficients, which increase with the market size for all drug types. As the assumed set of potential consumers expands, the model parameters adjust to match patterns in the data and effectively localize drug consumption to a smaller share of consumers. This is achieved through a combination of linear parameters, such as product dummies, that imply smaller mean utilities from drug use and higher variances of random coefficients. As a result, a smaller fraction of potential consumers who have drawn a large taste shock consistently chooses to buy drugs. This feature of the mixed logit model reduces the mechanical dependence of results on the outside share that happens in the standard logit model.

Table F.1: Robustness to market size: linear parameters

	70% of original		100% of original		150% of original		200% of original	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price per dose	-0.207	0.009	-0.187	0.008	-0.191	0.009	-0.194	0.009
2 doses	-1.029	0.151	-0.735	0.144	-0.707	0.147	-0.704	0.149
3 doses	-1.550	0.184	-1.197	0.173	-1.196	0.176	-1.202	0.178
4 doses	-1.636	0.159	-1.334	0.150	-1.340	0.152	-1.356	0.154
Magnet	0.801	0.113	0.647	0.109	0.678	0.112	0.696	0.114
Hidden	0.811	0.081	0.881	0.079	0.899	0.080	0.915	0.081
Crystal form	0.960	0.192	1.045	0.198	1.198	0.216	1.308	0.228
Very high quality	0.651	0.095	0.531	0.090	0.549	0.092	0.550	0.093
High quality	-0.219	0.091	-0.247	0.088	-0.235	0.091	-0.239	0.093
Product rating	0.152	0.031	0.154	0.030	0.158	0.030	0.159	0.031
Reviews sentiment	0.086	0.031	0.062	0.029	0.065	0.029	0.067	0.030
Shop age	-0.017	0.003	-0.017	0.003	-0.016	0.003	-0.016	0.003
Shop rating	0.028	0.018	0.029	0.018	0.026	0.018	0.025	0.018
"Trusted seller"	0.645	0.067	0.663	0.065	0.662	0.067	0.665	0.068
FE	Date		Date		Date		Date	
Markets	1,027		1,054		1,054		1,054	
Obs.	11,881		12,203		12,203		12,203	

Table F.2: Robustness to market size: effects of drug policies

	70% of original	100% of original	150% of original	200% of original
	(1)	(2)	(3)	(4)
Median own elasticity	-3.24	-2.95	-2.96	-2.98
Legalization ratio	3.39	4.20	4.50	4.62
Bath salts introduction	35.68%	36.30%	33.92%	32.37%
Total revenue elasticity	[-1%, 0%]	[-1%, 0%]	[-1%, 0%]	[-1%, 0%]
Diversion to no drug use	[56.99, 74.94]	[57.48, 82.40]	[54.02, 87.40]	[50.52, 91.35]

Table F.3: Robustness to market size: SD of random coefficients

	70% of original (1)	100% of original (2)	150% of original (3)	200% of original (4)
Hashish & Marijuana	1.47	1.78	2.41	2.82
MDMA	1.80	2.07	2.91	3.43
Amphetamine	2.79	3.30	4.33	5.00
Mephedrone	3.01	3.84	5.32	6.32
α-PVP	2.55	2.69	3.14	3.40
Cocaine	3.07	4.43	5.19	5.62

Next, we study how our results change under alternative IV specifications. In the baseline analysis, we employ three sets of instruments. First, we use geographic cost shifters: distance to the nearest port and distance to Saint Petersburg. Second, we include instruments capturing market competition, such as the number of drug types traded in the market and the number of shops. We explore how results change if we exclude each set of instruments.

Third, we use prices of the same product in other geographic markets on the same date, known as Hausman instruments (Hausman et al., 1994; Nevo, 2001). These instruments generate substantial variation for several drug types. As shown in Table 3, between 29% and 61% of the price variance for α-PVP, marijuana, and hashish arises from time variation. We believe most of this variation to be driven by supply shocks such as hashish enforcement. Moreover, we believe the exclusion restriction for Hausman IVs is more likely to hold in our context than in many other demand estimation settings. A potential concern would be nationwide demand shocks, many drivers of which such as ad campaigns are not present in illegal markets. There are other potential drivers of changes in the popularity of specific drugs across markets. We address this by including time trends for amphetamine and mephedrone, both of which experienced increases in popularity during the study period. Another example would be a deterioration in the purity of imported drugs. However, we have rich controls for quality in our demand model.

