Interventions and Illegal Drug Use: Evidence from a Darknet Marketplace*

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Abstract

When the government targets the supply of an illegal drug, consumers can substitute to other drugs. To study the effects of drug policies on total drug use, we develop a model of demand for illegal drugs of various types. We estimate it using a unique longitudinal dataset on prices, quantities, and individual decisions in the market for drugs we obtained by scraping a darknet marketplace that covered the majority of the retail illegal drug trade in Russia. Our estimation procedure exploits a novel set of micro-level moment conditions to identify correlations in preferences for specific drug types and the degree of attachment to them. We find that the median own-price elasticity of demand for illegal drugs is -3.6%, and that there is high substitution within two groups of drugs: medium-risk stimulants and types of cannabis. We employ our model to evaluate counterfactual drug policies. We find that the legalization of cannabis has the benefit of decreasing the use of riskier drugs: for each 4 more doses of cannabis used, 1 fewer non-cannabis dose would be used. Our estimates show that the recent introduction of a new family of synthetic drugs has increased total drug demand in the country by 40%, suggesting that governments should allocate resources to prevent emergence of new drug products. Finally, our model helps identify the optimal drugs to target, specifically those without close substitutes, such as α-PVP.

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1. Introduction

Illegal drugs are a global issue with meaningful implications for public health, property crime, violence, unemployment, and incarceration rates.[1] The U.S. government spends ever-increasing amounts in an attempt to address this problem.[2] Approximately half of these resources are dedicated to supply reduction measures, with the rationale that such measures decrease drug availability, raise prices, and consequently reduce drug use. However, the merits of supply-side enforcement are a topic of an ongoing debate (New York Times, 2023; The Economist, 2023). In many jurisdictions, including Canada and several U.S. states such as Arizona, Illinois, and New York, policymakers are implementing the radically different policy of legalizing cannabis, one of the popular drugs.

As these policies affect the availability of drugs, evaluating their effects on drug use requires an understanding of how consumers demand illegal drugs, and in particular, how they substitute between different drug types. Substitution is likely to decrease the efficiency of interventions targeting specific drugs, such as seizures or crop eradication. While the use of the targeted drug decreases, these actions may also increase the use of the drug types that serve as substitutes. Conversely, substitution can yield beneficial consequences from the legalization of cannabis if it results in a reduction in the use of more dangerous drugs.

This paper examines the demand for illegal drugs and the impact of drug policies on drug use. We develop and estimate a demand model that builds on the mixed logit framework (also known as BLP, see Berry, 1994; Berry et al., 1995). Our model accounts for consumer heterogeneity and flexible patterns in substitution between a large variety of illegal drugs. To estimate demand for drugs, we must address two significant challenges. First, the market for illegal drugs is predominantly unobservable. Second, drug types lack a clear set of differentiating product characteristics; therefore, representation within a low-dimensional characteristic space is not possible.

To address the first challenge, we leverage the distinctive context of a darknet marketplace known as Hydra, which operated from 2015 to 2022. Hydra was the largest darknet marketplace in the world, and in the later years of its existence spanned the majority of the

[1] According to the Centers for Disease Control and Prevention (CDC), drug overdose-related mortality in the U.S. has been steadily increasing and surpassed 100,000 deaths in the past two years (CDC, NCHS, 2022, 2023). Immense losses of human lives are not the only consequence of illegal drug use: drugs are associated with property crime, violence, and unemployment (Fryer et al., 2013). Harwood and Bouchery (2004) estimated that the total cost of drug abuse in the U.S. exceeds $200 billion per year. Moreover, drugs present a global issue, with the United Nations (UN) reporting that approximately 284 million people worldwide used drugs in 2020 (UN Office on Drugs and Crime, 2022).

[2] The U.S. National Drug Control budget exceeded $40 billion in 2022 (National Drug Control Budget, 2023). This "war on drugs" imposes a heavy burden on society: in 2020, almost 200,000 prisoners in the U.S. were sentenced for drug-related offenses (Carson, 2021).

retail drug trade in the major Russian cities. Thus, Hydra presents a unique opportunity to observe the market for illegal drugs and learn about the preferences of drug users. We compiled a novel micro-level panel dataset by regularly scraping data from the marketplace for over a year. From the perspective of demand estimation, a crucial advantage of our dataset is that it enables us to estimate the quantities and prices of drugs sold in each location where the market operated.

We combine data on drug listings with an individual-level panel dataset of user reviews from the marketplace. These posted reviews allow us to infer individual consumption patterns. Our findings indicate that consumers typically exhibit attachment to a specific drug, most often choosing the same type in multiple periods. However, the average degree of attachment varies among different drug types. For instance, consumers of cocaine tend to display much stronger attachment compared to MDMA users. Furthermore, our analysis reveals that consumers may demonstrate preferences for groups of drugs in addition to individual drug types. In particular, our review data suggests that individuals who have purchased amphetamine, MDMA, or mephedrone — three stimulants known to have similar effects — are substantially more likely to purchase these three drug types in other periods. Consequently, we can anticipate higher substitution within this group of drugs, which holds significant implications for the effects of drug policies. For example, amphetamine-focused drug enforcement is expected to reduce amphetamine demand but also increase the demand for MDMA and mephedrone. Importantly, predicting these substitution patterns *ex-ante* using the basic drug characteristics available from the medical and chemistry literature is challenging. For instance, we observe minimal substitution between mephedrone and $\alpha-$PVP, a widespread stimulant belonging to the same family.

We develop a model that can capture these patterns, building upon the BLP model. We account for consumer heterogeneity, which is critical for making accurate predictions regarding substitution patterns between different products. As there is no clear way to model drug types in a low-dimensional characteristic space, we allow for heterogeneity in preferences by introducing random coefficients for dummies for a set of the most important drug types. These coefficients are constant over time and describe consumers' idiosyncratic attachment to these drug types. BLP is particularly suited to our dataset, which comprises regular scrapes of listings from the marketplace. While the anonymous nature of the platform prevents us from observing who purchases a particular listing, we can calculate market shares for different products and use aggregated price-quantity data for estimation. Finally, BLP allows us to account for the potential endogeneity of prices.

While BLP enables more credible predictions in substitution patterns, estimating the non-linear parameters of the model is widely acknowledged as a formidable challenge. In our case, estimating the extensive set of parameters that capture covariances between random coefficients is particularly demanding because a large number of drug-specific price instruments would be needed. We address this by employing a novel set of moment conditions derived from our micro-level data on consumer reviews. These moments capture how the drug types chosen by the same user are correlated over time. They effectively identify covariances between random coefficients and facilitate BLP estimation in a manner akin to the use of second-choice data (Berry et al., 2004). We develop a procedure that allows us to utilize these moments when information on purchases is partially missing, which may occur because not all orders are reviewed or only a subset of all reviews is available. Our method yields significantly improved estimates for the non-linear parameters of the model in test simulations. Furthermore, it can find applicability in other settings where additional consumer-level information on repeated purchases is available. Such information can serve as an alternative to second-choice data, which often is not accessible. A particularly relevant scenario is when demand is estimated using data from an online marketplace, as reviews from its website can often be scraped at a low cost.

Our estimates reveal a significant degree of price sensitivity among drug users, with a median price elasticity for drug products estimated at -3.6%. We have identified four drugs characterized by a relatively high degree of substitution: amphetamine, hashish, marijuana, and MDMA. Importantly, we find substantial heterogeneity in substitution patterns. For instance, diversion ratios indicate that there is five times more substitution from amphetamine to MDMA than to α-PVP, despite the latter two drugs having roughly equal market shares. This shows that a model without consumer heterogeneity would yield inaccurate predictions regarding consumer responses to changes in drug prices.

We are able to validate our estimates by exploiting an exogenous supply-side shock that occurred during the period when we scraped Hydra. In the summer of 2019, the availability of hashish dramatically decreased due to a series of overseas operations targeting the trafficking of this drug. We find that our estimated model closely predicts the observed consumer response to increased prices.

We then employ our model to evaluate the outcomes of several counterfactual supply-side drug policies. First, we investigate the impact of cannabis legalization on the consumption of other drugs. Substitution can serve as a significant rationale for legalization if it leads to a reduction in the use of more dangerous drugs. We model legalization as a reduction in the price of cannabis, a phenomenon observed in studies following previous instances of legalization.[3] Our findings indicate that governments can achieve a reduction in the

[3] This approach is also valid for other aspects of legalization, such as diminished risks related to purchase and the elimination of the stigma of illegality, provided that their influence on utility is uniform across

consumption of the riskiest drugs, such as cocaine, but this reduction is accompanied by a significant increase in cannabis consumption. For instance, the model predicts that if the price of cannabis decreases by 50%, the use of other drugs will decrease by 15%, while cannabis use will increase by 320%. More broadly, we find in a series of experiments that for every four additional doses of cannabis used, approximately one less non-cannabis dose would be consumed. The gains from substitution toward legalized cannabis are also limited by the fact that a larger fraction of substitution occurs from medium-risk drugs rather than the most dangerous ones.

Second, we study the introduction of new drugs, a question of significant importance. In recent years, two categories of synthetic drugs, known as "synthetic cannabinoids" and "bath salts," have gained popularity in many countries. We study the impact of their introduction on overall drug use. To address this question, it is essential to consider that a portion of the demand for these new drugs represents substitution from preexisting drug types. We focus on bath salts, which have an extremely large market share in Russia, accounting for nearly half of all drugs sold. We simulate our model with all bath salts eliminated from consumers' choice sets. We find that the introduction of bath salts led to a 40% increase in total demand for illegal drugs. Thus, substitution from preexisting drug types was, in fact, limited, and the effect of these new drugs on overall drug use was significant. This result underscores that governments should allocate resources to prevent the emergence of new substances on the market.

Third, we apply our estimates to study the effects of targeted drug enforcement. We analyze how the demand for illegal drugs would be affected if a particular drug were eliminated. We conceptualize this scenario as an extreme case of successful supply-side interventions by the government. We observe that the impact on total consumption is least significant for drugs that have close substitutes, namely: amphetamine, MDMA, mephedrone, hashish, and marijuana. In contrast, our findings suggest the most substantial effects for drugs with no close substitutes, such as $\alpha-$PVP, cocaine, and opioids. Specifically, we find that the share of consumers who find a substitute is two times larger after eliminating amphetamine than after eliminating $\alpha-$PVP.

Finally, we study whether our estimates support the concern of Becker et al. (2006) that drug enforcement can increase the total revenue of the black market if demand for drugs is inelastic. We find that the effect on the total revenue is always negative but varies significantly across drugs. Specifically, we observe that targeting substances with many substitutes, such as amphetamine, is more likely to increase the total revenue of drug sellers. This is because enforcement increases the revenue from the substitutes of the targeted drug.

consumers and thus has a monetary equivalent.

1.1. Related literature

Demand for illegal drugs. Our contribution to the literature on the estimation of demand for illegal drugs is twofold. First, by utilizing data scraped from a large marketplace we obtain high-quality information about the consumption and prices of drugs.[4] Because of the illegal nature of the drug trade, researchers have generally been unable to access transaction data, which has long been recognized as a major problem (Manski et al., 2001).[5] 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; Van Ours and Williams, 2007), small-size experiments (Jofre-Bonet and Petry, 2008; Olmstead et al., 2015), or 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 low frequency, a number of methodological shortcomings (Manski et al., 2001), and overrepresents large transactions (Horowitz, 2001).

Second, we are the first to study demand for the full set of drugs popular in a particular market. To the best of our knowledge, we obtain the first estimates of price elasticities for new and highly popular synthetic drugs like mephedrone. Crucially, we study substitution between drug types that comprise nearly the whole drug market, while previous studies have predominantly considered substitution between just two drugs or sin goods (DeSimone and Farrelly, 2003; Anderson et al., 2013; Powell et al., 2018).[6]

See Gallet (2014) for a meta-analysis of the literature on demand for illegal drugs.

Drug policies. Our paper contributes to the literature on supply-side drug policies by presenting a structural model of the demand for various drug types. This allows us to address research questions pertaining to substitution and the effects of interventions on total drug use. Other structural models of the market for illegal drugs focused on particular drug types and did not take potential substitution into account (Kennedy et al., 1993; Galenianos et al., 2012; Adda et al., 2014; Mejia and Restrepo, 2016; Galenianos and Gavazza, 2017).

[4] 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).

[5] In some specific cases, researchers could utilize data from the regulated trade of drugs that are considered illegal in other contexts. For instance, Van Ours (1995) and Liu et al. (1999) employed data from actual transactions during the regulated opium trade of the early 20th century. Hollenbeck and Uetake (2021) estimated the demand for legalized marijuana using the BLP framework.

[6] Ramful and Zhao (2009) study the extensive margin of drug use for three drug types: marijuana, cocaine and heroin.

Moreover, a structural model allows us to study a range of counterfactuals, not only isolated large-scale shocks that occurred in the past, which are by nature very rare and thus provide limited insights for many important policies. This is in contrast to event studies that focused on particular supply-side interventions and their effects on drug use and crime (Dobkin and Nicosia, 2009; Dobkin et al., 2014; Moore and Schnepel, 2021).

The literature on supply-side policies has also investigated how the risks induced by policing, punishment, and incarceration affect the profits of drug dealers and the prices of illegal drugs (Levitt and Venkatesh, 2000; Kuziemko and Levitt, 2004). Several papers studied the effect of interventions on cartel violence (Angrist and Kugler, 2008; Dell, 2015; Castillo et al., 2020). Becker et al. (2006) provide a seminal theoretical analysis of drug enforcement.

Estimation of demand systems. We propose a new method to estimate nonlinear parameters in BLP. This problem presents a substantial challenge for researchers because it requires a large number of excluded IVs, and aggregate data often does not have enough variation. A potential solution is to use second-choice data (Berry et al., 2004; Conlon et al., 2021; Conlon and Gortmaker, 2023). Unfortunately, the availability of such data remains limited. Our method identifies non-linear parameters in BLP using correlations in choices across time, where choices are inferred from irregularly observed reviews. This approach can be particularly useful in the study of online marketplaces as review data can often be collected from these platforms at a small cost.

The rest of the paper is organized as follows. Section 2 describes the relevant aspects of 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

The market for drugs differs from other markets in several key aspects: consumption of products is associated with health risks and negative externalities, transactions are risky for market participants, and moral hazard is pronounced as contracts cannot be legally enforced. For researchers, another key feature of the drug market is its difficulty to observe. In this paper, we address this issue by leveraging a unique context in which the majority of the drug trade was concentrated on a single website called Hydra. We describe this online platform and the related context in this section.

2.1. Marketplace

The Hydra marketplace operated on the Tor network. It required a special browser for access and the government could not restrict access to it, unlike conventional websites. Similarly to other darknet markets, participation in the platform was anonymous. 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[7] in 2022. The unprecedented length of 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 yearly revenue of Hydra in 2020 to be $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., 2022).

In addition to the large proportion of the drug trade that operated through Hydra, another factor that makes it amenable to the current study is the nature of distribution, which enables us to estimate the market shares of various products in specific locations. Unlike most darknet marketplaces, which primarily deliver drugs through legitimate postal services, Hydra used a dead-drop distribution system (VICE, 2020). The system of dead-drops was first adopted by RAMP in response to a 2014 law that required the postal service to inspect packages for illegal substances (Saidashev and Meylakhs, 2021). To circumvent this, shops hired couriers to hide drugs throughout the city prior to purchase. The details of these hidden drugs would then be posted on the marketplace so that potential customers could select the listing that best suited their requirements. Appendix Figure F.2 provides an example of a page with listings. While a small proportion of drugs were still delivered via mail,[8] the majority of drugs sold for retail consumption were delivered via dead-drops. shops recruited couriers on the platform, posting job offers on the website.

Hydra provided mechanisms for shops to differentiate themselves from competitors. Similar to other darknet marketplaces (Janetos and Tilly, 2017), there was a reputation system. Buyers could review purchases, providing both a numeric rating as well as detailed text comments. In addition, there were marketing options for shops. One of the key forms of advertising that shops could engage in was purchasing one of the 20 positions on the main page

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

[8] Those were primarily drugs which are particularly difficult for law enforcement to detect such as LSD.

of the website (see Appendix Figure F.1 for an example). These positions were allocated via an auction and served to increase the visibility of the shops allocated these positions (Goonetilleke et al., 2022). These characteristics of shops appear to have been important factors in buyers' choice process and thus will be incorporated into our demand model in Section 4.

Finally, sales of fentanyl and several other synthetic opioids were prohibited on the marketplace. Thus, our analysis will not be informative of demand for this drug. Goonetilleke et al. (2022) provides a detailed discussion of the scope, structure, and rules of Hydra.

2.2. Drug types

In Table 1, we describe the characteristics of the most popular drug types on Hydra.[9] Illegal drugs can be categorized into three broad groups: those that increase the activity of the central nervous system (stimulants), those that decrease it (depressants), and those where the main effect is the altered perception of reality (hallucinogens). Common examples of stimulants are MDMA,[10] cocaine, amphetamine, and methamphetamine. Two other types of stimulants have high popularity in our data, mephedrone and $\alpha-$PVP.[11] These substances belong to the new family of drugs known as synthetic cathinones, which emerged in the late 2000s and are colloquially referred to as "bath salts."

Depressants include different types of cannabis, of which the two most popular ones are marijuana buds and hashish. Hashish is produced by compressing and processing cannabis plants. Depressants also include opioids, which are substances that produce morphine-like effects. Opioids, such as heroin and methadone, are commonly recognized for their potent effects and significant risks.[12] GHB is a substance that can be used for medical purposes but is also a popular recreational drug. Finally, popular hallucinogens in our sample include LSD and psilocybin.

Other categorizations of drugs are used. In particular, some drugs are considered "club" (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).

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

[10]MDMA is often referred to as ecstasy.

[11]Mephedrone is also known as 4-methylmethcathinone and often referred to as "meow meow." $\alpha-$PVP is also known as $\alpha-$pyrrolidinovalerophenone and often referred to as "flakka."

[12]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).

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: 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 are sourced from Nutt et al. (2007). Overdose ratios, also known as safety ratios, are defined as the ratio of the acute lethal dose to the dose most commonly used and are obtained from Gable (2004).

Table 1: Drug types most present on Hydra

Measuring the harmfulness of different drugs is non-trivial. One possible measure is the "overdose potential," which is defined as the ratio of the acute lethal dose to the dose most commonly used. However, this measure does not take into account overdose risks related to mixing with other drug types or the inability of consumers to control the exact dosage. It also ignores all kinds of risks not associated with overdoses. Therefore, we also consider the physical harm and dependence indexes provided by Nutt et al. (2007).[13] Based on all of these measures, heroin emerges as the most dangerous drug in our sample. Methadone and cocaine also are characterized by high levels of dependence and harm, while cannabis and MDMA have smaller risks according to these measures. Safety ratio and harm and dependence indexes are 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.

2.3. Production

Drugs differ significantly in production technology and whether they are imported or produced locally. From the perspective of the Russian, U.S., or European markets, some drug types are entirely imported. Production of cocaine requires coca leaves, a plant which is almost exclusively grown in Colombia, Peru, and Bolivia (UN Office on Drugs and Crime, 2022). Similarly, the production of heroin requires 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 mostly 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 that are imported from chemical suppliers in China (Baza.io, 2020).

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.

[13] These indexes are derived from averaged scores provided by surveyed experts, where a score of 0 indicates no risk, and scores of 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. In particular, the process of picking up drugs purchased on Hydra was risky for consumers because drug possession is illegal. The range of possible punishments depends on the amount registered during the arrest.[14] This can potentially affect the preferences of consumers, decreasing demand for dead-drops of large amounts. We address this possibility by including the size of the dead-drop in the set of product characteristics.

3. Data

3.1. Datasets

3.1.1. Listings

Our first source of data contains information on listings on Hydra. We collect this data by scraping the Hydra's website.[15] 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: preorder 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 will be deposited after the purchase is made. As is discussed in Goonetilleke et al. (2022), pre-order listings were more likely to be used for wholesale transactions or for more "exotic" drugs and thus constitute only a small fraction of all purchases. Further, they are only loosely connected to sales as posting pre-order listings did not imply any pre-commitment on the side of the shop. 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. Dead-drops are listed detailing the mode of hiding, amount (weight or

[14] The government defines several thresholds, which vary depending on the type of drug (Government of Russia, 2012). Among these thresholds, the one that is closest to retail purchases is the "significant amount" threshold. Consumers with an amount registered above this threshold can receive a prison sentence. Risks can be very high for all consumers, as the legal system tends to over-classify cases as offenses with the intent to supply.

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

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 F.3 for an example). We describe the details of data cleaning in Appendix Section A.2.

Definition of dose. Drug potency per gram can depend on the substance. Moreover, MDMA is sold both as pills and crystals, which complicates the calculation of market shares for this drug. Finally, GHB is typically sold in the liquid form. Thus, using the units listed by shops raises the issue of non-comparability. We normalize listed amounts using the "standard amount" for each drug. We discuss our definition of standard amounts in Appendix Section A.3. The chosen standard amounts and the distributions of quantities for different drug types are provided in Appendix Table A.2. For simplicity, we call standard amounts "doses" further in the text.[16]

3.1.2. Reviews

The second dataset we use is purchased from a private firm established in Pittsburgh, Pennsylvania, USA.[17] This dataset allows us to see a large subset of the customer reviews posted on the platform. For each review, we observe the associated text, the purchased product, the shop, the nickname of the reviewer, the time when the review was posted, and the numerical rating the buyer has given. We end up with approximately 215,000 reviews. We observe reviews for 784 shops on Hydra, which account for 47% of the shops in our listings data.

3.1.3. Supplementary data from Hydra

We use additional data sources to derive characteristics of products that are likely to be relevant from the perspective of consumers. 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). Considering that consumers may prefer shops with established reputations, we incorporate the duration of a shop's presence in

[16]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.

[17]The firm, which was spun out from the CyLab Security and Privacy Institute at Carnegie Mellon University, scrapes data from several dozen darknet marketplaces. This data was used in United Nations Office on Drugs and Crime (2021). Details about the project can be found in Soska and Christin (2015) and Christin (2022).

the marketplace into the model. To achieve this, we access historical data on the aggregate number of reviews for Hydra on a shop-drug level since late 2016, encompassing six different cities.[18] We use this information to identify the age of shops on Hydra.[19]

3.1.4. Demographic data

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 largest cities in the country. We exclude cities with a small presence of Hydra (defined as the ratio of listings to population). We also observe an unusually high presence in satellite cities around Moscow. We interpret this as evidence that dead-drops hidden there also serve consumers from Moscow. For this reason, we consider these locations to be the same market as Moscow. We use 34 large cities in our data.

3.2. Descriptive statistics

Table 2 presents summary statistics for the most popular drug types traded on Hydra, where listings were restricted to the cities of interest. In terms of total listings, the four most popular drug types are stimulants: mephedrone, amphetamine, $\alpha-$PVP, and MDMA. They are followed by marijuana, hashish, and cocaine. Other drug types had substantially lower popularity on Hydra. 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 around three times lower. Among drug types with large market shares, $\alpha-$PVP is the cheapest drug, with an average price per dose of $14.

The last column of Table 2 shows that each drug type could be purchased from a large number of shops. Goonetilleke et al. (2022) presents additional evidence that Hydra had a high degree of competition. This motivates our approach to restrict attention to the demand side only. Changes in demand should be close to the equilibrium change in consumption if supply of drugs was elastic.

Table 3 describes variation in prices of drug listings on Hydra. Several patterns are noticeable there. First, there is a large variation in price across shops. This suggests that the quality of products might vary across shops. To account for this, we include a set of proxies for quality in our demand model. In particular, we include a set of shop characteristics. Ap-

[18]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 information on prices, we cannot use it for demand estimation.

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

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. Data includes listings from 34 cities of interest. Prices are converted to USD using an exchange rate of 74 RUB per USD.

pendix Table A.3 presents summary statistics of variables describing shops on the platform. Second, the last column of Table 3 shows that the proportion of price variation occurring over time was the largest for hashish. This is explained by the policing shock to the supply of this drug that occurred in the sample period. In Section 4.4, we use this variation to validate our model estimates.

3.3. Proxies for sales

As we cannot directly observe sales on Hydra, we use instantaneous listings as our proxy for sales. To calculate market shares of different products, we assume that the number of listings with certain characteristics is proportional to the number of transactions with the same characteristics. Our assumption is motivated by the fact that depositing a dead-drop was expensive for shops, which is described in Goonetilleke et al. (2022). Therefore, we expect that posted instantaneous listings represent a strong commitment to sell.

The credibility of this assumption is supported by the strong correlation between listings and several proxies for sales on Hydra that are available on aggregate levels. First, as we observe rounded total shop deals for each shop, we can calculate the difference between the total deals at the end and the beginning of the observed period. Table 4 demonstrates that

Table 3: Variation in prices

Drug type	Price per gram Mean	Median	Std	Variation 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. Only the median quantity for each drug type is considered.

the correlation between the observed change in total shop deals and the number of listings is 0.7.

Second, the number of reviews in our data can serve as another proxy for sales of the shop. As can be seen in Table 4, the correlation between the number of reviews and the number of listings is 0.62. It is important to note that the observed correlations between listings and the two proxies for sales should be lower than the actual correlation between listings and sales due to the inherent noise in these proxies. In particular, the difference in deals is susceptible to large rounding errors[20] and the total number of reviews in our dataset suffers from incomplete coverage of scraping.