Table F.4 reports the linear estimates for each IV specification. For comparison, columns (1) and (2) reproduce the baseline results. Columns (3) through (8) present estimates for three specifications in which each set of instruments is removed. Excluding either the competition or the distance instruments changes the linear price coefficient only modestly, from the baseline value of -0.19 to -0.15 and -0.20, respectively. In contrast, excluding the Hausman instruments leads to a substantially larger estimate of price sensitivity, with the coefficient

increasing in magnitude to -0.32.

Table F.5 presents the effects of the counterfactual policies under each IV specification and shows that they are highly robust to the choice of instruments. The median own-price elasticities vary in a manner consistent with the linear price coefficients discussed above, with the highest elasticity arising in the specification that excludes Hausman instruments. For the legalization counterfactual, the ratio of increased cannabis consumption to the reduction in the use of other drugs is very stable across specifications, varying from 4.17 to 4.21. Although higher price sensitivity leads to larger absolute changes in consumption, the relative change remains similar because higher elasticity amplifies both the increase in cannabis use and the decline in the use of other drugs. Results for both the bath salts introduction and drug elimination counterfactuals do not depend on price sensitivity. This is because in these counterfactual experiments outcomes move due to changes in the choice sets as opposed to changes in drug prices (in terms of the model, these outcomes only depend on mean utilities δ_{jct}, which are identified by market shares and do not depend on observed prices). Finally, greater price sensitivity reduces the elasticity of total revenue. In the specification without Hausman instruments, the estimated total revenue elasticity is negative for all drugs.

Table F.4: Robustness to different IV specifications: linear parameters

	Baseline		No competition IVs		No Hausman IVs		No distance IVs	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price per dose	-0.187	0.008	-0.151	0.008	-0.321	0.017	-0.203	0.010
2 doses	-0.735	0.144	-0.378	0.136	-2.052	0.231	-0.888	0.154
3 doses	-1.197	0.173	-0.703	0.165	-3.018	0.286	-1.407	0.187
4 doses	-1.334	0.150	-0.890	0.141	-2.973	0.256	-1.524	0.164
Magnet	0.647	0.109	0.566	0.103	0.946	0.144	0.681	0.112
Hidden	0.881	0.079	0.911	0.075	0.770	0.103	0.868	0.081
Crystal form	1.045	0.198	1.121	0.194	0.767	0.231	1.013	0.201
Very high quality	0.531	0.090	0.481	0.084	0.718	0.124	0.553	0.093
High quality	-0.247	0.088	-0.226	0.083	-0.326	0.119	-0.256	0.091
Product rating	0.154	0.030	0.149	0.028	0.171	0.041	0.156	0.031
Reviews sentiment	0.062	0.029	0.046	0.027	0.124	0.041	0.069	0.030
Shop age	-0.017	0.003	-0.014	0.003	-0.029	0.004	-0.018	0.003
Shop rating	0.029	0.018	0.028	0.016	0.034	0.028	0.029	0.019
"Trusted seller"	0.663	0.065	0.615	0.061	0.842	0.088	0.684	0.067
FE	Date		Date		Date		Date	
Markets	1,054		1,054		1,054		1,054	
Obs.	12,203		12,203		12,203		12,203	