Finally, listings exhibit a strong time correlation with cryptocurrency inflows to Hydra. Flashpoint, Chainanalysis (2021) provide estimates of the monthly revenue of Hydra over time. These estimates are based on counting transactions in the Bitcoin blockchain to wallets that were identified by analysts as belonging to Hydra. Appendix Figure A.1 demonstrates the similarity between the dynamics for listings and cryptocurrency inflows.

We need to assume that listings are proportional to transactions as there were several potential mechanisms that could make the number of listings differ from the number of sales on a particular day. First, it is highly possible that it took several days for a particular listing to be sold. Second, each courier likely deposited several dead-drops in the same neighborhood. If a shop had multiple dead-drops of the same drug type, amount, hiding mode, and price in the same approximate location, these dead-drops appeared on the

[20]For example, the platform would display the same number of total deals for shops with 149,000 and 100,000 actual sales.

Table 4: Correlations between different proxies for sales

	Listings observed	Cumulative deals	ΔCumulative deals	Reviews observed
Listings observed	-	0.74	0.70	0.62
Cumulative deals	0.74	-	0.93	0.65
ΔCumulative deals	0.70	0.93	-	0.70
Reviews observed	0.62	0.65	0.70	-

Correlations are reported on shop level.

marketplace under the same listing.[21] Therefore, one listing could potentially correspond to several transactions. Third, a particular dead-drop could remain unsold, resulting in no transactions. Fourthly, 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.

As our estimation procedure is based on market shares of different drug types, it would be affected if the ratio of listings to dead-drops was different across drug types. In particular, it is possible that cases where several dead-drops of the same weight and hiding type are hidden in the same neighborhood are more common for more popular drug types. If this is the case, listings may disproportionally underestimate transactions for more popular drugs. To examine this possibility, we employ reviews as an alternative proxy for sales. Appendix Table A.5 presents the market shares of different drug types, as defined using both listings and reviews. While we observe some minor differences, overall, we find that the shares calculated using both methods are very close to each other.

3.4. Proxies for quality

Potential heterogeneity in unobserved quality creates an identification problem in demand estimation. Quality is likely to be positively correlated with price and demand, so not including quality in the model can lead to an underestimation of the sensitivity of demand to price. In the context considered here, "quality" is likely to be related to purity and potency of the drug or ease of recovering the dead drop. To mitigate the issue of confounding quality, 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

[21]This feature of the platform was described in the shop's instructions, which were published on the website.

users on online platforms are likely to be a function of both quality *and price*.[22] Luca and Reshef (2021) find that ratings can be highly responsive to prices: they estimated that a price increase of 1% leads to a 3%-5% decrease in 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). Average ratings of shops and products that were displayed by the platform were even higher, as the platform automatically assigned the highest rating to an order if the consumer did not rate it. Thus, ratings can contain little information about underlying product quality.

To address the issue, we construct another proxy for quality by employing natural language processing techniques. We determine the sentiment of each review in our dataset. Filippas et al. (2022) suggest that written feedback can provide more information about fundamentals of obtained quality. We find evidence that supports this idea in the context of Hydra. Appendix Table A.4 shows that an average review consists of 16 words, indicating the potential informativeness of the reviews. Moreover, Appendix Table B.1 provides examples of reviews that have negative sentiment despite the highest possible rating being given by the consumer. We utilize the average sentiment score of reviews for each specific shop as an additional proxy for quality. Further details of the text analysis are provided in Appendix B.

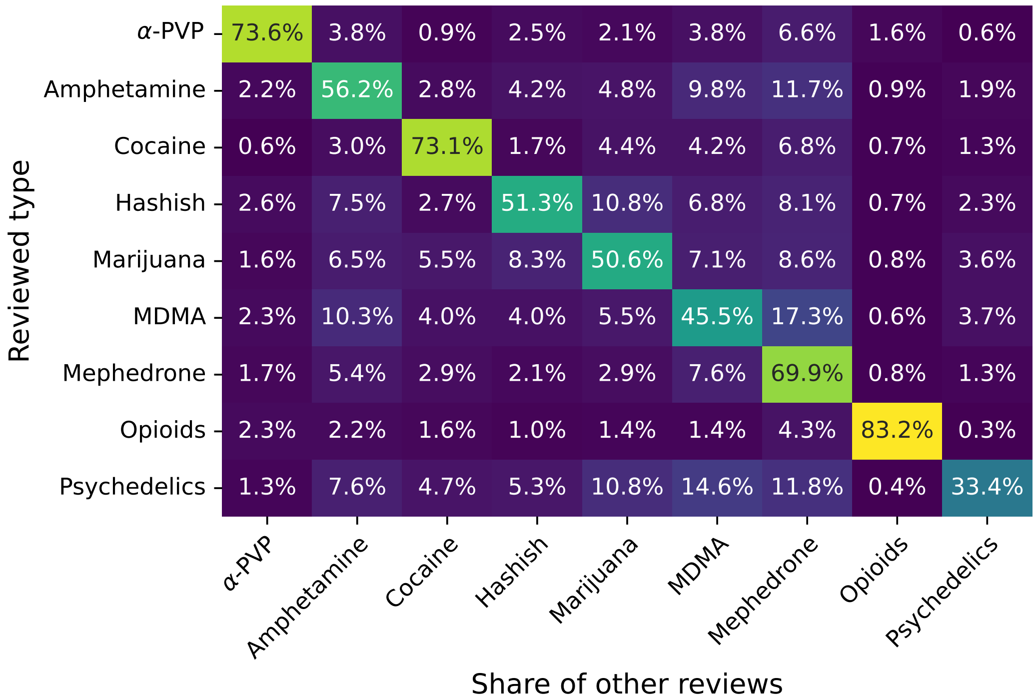
3.5. Reviewer behavior

Data on reviews provides us with a unique opportunity to elicit information about the behavior of individual drug consumers. We identify reviews made by the same consumer using usernames displayed on the platform. Appendix Table A.4 presents summary statistics for our review data. As we only observe a subsample of reviews on the platform, most of the reviews are not included in our sample, and some users appear in our data only once. We have identified 43,381 users who have left more than one review in our dataset. Among them, almost half reviewed different types of drugs, which suggests the significance of substitution for illegal drugs. For users with more than one review, we have a total of 132,855 reviews.

We utilize these cases to estimate the correlation between choices made by the same consumer over time. Figure 1 presents a matrix of drugs' market shares conditional on reviewing a particular drug. This matrix shows the expected probability that a different

[22]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.

Figure 1. Conditional shares of different drug types



Note: Opioids include heroin and methadone. Psychedelics include mushrooms and LSD.

random review by the same user is for drug k conditional on observing a random review for drug j.[23]

Several patterns are noticeable in Figure 1. First, the diagonal elements of the matrix are the largest. This means that conditional on having consumed a drug, most consumers purchase the same drug in other periods. However, the degree of attachment is different between drugs. For example, the share of opioids is very large conditional on reviewing an opioid, despite opioids having a small market share. Cocaine consumers also have a high probability of consuming cocaine in other periods. This is in line with the dependence index (DI) provided in Table 1, which is the largest for opioids and cocaine (heroin has DI equal to 3.0, methadone has DI 2.08, and cocaine has DI 2.33). Moreover, the ranking of drugs

[23]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:

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

For $j = k$, the elements are $P_{jj} = \big(\sum_{i:R_i>1} R_{ij}(R_{ij} - 1)/(R_i - 1)\big)/\big(\sum\limits_{i':R_{i'}>1} R_{i'j}\big)$. 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.

by dependence index coincides with the ranking by diagonal elements for the most popular drugs: amphetamine (DI 1.67), cannabis (DI 1.51), and MDMA (DI 1.13). At the same time, while DI is not available for bath salts, $\alpha-$PVP and mephedrone, our estimates show that consumers of these drugs have a high degree of attachment. This suggests that dependence on bath salts is comparable to that of cocaine.

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

Third, we see that substitution is more likely to happen within certain groups of products. The following group of drugs is particularly noticeable: amphetamine, MDMA, and mephedrone. For example, for a consumer who purchased amphetamine the two other most likely choices are mephedrone (11.7%) and MDMA (9.8%). Similarly, for a consumer who purchased MDMA the two other most likely choices are mephedrone (17.3%) and amphetamine (10.3%). Finally, for a consumer who purchased mephedrone the two other most likely choices are MDMA (7.6%) and amphetamine (5.4%). The similarity of their effects might explain this pattern. In Section 2.2, we discuss that all these drugs are stimulants, have the same mode of administration, and fall into the category of club drugs. Medical studies also found strong similarities in the effects induced by these drugs (Poyatos et al., 2022). However, the observed substitution patterns would be hard to predict ex-ante based on characteristics of drugs. For example, $\alpha-$PVP is another popular bath salt with similar characteristics, but consumers who purchased any of the three drugs switch to it much less often.

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.[24] At the same time, these two drugs have substantial flow to and from the three stimulants mentioned above.

In Figure 1, we provide novel evidence of large taste heterogeneity between drug consumers. The observed patterns have interpretation in terms of drug properties, and we can expect them to affect how consumers substitute between drug types. 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.

[24]The same is not true for marijuana, for which the second choice is mephedrone. This can be explained by the fact that hashish was disappearing from the market during the period we observe (see Section 4.4).

4. Demand Model

To account for taste heterogeneity documented in Section 3.5, we use the BLP approach, which was introduced in Berry (1994) and Berry et al. (1995) and has become the workhorse method for demand estimation. Because we are particularly interested in substitution between different drug types, we define products as individual drug types. The indirect utility that a consumer i can obtain from buying a drug of type j in city c in period 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 in period 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.[25] We also include date-level fixed effects to account for growth of the platform and potential differences in drug consumption across seasons and days of the week. We include time trends for mephedrone and amphetamine because these drugs exhibited growth in popularity over our sample period. Preferences for linear characteristics p_{jct} and x_{jct} are given by α and β and are the same for all consumers.

We include random coefficients for dummies for several of the most popular drugs or broader drug categories $g \in G$. These coefficients are assumed to be constant across all time periods. This is the key component of the model that allows us to incorporate 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 $\Sigma^T\Sigma$. As 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. Because of their

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

similarity, we use a common dummy variable for the two types of cannabis: hashish and marijuana. Otherwise, we choose to not impose any *ex-ante* restrictions and define g to be individual drug types for $\alpha-$PVP, amphetamine, cocaine, MDMA, and mephedrone.

The interpretation for 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 to other drug types. However, 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 have a large draw of λ^k as well. In this case, a large proportion of consumers of j would be willing to substitute from drug j to 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. Heterogeneity in the consumption of drugs also is widely discussed in studies of addiction.[26]

The unobserved product characteristics ξ_{jct} are common across all agents for each market-drug combination and can be correlated with p_{jct}. This accounts for potential endogeneity, which is possible, for example, because of unobserved quality or if 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: $U_{i0ct} = \varepsilon_{i0ct}$. In each period, the consumer chooses the option that provides the highest indirect utility.

Discussion. We employ a semi-parametric approach and include dummies for the most popular drug types to account for consumer heterogeneity. We choose this approach because it is inherently challenging to identify a small set of characteristics that would adequately capture the relevant differences between drugs. This is due to a combination of issues. To begin with, there is no consensus on how to measure attributes such as “pleasure,” which likely play a significant role in determining drug consumption. Moreover, in cases where a well-defined measure does exist, such as the overdose ratio, it is not be available for all types of drugs. Finally, the characteristics provided in medical and chemistry literature are typically categorical and describe the grouping of substances into broader categories. The example of $\alpha-$PVP highlights that a simple categorization by psychoactive class cannot adequately capture the relevant substitution patterns. At the same time, introducing dummies for additional categorizations would rapidly inflate the dimensionality of the characteristic space.

[26] See Reuter (2010). In particular, one can expect that males consume more drugs (Pacula, 1997) or that younger people may have a preference for party drugs.

4.1. Micro moments

Identification of the non-linear parameters in the mixed logit model is a well-known challenge. In our case, Σ has a particularly large dimensionality and has $K(K+1)/2 = 21$ parameters to estimate. Theoretically, this can be done using aggregate data alone. However, there are two restrictive requirements for this. First, we would need a large variation in the data or many observed markets to have enough statistical power. Second, and perhaps more restrictive, we would need a large number of excluded instruments shifting prices of individual drug types. This is particularly challenging in the context of illegal drugs, where some of the traditionally used instruments such as taxes, tariffs, and firm-level costs are not available because of the illegal nature of the market. One way to simplify estimation of Σ is to impose additional restrictions, for example, by assuming that random coefficients are uncorrelated. However, our empirical analysis of reviews suggests that correlation between preferences for particular drug types is crucial and the model is likely to predict incorrect substitution patterns if it does not account for it.

This problem can be addressed by utilizing additional micro-level data when available (Chintagunta and Dubé, 2005; Bayer et al., 2007). In particular, micro-level data can be incorporated as additional moment conditions. Moment conditions often utilize variation in choice sets, e.g., when consumers are asked about their second choices by a survey (Berry et al., 2004; Conlon et al., 2021), or the relationship between choices and demographics of particular consumers (Petrin, 2002). We do not observe demographics of anonymous users. However, we observe the reviews they post on the website. Section 3.5 provides evidence that a choice in a particular period has substantial predictive power about the consumer's choices in other periods. Our demand model allows for such patterns through random coefficients that are fixed across periods. Thus, the panel structure of our review data can help identify the covariances between random coefficients.

We capture correlation in tastes for particular drug types by matching comovements 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:

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

Intuitively, if consumers who like drug j usually like drug k, then $R_{ij}R_{ik}$ should be larger on average, all else equal. These moments are also related to conditional market shares, as can be seen from equation 1. Because our sample is subject to selection as it only has users with at least one review observed, the appropriate model counterpart of these quantities 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 left by consumer i.

To generate these values using our demand model, we must account for two possibilities. 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 periods over which consumers can make purchases and leave reviews. We assume that each purchase is reviewed randomly. The probability of leaving a review conditional on a purchase is allowed to depend on the drug type and equals π_j^{review}.[27] We 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.[28] The product of these numbers $\pi_{jt} = \pi_j^{review}\pi_t^{scrape}$ is the probability that a purchase is converted into a scraped review. Therefore, the probability of observing a review by user i for drug j at period t equals $\mathbb{P}(R_{ijt} = 1) = \pi_{jt}s_{ijt}$, where s_{ijt} is the predicted probability that consumer i purchases j in period t.

We can use this to find the expectations for particular agents. First, the expected product of total reviews for consumer i is

$$\begin{aligned}\mathbb{E}\Big[R_{ij}R_{ik} \mid i\Big] &= \mathbb{E}\Big[\big(\sum_{t=1}^{T} R_{ijt}\big)\big(\sum_{t=1}^{T} R_{ikt}\big) \mid i\Big] = \sum_{t_1,t_2}\mathbb{E}\Big[R_{ijt_1}R_{ikt_2} \mid i\Big] \\ &= \sum_{t_1\neq t_2}\pi_{jt_1}\pi_{kt_2}s_{ijt_1}s_{ikt_2} + I(j=k)\sum_t \pi_{jt}s_{ijt}.\end{aligned} \tag{6}$$

Second, the probability of selection into the observed sample equals

$$\mathbb{P}\big(R_i > 0 \mid i\big) = 1 - \prod_{t=1}^{T}\Big(1 - \sum_{j=1}^{J}\pi_{jt}s_{ijt}\Big). \tag{7}$$

The moments defined by equation 5 can be approximated using averages over N simulated

[27] Probability of reviewing can be different for different drug types, for example, if people exert the effort to review a purchase more often for more expensive drug types.

[28] The main reason why scraping coverage fluctuated is that the data provider used a varying number of active scraping bots. See Section 2.4 for a discussion of our review data.

consumers:[29]

$$\mathbb{E}\Big[R_{ij}R_{ik} \mid R_i > 0\Big] \approx \frac{\frac{1}{N}\sum_{i=1}^{N}\mathbb{E}\big[R_{ij}R_{ik} \mid i\big]}{\frac{1}{N}\sum_{i=1}^{N}\mathbb{P}\big(R_i > 0 \mid i\big)}. \tag{8}$$

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 observed reviews for day t and type j, N is the total market size, and s_{jt} is the market share of drug j in period t respectively.[30]

We split time into $T = 31$ discrete periods, where each period corresponds to one of the days where listings were scraped. Because scraping happened at varying frequency, our time periods have varying lengths. In Appendix C.2, we present the details of how we apply equations 6 and 7 to this case.

4.2. Estimation

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

It is convenient to 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 the component that 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

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

Each value of Σ defines a distribution $F(\mu|\Sigma)$ of idiosyncratic utilities. The predicted share

[29] 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 periods.

[30] 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.

of consumers in city c who purchase product j in period t equals

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

and can be approximated by numerical integration.[31] The system defined by equation 11 can be inverted (Berry et al., 1995), that is, values $\delta_{jct}(\Sigma)$ can be found such that predicted market shares match the observed market shares. We then can 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 is outlined in Algorithm 1 and is similar to the procedure described in Conlon and Gortmaker (2023) for survey-type micro moments. Our code is based on the PyBLP package (Conlon and Gortmaker, 2020).[32]

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 $g(\Sigma)'Wg(\Sigma)$.

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

In Appendix Section C.1, we show that our micro moments substantially improve estimation precision in test simulations compared to the standard BLP estimation procedure. We use the optimal weighting matrix W_B for BLP moments. We use diagonal weighting (Altonji and Segal, 1996), with matrix W_M that scales each moment by its variance predicted by the logit model. We simulate $N = 100,000$ agents, with the number of agents from each city being proportional to the corresponding market size. In Appendix Section C.3, we provide analytical expressions for gradients, which enable a substantial reduction in estimation time.

We include all pairs of drugs for which we have random coefficients in the set of product pairs P for constructing our micro moments. Because we use a common dummy for hashish and marijuana, we structure our moments for cannabis in the same way, considering products

[31] We use 1,000 Halton draws for numerical integration.

[32] We are extremely grateful to Jeff Gortmaker for helpful suggestions about using PyBLP for our purposes.

of reviews for cannabis and reviews for other drugs in the moments. Thus, we have $K(K+1)/2$ moments, and the parameters of the model are exactly identified.

We include several different variables in the set of instruments Z. First, we use prices in other geographic markets in the same period (Hausman et al., 1994; Nevo, 2001). Second, we use the "differentiation IVs" of Gandhi and Houde (2019), which measure the extent to which observed product characteristics distinguish each product from others in the market. Third, we use several instruments that measure the degree of competition in each market, such as the number of listings and the number of shops. Fourth, we use distance to the nearest port, motivated by the fact that some drugs are entirely imported from abroad and the cost of within-country transportation increases with distance from the point of entry (see the discussion in Section 2.3).[33]

Because we allow for an outside option, we need to define the total market size to calculate market shares. In Section 3.3, we discuss our assumption that the number of listings is proportional to the number of transactions and provide supporting evidence. To define the market size in terms of transactions, we need to calculate the coefficient of proportionality between listings and transactions. We use change in shop-level cumulative deals over the observed period for that and find the ratio of daily transactions to listings to be approximately equal to 0.7. We assume that each person between 18 and 45 can consume drugs 1 time per month and 1 standard purchase is enough to consume drugs 3 times.[34] This is motivated by the data on mortality causes in Russia, where we find that the majority of deaths associated with drug consumption are of individuals aged between 18 and 45. We present the details of our definition of the market size in Appendix Section D.

4.3. Estimates

Table 5 presents point estimates and standard errors for the linear parameters. The first two columns provide the estimates from the standard logit model for comparison. We find a negative relationship between demand and price. We discuss the implied price elasticities further in this section. The estimates for other linear coefficients have interpretable parameters. In particular, we find that consumers prefer the hidden and magnet delivery methods over the third hiding method, dug in the soil. This is realistic, given that retrieving dead-drops from soil is riskier and less convenient. This is consistent with how shops advertised their goods on Hydra, as can be seen in Appendix Figure F.4. We find that consumers had

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

[34] 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.

Table 5: Coefficient estimates with standard errors

	Logit		Mixed logit	
	Coef.	S.E.	Coef.	S.E.
Price	-0.219	0.008	-0.243	0.032
Magnet	1.240	0.097	0.775	0.251
Hidden	0.548	0.072	0.799	0.360
Crystal form	2.417	0.122	0.148	1.143
Very high quality	0.445	0.087	0.600	0.176
High quality	-0.492	0.085	-0.160	0.260
Product rating	0.083	0.029	0.149	0.045
Reviews sentiment	0.156	0.027	0.049	0.056
Shop age	-0.024	0.003	-0.023	0.010
Shop rating	0.036	0.015	0.034	0.027
"Trusted seller"	0.710	0.065	0.680	0.232
2 doses	-1.013	0.138	-1.433	0.347
3 doses	-1.783	0.164	-2.082	0.530
4 doses	-1.776	0.141	-2.178	0.474
FE	Date		Date	
Markets	1,054		1,054	
Obs.	12,203		12,203	

a preference for drugs listed as "very high quality."[35] However, we find that reputation measures, such as review sentiment and product and shop ratings, have a relatively small effect on utility. At the same time, the label of a trusted shop, which could be purchased by shops that met a set of criteria, had a substantial positive effect on utility. Finally, because our demand model considers price per gram, we find that consumers prefer smaller dead-drops, other things equal. This can be rationalized by buyers facing budget constraints or incurring inventory holding costs. It can also be rationalized by the risks associated with purchasing larger quantities of drugs, as discussed in Section 2.4.

Figure 2 shows the matrix of covariances between random coefficients. Our findings are consistent with the evidence from reviewing behavior we discuss in Section 3.5. First, we find substantive variances for each random coefficient, which corresponds to our finding that consumers most often review the same drug in different periods. Second, we find relatively higher variance for amphetamine, mephedrone, $\alpha-$PVP, and cocaine. We find lower variance for MDMA and cannabis, which is consistent with both smaller attachment found in review

[35] The platform introduced quality labels, VHQ (very high quality) and HQ (high quality), which represented substance purity levels above 98% and 95%, respectively. Although shops self-reported these labels, Hydra supposedly conducted random tests to ensure that the drugs sold met these standards (Goonetilleke et al., 2022).

Figure 2. Estimated covariances of random coefficients: $\Sigma^T\Sigma$

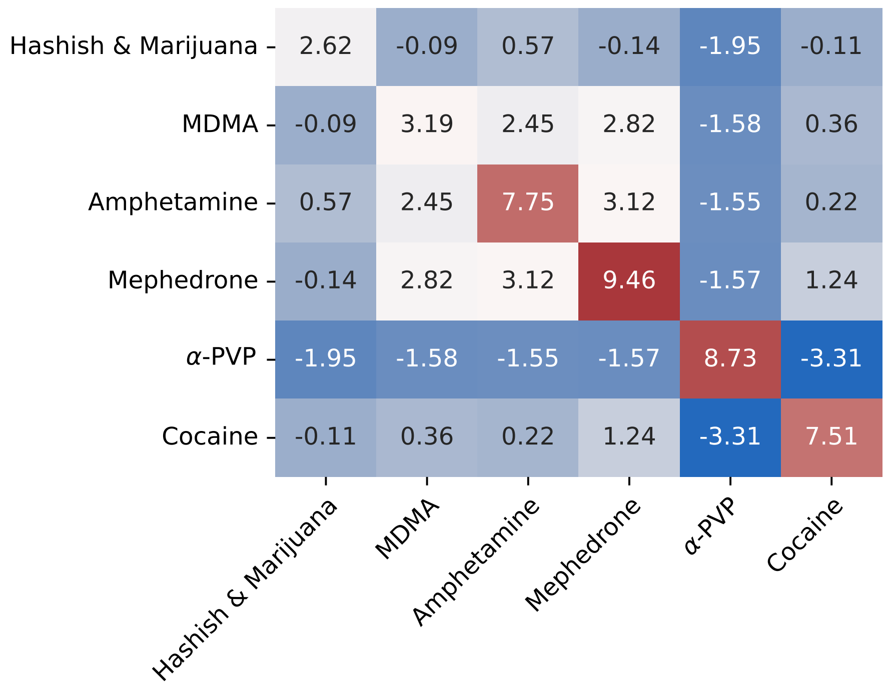


Figure 3. Estimated correlations of random coefficients: $corr(\lambda^j, \lambda^k)$