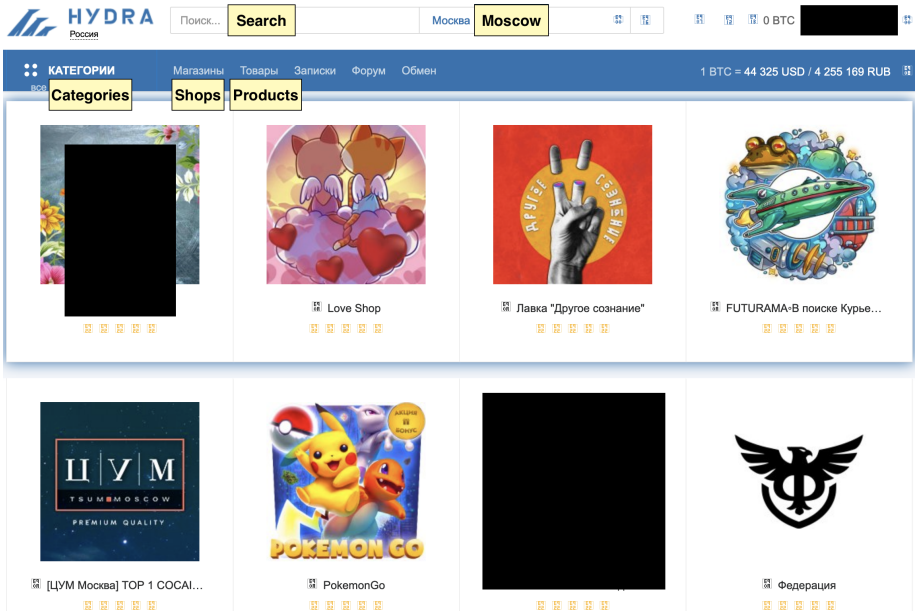
Table F.5: Robustness to different IV specifications: effects of drug policies

	Baseline	No competition IVs	No Hausman IVs	No distance IVs
	(1)	(2)	(3)	(4)
Median own elasticity	-2.95	-2.38	-5.07	-3.20
Legalization ratio	4.20	4.21	4.17	4.19
Bath salts introduction	36.30%	36.30%	36.30%	36.30%
Total revenue elasticity	[-1%, 0%]	[-1%, 0%]	[-2%, -0%]	[-1%, 0%]
Diversion to no drug use	[57.48, 82.40]	[57.48, 82.40]	[57.48, 82.40]	[57.48, 82.40]

G. Screenshots and Other Materials

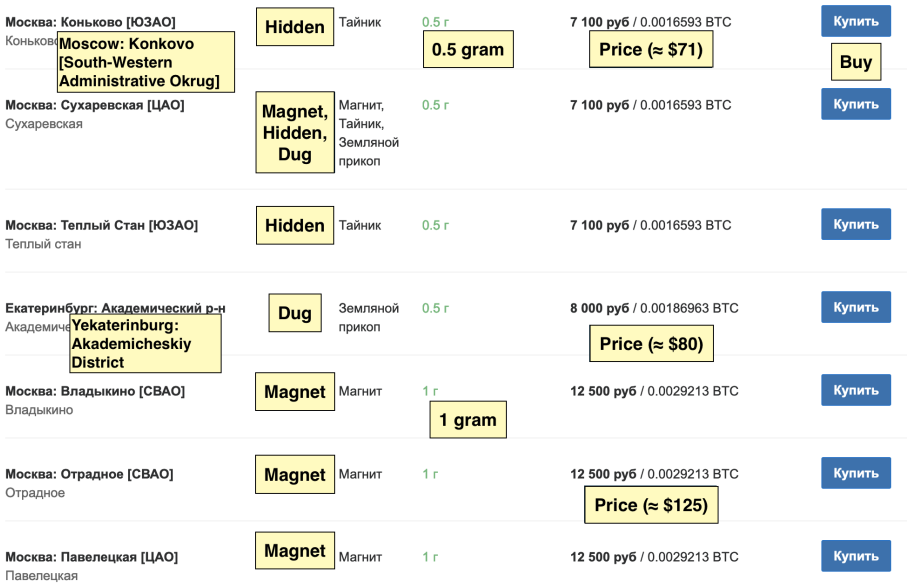
To illustrate and support some of the points we make in the paper, we provide several screenshots from the marketplace.