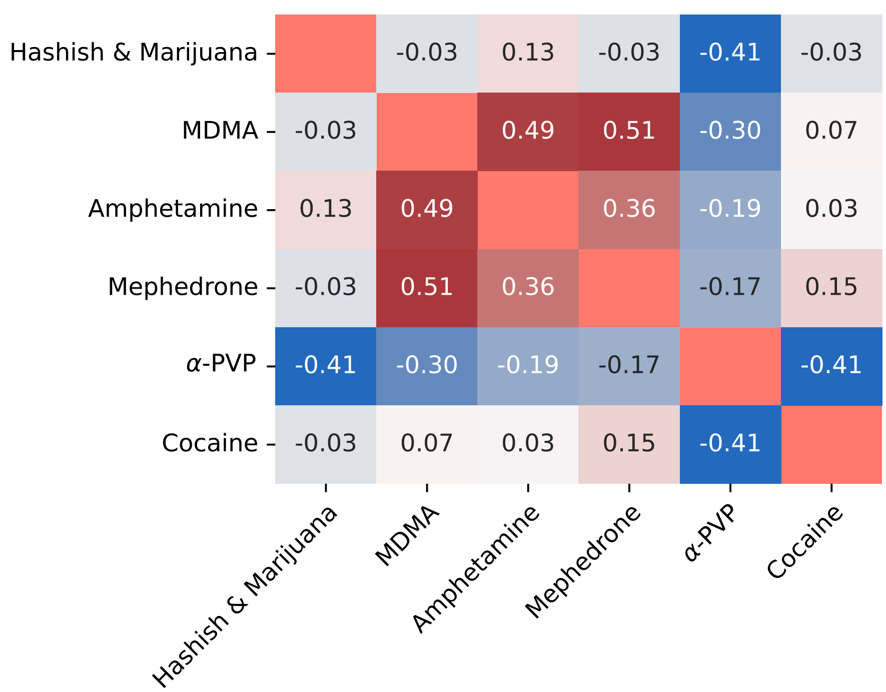
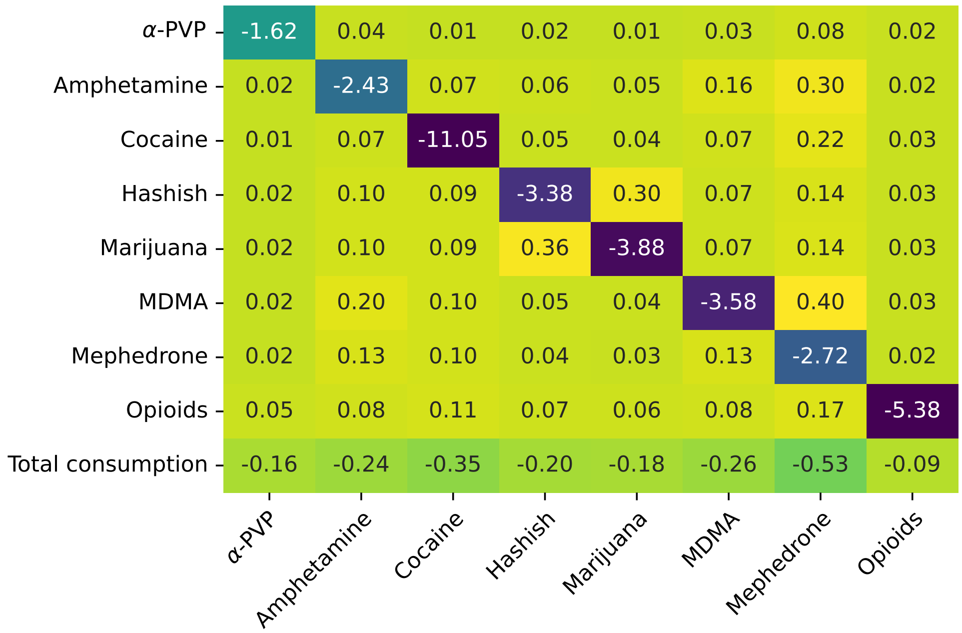


Figure 4. Median cross-price elasticities of demand, $\varepsilon_{jk} = \dfrac{\partial s_{jct}}{\partial p_{kct}}$



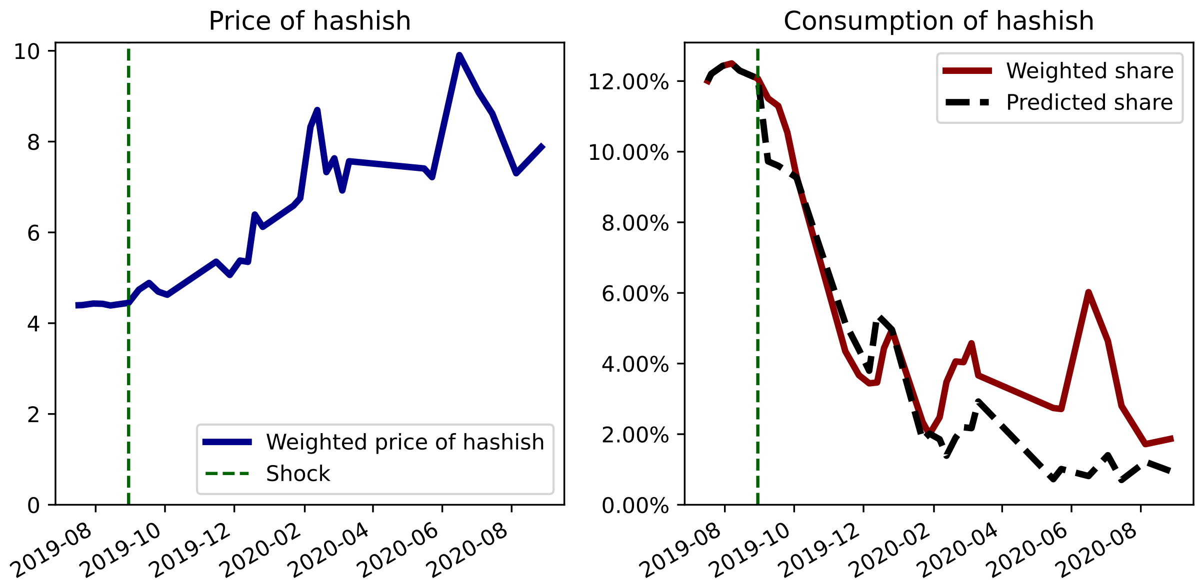
data and lower dependence indexes for these drugs.

Figure 3 shows estimated correlations between random coefficients. Consistent with our discussion in Section 3.5, we find that taste shocks are positively correlated for three stimulants: amphetamine, MDMA, and mephedrone. At the same time, we find a negative correlation between the random coefficient for $\alpha-$PVP and the random coefficients for all other drugs. This is in line with the observation that consumers who reviewed $\alpha-$PVP rarely review any other drug type.

Figure 4 presents median cross-price elasticities in all markets, where a market is defined as a city-period combination. Appendix Figure E.1 also shows the distributions of own-price elasticities for the eight most popular drug types. Several factors determine the scale of elasticity. First, products with many close substitutes should have more elastic demand. Second, products with high attachment (variance of the corresponding random coefficient) should have less elastic demand. Finally, models built on the logit framework tend to predict higher elasticity for more expensive products. We find the lowest own-price elasticity for $\alpha-$PVP, which can be explained by a combination of its high attachment and the relatively low price for this drug. Amphetamine, MDMA, and mephedrone have relatively small elasticities, which can be explained by the fact that each of them has close substitutes. We find the highest own-price elasticity for cocaine, which is likely explained by its high price.

Meta-analysis of Gallet (2014) reports that the median price elasticity obtained in studies

Figure 5. Actual and predicted consumption of hashish



on demand for drugs is -0.33, which is lower than the own-price elasticities we obtain. However, as discussed in Section 1.1, previous studies typically relied on crude proxies for drug consumption and lower-quality price data. Our estimates are close to Miravete et al. (2018), who find an average elasticity of demand for hard liquor of -2.8. Moreover, we are able to validate our estimates for price sensitivity by examining the effects of an exogenous supply shock, as discussed in Section 4.4.

Estimates for cross-price elasticities reflect our findings in Sections 3.5 and 4.3. In particular, an increase in the price of hashish is predicted to have the greatest impact on the demand for marijuana, and vice versa. An increase in the price of mephedrone should have the largest effect on demand for MDMA and amphetamine. The same is true for price changes affecting these two drugs: consumers will be more likely to substitute to the other two stimulants we have identified as related.

4.4. Validation: hashish shock

In 2019, increased enforcement targeting the production and trafficking of Moroccan hashish substantially decreased the supply of this drug in the European markets (EMCDDA and Europol, 2020). This coincided in time with a major hashish seizure within Russia (TASS, 2019). These shocks were followed by a significant increase in the price of hashish on the Russian drug market (FilterMag, 2020). Because this price change can be attributed to particular shocks of supply and, therefore is unlikely to result from a shift in demand, we use it to validate our model estimates.

Figure 5 shows predicted demand for hashish given the observed prices on the market, where values of ξ_{jct} are fixed at the average over the period preceding the shock for each product-market combination. Our model closely predicts the decline in hashish consumption for the first four months after the price starts to go up. Over time, the quality of prediction declines, which can be explained by the unaccounted effect of demand-side shocks accumulating over time. However, even in the long run, the fit of our prediction is reasonably good.

5. Effects of Interventions

We employ our model of demand for illegal drugs to assess the effects of drug policies accounting for substitution to other drug types.

5.1. Cannabis legalization

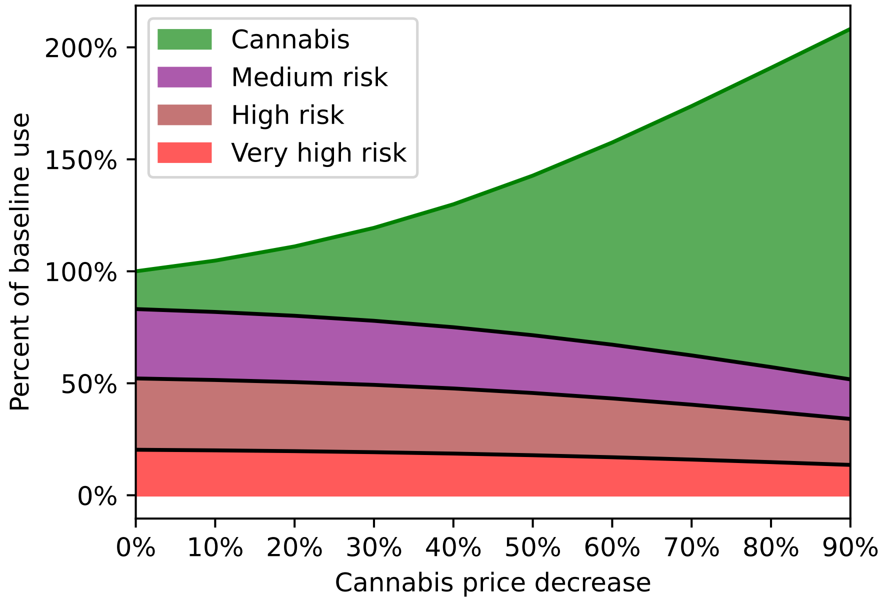
Cannabis legalization is one of the most discussed drug policies, recently adopted by various jurisdictions in the U.S. and around the world. The extent of legalization can vary; some jurisdictions have legalized only the medical use of marijuana while others have legalized recreational use as well. 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.

While legalization stems from various motivations, including the reduction of incarceration and policing costs, one widely discussed aspect is its potential impact on the use of other drugs. Previous studies have primarily focused on the effect of legalization on opioid consumption, driven by the high mortality associated with them and the potential for marijuana to serve as a substitute for prescription opioids in the treatment of chronic pain.[36] State-level event studies provide mixed evidence regarding the impact of legalization on opioid use. Bachhuber et al. (2014), Powell et al. (2018), Chan et al. (2020) have reported that legalization 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.

This aligns with our analysis of drug reviews in Section 3.5, where we find that consumers who purchase opioids rarely review cannabis and other drugs. Thus, cannabis is unlikely to

[36] Hurd et al. (2019) suggest that cannabis also can alleviate the symptoms of opioid use disorder.

Figure 6. Cannabis prices and predicted drug use



Note: This plot shows predicted consumption of different drug groups when the price of cannabis (hashish and marijuana) decreases by $x\%$. Very high-risk drugs include $\alpha-$PVP, cocaine, and opioids; high-risk drugs include mephedrone and stimulants not listed as medium-risk drugs; medium-risk drugs include amphetamine, GHB, MDMA, LSD, and other psychedelics.

function as a substitute for opioids, and legalization has low potential to decrease their use. However, our analysis suggests larger substitutability between cannabis and other drugs, particularly amphetamine, cocaine, and MDMA. Consequentially, legalization might have the potential to reduce the consumption of these drug types. This aspect could serve as a significant motivation for legalization, as the risks associated with cannabis are likely to be smaller than those associated with other drugs.

However, this benefit should be weighed against the potential increase in cannabis consumption. We apply our model to quantify the trade-off between the consumption of cannabis and the consumption of other drugs, and whether substitution towards marijuana happens from drug types with large or small harm.

We model legalization as a reduction in the price of cannabis. This has two complementary interpretations.[37] First, legalization was found to decrease cannabis prices in the U.S. (Anderson et al., 2013) and Canada (Hall et al., 2023). The production costs of legal marijuana are known to be very low, and a price decrease can occur after legalization because sellers do not incur costs and risks associated with illegal production, transportation, and

[37]This exercise ignores the effects of legalization that are not directly related to the demand for drugs. For example, Adda et al. (2014) and Gavrilova et al. (2019) study the effect of legalization on crime.

Table 6: Cannabis prices and predicted consumption change

	10.0% reduction	25.0% reduction	50.0% reduction	75.0% reduction	90.0% reduction
Panel A: Change in use					
α-PVP	-0.8%	-2.5%	-7.8%	-17.4%	-25.0%
Amphetamine	-1.8%	-5.7%	-16.2%	-31.5%	-42.0%
Cocaine	-1.8%	-5.5%	-15.6%	-30.5%	-40.8%
Hashish	31.6%	99.6%	289.1%	555.0%	720.9%
Marijuana	40.3%	126.5%	357.5%	699.3%	940.1%
MDMA	-1.8%	-5.6%	-16.1%	-31.6%	-42.2%
Mephedrone	-1.2%	-3.8%	-11.7%	-24.5%	-33.9%
Non-cannabis use	-1.5%	-4.9%	-14.0%	-28.0%	-37.8%
Cannabis use	35.8%	112.7%	322.3%	625.0%	827.2%
Total use	4.8%	15.0%	42.7%	82.2%	108.2%
Panel B: Change per 1 dose decrease in use of non-cannabis drugs					
Cannabis use	4.7 doses	4.7 doses	4.7 doses	4.5 doses	4.4 doses
Total use	3.7 doses	3.7 doses	3.7 doses	3.5 doses	3.4 doses

sale (Caulkins, 2010). The second interpretation is that many of the effects of legalization on consumers, such as diminished risks related to purchase and the elimination of the stigma of illegality, can be considered equivalent to a reduction in price. If the effect of these factors on indirect utility from marijuana consumption is positive and homogeneous across consumers, then it is equivalent to a price reduction.

In practice, policymakers often choose policies that limit the extent of the price reduction after legalization.[38] The governments could achieve further price decreases by setting lower taxes and increasing the number of licenses granted. For this reason, we consider a range of counterfactual price reductions from the current price levels of marijuana and hashish. Figure 6 shows predicted consumption of cannabis and other drugs, where we group drugs by estimated risk using the harm index from Nutt et al. (2007).[39] Table 6 shows predicted consumption for individual drug types.

We find that the government can achieve significant success in reducing the consumption of more dangerous drugs. However, this will be accompanied by a substantial increase in cannabis consumption. For instance, if the price of cannabis falls by 50%, the use of other

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

[39] We include $\alpha-$PVP in the list of high-risk drugs because Patocka et al. (2020) reports substantial risk of overdoses from this drug.

drugs will decrease by 14%, while cannabis use will increase by 322%.

To predict the absolute effect of legalization, we would need to estimate the associated price reduction. This number depends on the government's choices and consumers' utility costs associated with illegality and thus is hard to determine. However, Panel B of Table 6 shows that the relative change in use remains approximately consistent across a range of experiments. To achieve a reduction in the consumption of other drugs by one dose, society would need to accept 4.5 additional doses of cannabis. Therefore, the relevant policy consideration is whether the average social cost of the use of one dose of other drugs exceeds the social cost associated with the use of 4.5 doses of cannabis.

We can also observe that gains from substitution can be limited due to the fact that the primary substitutes for marijuana and hashish are typically considered lower to medium-risk drugs. Figure 6 illustrates that substitution primarily occurs with the least dangerous drugs. Panel A of Table 6 indicates that an increase in the availability of cannabis should have the most significant impact on the demand for MDMA and amphetamine, while its effect on $\alpha-$PVP would be relatively smaller. Thus, the potential benefits of substitution toward legalized cannabis are constrained because the reduction in consumption is more pronounced for drugs with medium risks rather than those with high or very high risks.

5.2. Introduction of new drugs

As discussed in Section 3.2, the two new drugs, mephedrone and α-PVP, had significant market shares on Hydra, accounting for 28% and 11%, respectively. These drugs fall under the category of synthetic cathinones, commonly referred to as "bath salts" (Soares et al., 2021). They can be considered a part of the broader phenomenon of "legal highs." Legal highs are newly synthesized substances that mimic the effects of conventional drugs.[40] These substances typically maintained legal status for several years before governments adjusted legislation to ban them. Another prominent category of legal highs is "synthetic cannabinoids," which gained popularity in the U.K., U.S., New Zealand, and several European countries Peacock et al. (2019).

The introduction of these products to the market potentially increased total drug consumption. First, the price of these substances might be lower than that of traditional drugs. Second, these new substances might possess characteristics different from those of "established" illegal drugs, making them attractive to some of the consumers who previously did not purchase any drugs. We are unaware of any attempts to estimate the effect of emerging drugs on drug use. This question holds significant policy implications, as governments may

[40] 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 after that.

Table 7: Effect of introduction bath salts on demand

Drug type	Estimated effect
Amphetamine	-17.0%
Cocaine	-11.9%
Hashish	-8.0%
LSD	-13.1%
Marijuana	-9.3%
MDMA	-22.7%
Opioids	-15.7%
Other cannabis	-15.6%
Other stimulants	-15.2%
Other psychedelics	-14.5%
Total (with bath salts)	40.8%

allocate resources to prevent the discovery or adoption of new illegal drugs. This includes faster legislative responses to ban new products and more stringent regulations governing research into new substances. Our estimates could provide insights into the potential benefits of these interventions.[41]

With a sizable 39% share, bath salts dominate the market in Russia. The causal effect of their introduction is between two extreme cases. The first scenario is that there was no substitution from other drug types, and all consumers of bath salts would buy no drugs instead if bath salts never appeared on the market. The second scenario is perfect substitution: all consumers of bath salts would otherwise have consumed another drug type. We apply our estimated model and simulate it under the assumption that all bath salts were eliminated from the market during the period when our dataset was collected. The results are presented in Table 7.

We estimate that the introduction of bath salts has increased the total demand for illegal drugs by 41%. A naive calculation that ignores substitution from other drug types would suggest that their introduction had a larger hypothetical effect of $1/(1-0.39)-1 \approx 64\%$. Thus, the substitution from the types that previously existed was substantial but does not affect the main conclusion. The introduction had a large effect on total drug use and brought many new consumers to the market. This effect results from two mechanisms. First, the attachment to specific drug types, which we discuss in Sections 3.5 and 4.3, limits the scope

[41] Additionally, our estimates can allow us to disentangle the effect of the introduction of bath salts from other factors affecting the drug market, thus helping to evaluate relevant policies, regulations, and other market shifts.

of potential substitutions between drugs. Second, we find that $\alpha-$PVP, one of the bath salts, lacks any close substitutes.

Our model also enables us to estimate how the introduction of bath salts has affected the demand for specific preexisting drugs. As is shown in Table 7, the drugs most significantly impacted are MDMA and amphetamine, which are the closest substitutes of mephedrone. Their consumption is 23% and 17% lower relative to what is predicted in the counterfactual scenario without competition from bath salts. Conversely, the drugs least affected are hashish and marijuana. For other drugs, the effect is approximately -15%, but our ability to estimate substitution from them is limited because we do not include random coefficients for these drug types.

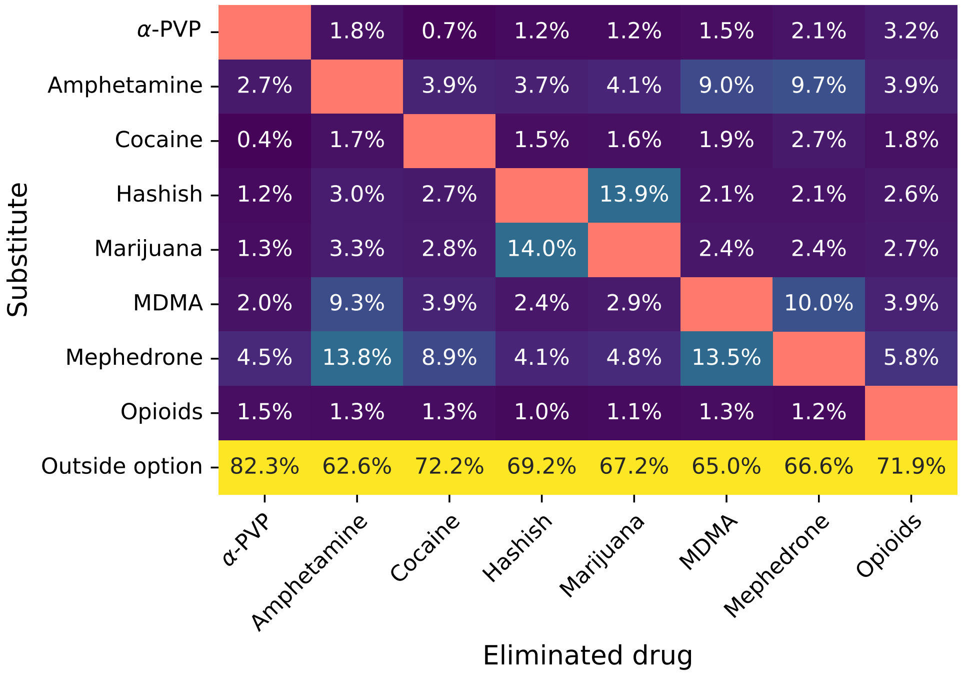
Forecasting changes in the consumption of illegal drugs if new synthetic drugs are introduced in the future is difficult. The effect of such introduction depends on the price of new drugs and the substitutability between them and the existing drug types. However, our estimates suggest that the effect of new products can be dramatic, and governments should allocate resources to prevent the emergence of new drugs in the future.

5.3. Drug elimination

Supply-side interventions may increase the consumption of other drugs if different types of illegal drugs are substitutes. Manski et al. (2001) hypothesized that this could offset the benefits of reducing the availability of the targeted drug. Moreover, such substitution may be towards drug types that are more dangerous than the targeted drug. For example, Alpert et al. (2018) and Evans et al. (2019) found that mortality from heroin drastically increased after a supply-side intervention changed the formulation of Oxycontin, as individuals addicted to Oxycontin switched to heroin. This raises the question: What are the effects of drug reduction policies given potential substitutions between drugs? We examine how the demand for illegal drugs would be impacted if a particular drug were to be eliminated. We conceptualize this scenario as an extreme case of a successful targeted intervention by the government. However, specific interventions may actually have effects that are close to complete elimination, at least in the short run, as seen in examples such as crackdowns on heroin in Australia (Moore and Schnepel, 2021) or on methamphetamine in the U.S. (Dobkin and Nicosia, 2009).

Figure 7 presents diversion ratios resulting from elimination, which indicate the fraction of drug k's consumption that would shift to each of the potential substitutes (including the outside option). Our findings largely align with the discussions in Sections 3.5 and 4.3. For instance, following the elimination of hashish, consumers will switch to marijuana more

Figure 7. Diversion ratios for most popular drug types



Note: 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 deleted from all choice sets.

than to any other drug, and vice versa. Similarly, if amphetamine, MDMA, or mephedrone were eliminated, consumers would disproportionately transition to the remaining two drugs. Consequently, our findings suggest that the impact on total consumption is least significant for drugs that have close substitutes, namely amphetamine, MDMA, mephedrone, hashish, and marijuana.

In contrast, we observe the most substantial effects for drugs with no close substitutes, such as $\alpha-$PVP and cocaine. For example, our model predicts that after the elimination of α-PVP, only 18% of its consumers will switch to another drug type. By the same measure, enforcement would be half as effective for amphetamine, as 38% of consumers would find another drug to switch to. Our findings suggest that all else being equal, the government should prioritize the enforcement of drugs with few close substitutes. Finally, while we do not have a random coefficient for opioids in our demand model, we find a very strong attachment to these drugs in Section 3.5. We can reasonably assume that our model overestimates substitution from opioids, and therefore the conclusion applies to them as well.

Table 8: Elasticity of revenue with respect to drug prices

	Own revenue	Total revenue (w/o substitution)	Total revenue (with substitution)
α-PVP	-0.577	-0.036	-0.006
Amphetamine	-1.317	-0.160	-0.038
Cocaine	-8.547	-1.522	-1.382
Hashish	-2.693	-0.185	-0.104
Marijuana	-2.959	-0.230	-0.136
MDMA	-2.417	-0.224	-0.105
Mephedrone	-1.418	-0.410	-0.206
Opioids	-3.980	-0.121	-0.085

5.4. Enforcement and revenue

The model of Becker et al. (2006) highlights the key role of price elasticities in determining the effects of drug enforcement.[42] Supply-side interventions such as seizures or crop eradication increase the price of the drug type targeted. However, if the demand for this drug is inelastic, enforcement leads to a decrease in consumption that is relatively small compared to the price increase. This poses a difficult dilemma for the government: the total revenue of the black market can increase as a result of drug enforcement. Higher revenue in drug markets can lead to increased resources devoted to drug smuggling or greater incentives to fight for control over the drug trade (Becker et al., 2006; Castillo et al., 2020). Even if the goal of reducing consumption is achieved, society will face a larger scope of associated illegal activities, which include gang wars, corruption of officials, and attacks on journalists and civil activists.