Figure G.1. Front page of Hydra



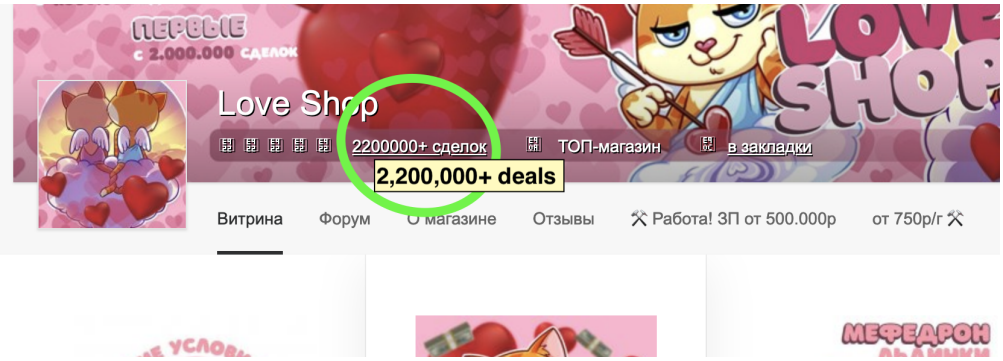
Note: Screenshot from March 26, 2022.

Figure G.2. Example of a product page with cocaine listings



Note: Screenshot from March 26, 2022.

Figure G.3. Example of shop's cumulative number of deals displayed by the platform

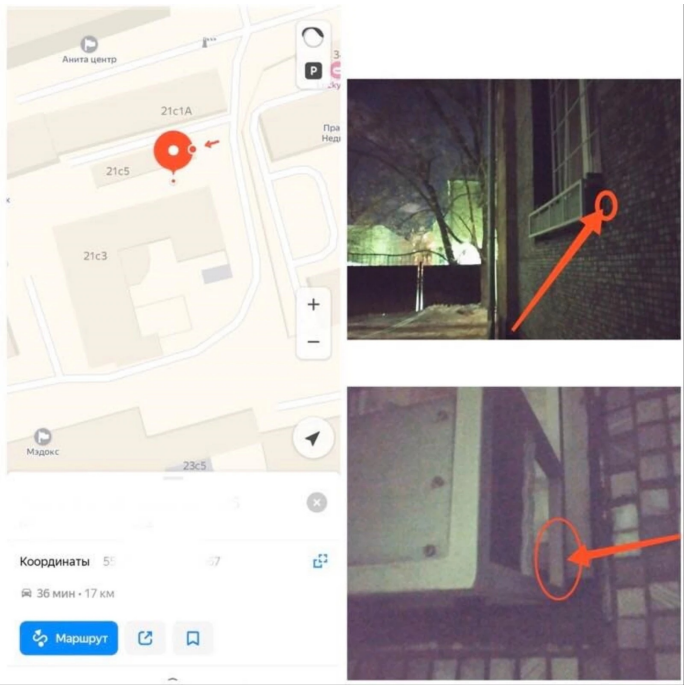


Note: Screenshot from March 17, 2022.

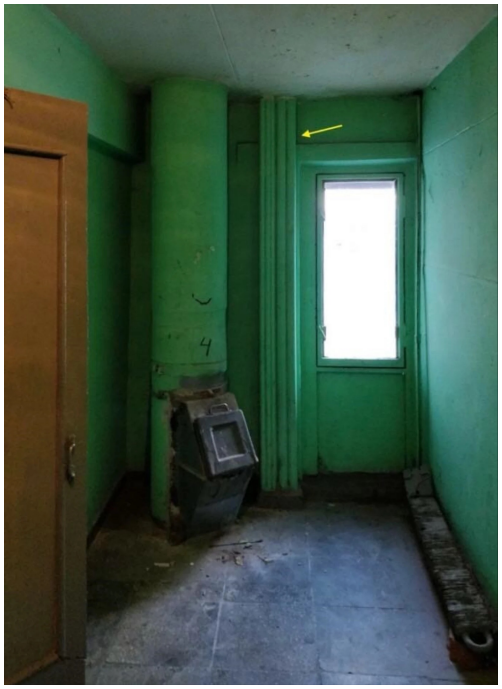
Figure G.4. Example of advertising of a "premium" shop



Figure G.5. Examples of information provided to buyers



(a) Coordinates and photo of hiding place



(b) Photo of hiding place

Source: VICE.com