The elasticity of revenue for product j with respect to p_j equals $1 + \varepsilon_{jj}$, where ε_{jj} is its own-price elasticity. This motivates an approach popular in the literature on demand for illegal drugs, where the elasticity of demand for a particular drug is estimated and compared with -1 (see Gallet, 2014 for a review). However, this approach ignores the possibility of substitution. The revenue of the black market from other drugs increases if people who stop consuming the targeted drug do not leave the market but substitute towards another drug. The elasticity of the total revenue of the black market for drugs with respect to the price of

[42]See White and Luksetich (1983) for an earlier discussion of this idea, who also suggest that demand elasticity is crucial for determining the effect of enforcement targeting drug users.

drug j 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, total revenue can increase from enforcement. The correct assessment of this possibility requires estimates not only of the own-price elasticity but also of the cross-price elasticities of demand for different drug types.

We apply our model estimates to evaluate how drug-specific enforcement affects total revenue. In Table 8, we report the revenue elasticities for the most popular drug types.[43] In the first column, we report the effect on revenue from sales of the targeted drug. In the second column, we apply the formula for total revenue without the second term to highlight the effect of substitution in our estimates, which would be the effect on total revenue if all $\varepsilon_{jk} = 0$ for $j \neq k$. In the third column, we report the elasticity of total revenue.

Our estimates suggest that enforcement does not increase revenue for any major drug type. However, our findings indicate that enforcement actions against $\alpha-$PVP cause only a minimal decrease in revenue for drug sellers due to its low own-price elasticity. At the same time, our estimates show that the effect on total revenue can be miscalculated for types with close substitutes if researchers ignore substitution. For example, when considering potential substitution, we find that enforcement of amphetamine, which has two close substitutes (MDMA and mephedrone), is almost revenue-neutral.

5.5. External validity

The external validity of our analysis might have several limitations due to the differences between the markets for drugs in Russia and other countries. First, the composition of drugs in the consumption bundle might be different. In particular, bath salts are significantly less popular in the U.S. or Europe than they are in Russia. In addition to this, sales of fentanyl were prohibited on the Hydra marketplace, and thus our analysis is not informative of demand for this drug. Second, darknet markets have a relatively small market share in the U.S., and most of the trade happens through offline dealers. Search costs are likely to be much larger for consumers buying drugs on the street, therefore, sellers in the U.S. might have larger market power than the sellers operating on Hydra. Moreover, the context of an online marketplace can lead to more substitution, as buying drugs of different types is easier.

[43] We use the version of the formula for many markets and report the elasticity of total revenue.

Third, the U.S. population generally has higher incomes, resulting in potentially lower price elasticity among American consumers.

6. Conclusion

We analyze the market for illegal drugs utilizing data scraped from Hydra, the 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 substances demonstrate close substitutability: the three medium-risk stimulants and the two types of cannabis. We employ our model to evaluate the effects of key drug policies affecting the supply of illegal drugs. 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. Governments should proactively seek to prevent the introduction of new drugs into the market because recent instances, such as the emergence of bath salts, have had a pronounced effect on overall drug consumption. Drug enforcement is likely to be more successful when it targets drugs with few substitutes.

There are several important directions for future research. First, our paper models consumer preferences as static. A valuable extension of this framework might involve a demand model in which preferences can change over time, particularly in the form of accumulating addiction. In particular, such a model would allow us to separately study short-term and long-term effects of drug policies.[44] Second, our discussion focuses on the demand for drugs and abstracts from the supply side, effectively assuming that the market is competitive and the supply of drugs is perfectly elastic. For instance, this assumption might be violated if some drug sellers possess market power. In particular, there may be less competition between upstream suppliers. This assumption is also less realistic in the traditional drug trade, where search costs should be higher than in an online platform. A model incorporating endogenous supply would allow us to relax this assumption or study interventions targeting particular sellers.

[44] See, in particular, Becker and Murphy (1988) and Gruber and Köszegi (2001). See Hui (2023) for a review of the recent economic studies incorporating addiction.

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Appendices

A. Data

A.1. Scraping of Hydra

The scraping process was done by running a program on a personal computer located in one of the buildings of the Higher School of Economics in Moscow.[45] The computer operated on OS Windows 10 and had AMD processor and 4GB RAM. The process was organized in two stages. In the first stage, the program scraped all pages with output of search within 62 categories of the Hydra website.[46] This stage took between 30 and 60 minutes and allowed the program to collect and save the universe of products on Hydra present on a particular day. 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. The second stage took between 2 and 4 hours.

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				

[45]The code is available upon request.

[46]For example, $\star$.onion/catalog/3?page=1 was the first page listing marijuana products.

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 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

We drop all listings with price per gram greater than 3 times the median price of the same drug type and amount. This is necessary because shops on Hydra sometimes set prohibitively high prices instead of deleting a listing when they are out of stock.[47] We also observe several shops with many thousands of listings and much smaller cumulative number of fulfilled orders. A common feature of such shops is that they operate 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 for this is that this is a form of drop shipping: these shops could copy listings of other shops and sell their products with a premium. Given that listings by drop shipping merchants likely copied listings of other shops, including them would lead to double-counting dead-drops. We drop from our data all shops for which there are more listings than total sales.

We exclude all reviews related to 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, to 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% and at least 40% of the frequency of any other higher quantity.

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

[47] 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, amount is in counts. Amount is grams for all other drug types. The standard amount for each drug type is highlighted in bold and is defined as an amount with frequency of at least 15% and frequency that is at least 40% of frequency of any other higher amount.

A.4. Descriptive statistics

Shops characteristics. Table A.3 presents descriptive statistics for characteristics of shops on Hydra.

Reviews. Table A.4 presents summary statistics for our data on reviews.

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	215,733
	By users with 1 review	82,878
	By users with > 1 reviews	132,855
Users	Total	126,259
	With 1 review	82,878
	With > 1 reviews	43,381
	With > 1 purchased types	21,864
Shops	Total	784

Panel B: Descriptive statistics	Mean	Median	Std	Min	Max
Rating	9.57	10	1.88	0	10
Number of words	16.39	8	26.76	0	1596
Reviews per nickname	1.71	1	1.54	1	63
Days between reviews	58.11	14	97.98	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.

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

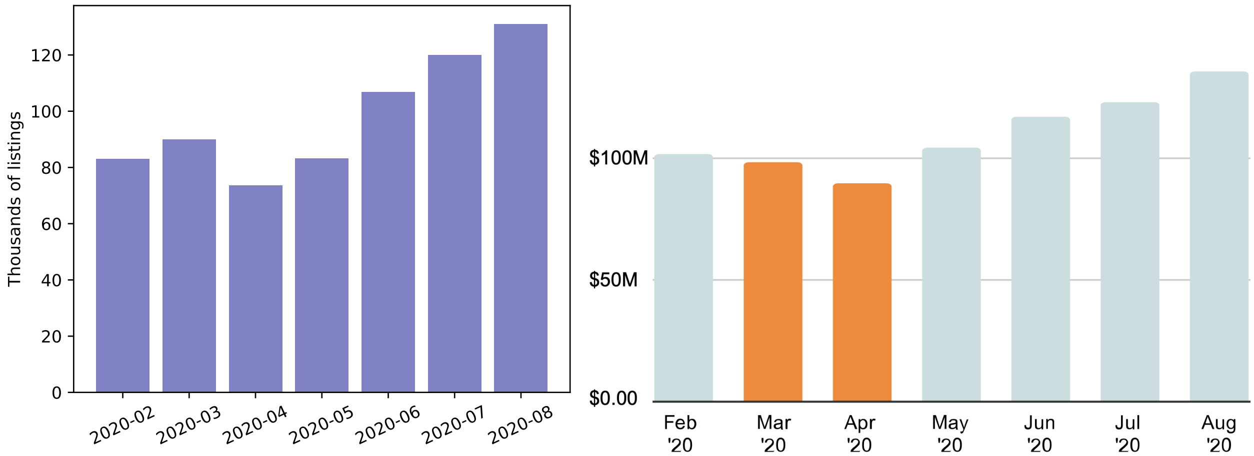
Drug type	Share of listings	Share of reviews	Drug type	Share of listings	Share of reviews
Mephedrone	29.6%	26.3%	Heroin	0.8%	1.4%
Amphetamine	13.9%	12.8%	Marijuana (leaves)	0.7%	0.6%
α-PVP	12.5%	8.6%	NBOME	0.7%	0.7%
MDMA	10.8%	12.4%	Synthetic cannabinoids	0.7%	1.1%
Marijuana (buds)	7.9%	10.4%	Mushrooms	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%

A.5. Proxies for sales

Shares of 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 numbers generally are close to each other. The largest absolute discrepancies are observed for mephedrone, $\alpha-$PVP, MDMA, and marijuana.

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

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



(a) Mean daily number of listings (b) Estimated monthly revenue

Note: For monthly revenue, estimates and the plot are from Flashpoint, Chainanalysis (2021)[p. 5]. To calculate mean listings for April 2020, we use another dataset, which was purchased from an independent data collector for this particular month and was also used in Goonetilleke et al. (2022). This data is not used for demand estimation.

B. Sentiment of Reviews

We apply two approaches to extract sentiment of reviews: lexicon approach and LLM embeddings. In the first approach, we start with constructing a balanced sample of reviews with positive and negative ratings. We label a review as positive if it has rating 10/10. We label a review as negative if it has 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," in particular, prepositions or pronouns. We find 200 most common words in the corpus of processed reviews. We use frequencies of these words to generates 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

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

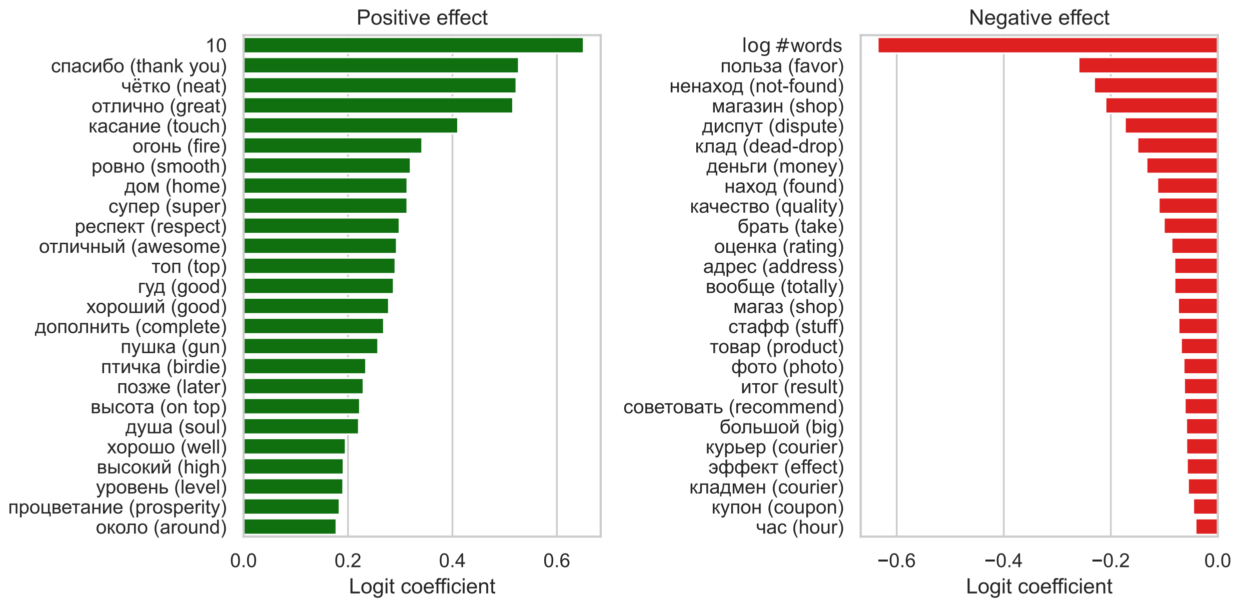
We obtain out-of-sample accuracy of 85% with this algorithm. We use $\mathbb{X}_i'\hat{\beta}$ as our measure of (positive) sentiment of the review.

The intuition behind this method is the following. From rating-based labels of reviews, the algorithm learns which words have good and bad sentiment. Then, weighting these words allows us to distinguish differences in the sentiment even within the 96% of reviews with the best possible rating. Figure B.1 describes the words that have the largest power for predicting positive or negative label. The most predictive signal for positive feedback is "10": reviewers type numerical rating to express satisfaction. Length of review is a strong predictor of negative feedback. Most of the words we find predictive for positive feedback describe general satisfaction with the purchase, e.g., "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 for complains 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." Finally, some words describe the process of disputes, e.g., "favor," "dispute," or "coupon."

However, this method is not taking into account many properties of language, e.g., 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.[48]. We then manually

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

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



choose a small sample[49] 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 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 for regularization of the obtained shop-level average sentiment.

[49]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. (2022).

C. Micro Moments

Here we provide a more detailed discussion of our micro-level moment conditions. We start with 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

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

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:

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

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

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

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 the agent chooses product $j = j(i, t)$ this choice is observed with probability $\pi = 0.1$ and added to R_{ij}. Because the econometrician only can 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 made 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 try to 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 z^n and 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 4.2, and obtain estimates $\hat{\Sigma}^{Micro}, \hat{\alpha}^{Micro}, \hat{\beta}^{Micro}$. Our results are provided below:

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

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

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

As can be seen, 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 when price-quantity data is only available for a subset of days. Suppose that reviews can be observed over days $t = 1, \ldots, T$. However, quantities and prices only can be observed for several particular 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 reviews 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 $t = 1, \ldots, T$, the expected value of the product term for consumer i is

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

As 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 one order of magnitude smaller than terms $\big(\sum_{\tau(t)=\tau_1}\pi_{jt}\big)\big(\sum_{\tau(t)=\tau_2}\pi_{kt}\big)$.[50] 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.

If we apply the approximation by the closest observed day to conversion into reviews, we

[50] 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.

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 $N s_{j\tau}$, similarly to equation 9.

Finally, we also can 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.

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	1,815	Jan 22, 2020	Jan 09, 2020	Jan 25, 2020	30	2,127
Jul 20, 2019	Jul 19, 2019	Jul 25, 2019	8	4,991	Jan 28, 2020	Jan 26, 2020	Feb 01, 2020	10	1,798
Jul 30, 2019	Jul 26, 2019	Aug 03, 2019	14	6,566	Feb 06, 2020	Feb 02, 2020	Feb 09, 2020	12	8,688
Aug 07, 2019	Aug 04, 2019	Aug 10, 2019	11	1,097	Feb 12, 2020	Feb 10, 2020	Feb 16, 2020	10	5,158
Aug 14, 2019	Aug 11, 2019	Aug 22, 2019	15	5,784	Feb 20, 2020	Feb 17, 2020	Feb 23, 2020	11	2,933
Aug 30, 2019	Aug 23, 2019	Sep 03, 2019	20	2,015	Feb 27, 2020	Feb 24, 2020	Mar 01, 2020	10	536
Sep 08, 2019	Sep 04, 2019	Sep 12, 2019	13	1,041	Mar 05, 2020	Mar 02, 2020	Mar 08, 2020	10	686
Sep 17, 2019	Sep 13, 2019	Sep 21, 2019	13	1,254	Mar 11, 2020	Mar 09, 2020	Apr 13, 2020	39	15,180
Sep 25, 2019	Sep 22, 2019	Sep 29, 2019	12	110	May 16, 2020	Apr 14, 2020	May 19, 2020	69	25,365
Oct 03, 2019	Sep 30, 2019	Oct 24, 2019	29	642	May 23, 2020	May 20, 2020	Jun 04, 2020	19	34,198
Nov 15, 2019	Oct 25, 2019	Nov 21, 2019	49	761	Jun 16, 2020	Jun 05, 2020	Jun 24, 2020	32	18,457
Nov 27, 2019	Nov 22, 2019	Dec 01, 2019	16	380	Jul 03, 2020	Jun 25, 2020	Jul 09, 2020	23	11,005
Dec 06, 2019	Dec 02, 2019	Dec 09, 2019	12	297	Jul 15, 2020	Jul 10, 2020	Jul 25, 2020	22	15,420
Dec 13, 2019	Dec 10, 2019	Dec 16, 2019	10	316	Aug 05, 2020	Jul 26, 2020	Aug 16, 2020	32	34,561
Dec 19, 2019	Dec 17, 2019	Dec 22, 2019	9	334	Aug 27, 2020	Aug 17, 2020	Sep 15, 2020	41	24,705
Dec 26, 2019	Dec 23, 2019	Jan 08, 2020	20	1,354					

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

C.3. Gradients

To facilitate stability and speed of convergence, we use analytical gradients for the estimation procedure outlined in Section 4.2. We provide our derivations here. To simplify notation, we omit the city index, as 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[51] to calculate the gradient for our moments

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

which equals

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

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

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

$$\mathbb{P}\big(R_i > 0 \mid i\big) = 1 - \prod_{t=1}^{T}\Big(1 - \sum_{j=1}^{J}\pi_{jt}s_{ijt}(\theta)\Big), \tag{7}$$

we obtain

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

D. Market Size

As discussed in Section 3.3, we assume that the number of transactions is proportional to the number of listings with 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 be not equal to 1. First, as deposited dead-drops can stay unsold for several days, a listing observed on a particular day does not necessarily correspond to a transaction on this 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

$$\sum_{t=1}^{T} L_t \approx \omega \sum_{t=1}^{T} L_t^{new}, \tag{33}$$

$$\sum_{t=1}^{T} S_t \approx \kappa \sum_{t=1}^{T} L_t^{new}. \tag{34}$$

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 at 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 $\kappa/\omega \approx 0.7$.

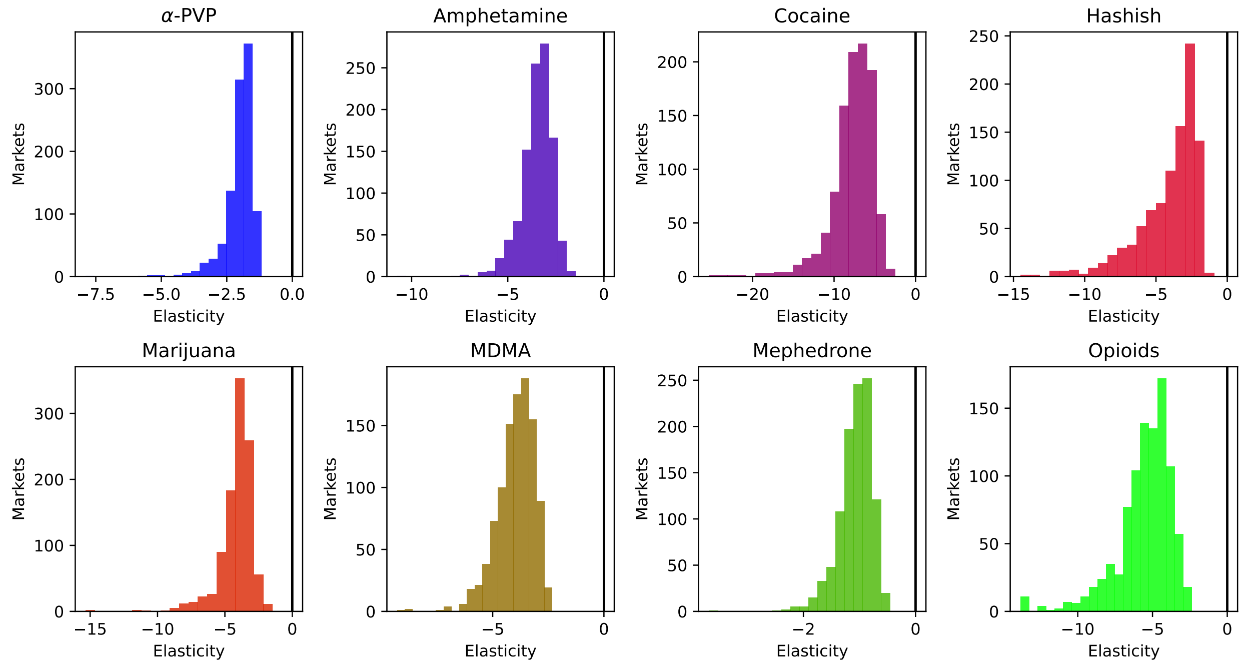
In the Russian mortality data, the majority of deaths associated with drug use occur among individuals aged between 18 and 45. Motivated by this fact, we assume that each person between 18 and 45 can consume drugs 1 time per month. We assume that 1 standard amount is enough to consume drugs 3 times.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

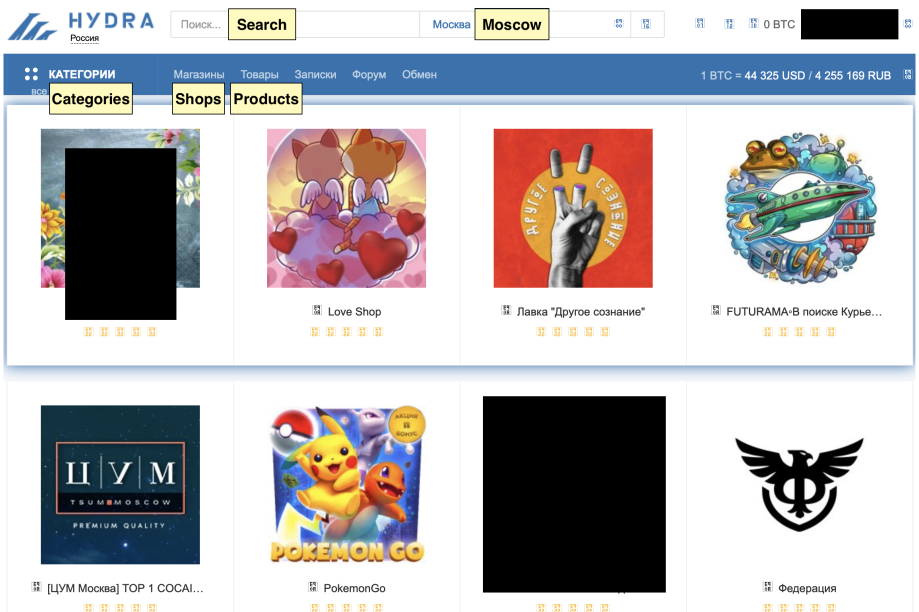
Figure E.1. Distribution of own-price elasticities of demand



F. Screenshots

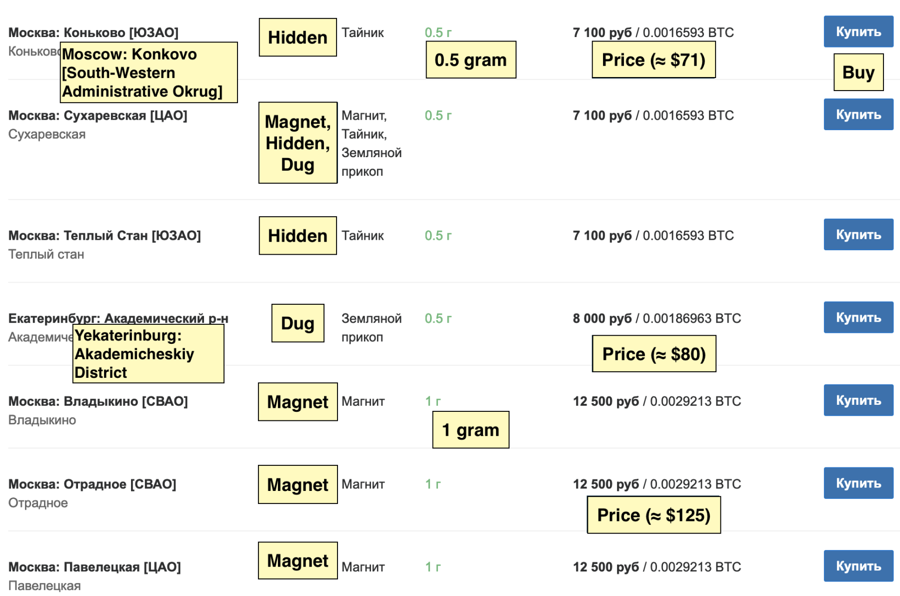
To illustrate and support some of the points we make in the paper, we provide several screenshots from the marketplace.

Figure F.1. Front page of Hydra



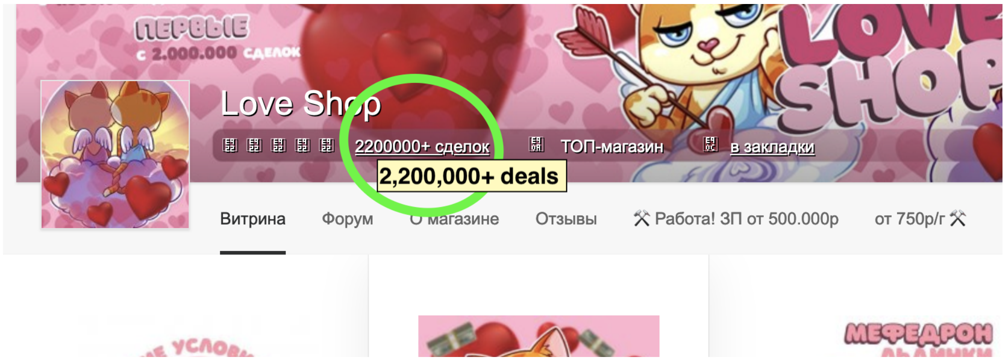
Note: Screenshot from March 26, 2022.

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



Note: Screenshot from March 26, 2022.

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



Note: Screenshot from March 17, 2022.

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