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Abstract

Darknet markets for illicit goods face law enforcement and public health researchers with new challenges and give economists a unique opportunity to study production under uncertainty. While current cryptomarket research focuses on the effects of police intervention on market participants, this thesis extends the literature by exploring the effects of Bitcoin price volatility, which is the main currency used on cryptomarkets. Using scraped data from the largest cryptomarkets between 2014 and 2015, I exploit an event study design to causally estimate dynamic paths of shocks to these two types of production risk. Within a month, high levels of police intervention and Bitcoin volatility significantly decrease the expected probability of market entry by 4.3% and 6.4%. While established vendors only show weak reactions to impulses in terms of drug supply, they pass on the added risk to buyers in the form of a short-term risk premium of around 4.8% (8.7%) in the case of an arrest (volatility) shock. To my knowledge, this is the first study to establish a causal link between Bitcoin volatility and market outcomes on cryptomarkets, showing that criminals see police intervention as one of several production risks that vendors respond to with higher prices rather than lower supply.

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Contents

List of Figures

List of Tables

1 Introduction

Uncertainty is an ever-present aspect of economic activity. The SARS-CoV-2 pandemic has shown what happens when private households, firms, and lawmakers alike, have their planning horizons reduced to a time frame that is barely longer than a few weeks or months. Not only is it hard to predict the immediate risk of the virus itself, but also how other agents react to this new environment. Economic theory may offer a framework to understand how consumption, production, and investment react in the face of uncertainty. I study how producers respond to shocks to production uncertainty, where different types of risk may affect specific transactions, target a firm's entire production or even the entire market.

I explore the possibility that uncertainty can have different effects on agents' choices depending on whether it affects their holding cost or their transaction cost. Holding risk occurs during the production process and can be thought of as the cost of holding goods, where for each unit in stock, a certain expense has to be paid. Holding cost can be directly linked to the amount of units in stock, where common examples include inventory cost, damage or spoilage of goods. Transaction risk is another risk faced in the transaction stage after a product has been produced, for example, exchange rate risk or customer default risk. Increased levels of holding risk give incentives to reduce the amount of goods in stock by selling at lower prices or delaying the production of new goods. Transaction risk, on the other hand, provides incentives to postpone sales into the future where uncertainty is lower. While the way market participants react to these varying types of risk depends on the features and structure of markets, the central question to this research is which dynamic paths do shocks in holding and transaction risk take.

Cryptomarkets are a promising setting to observe different types and levels of risk, as well as the responses of market participants. They offer an unprecedented opportunity in drug policy research, as they allow researchers to observe the decisions of vendors directly and at any point in time. Darknet markets, or cryptomarkets as they are preferably called in the academic literature, are a relatively new phenomenon that started with the platform *Silk Road* that went online in 2011 and was closed by the FBI in 2013 (Barratt and Aldridge, 2016). New anonymization technologies gave rise to these darknet platforms. *The Onion Router* (TOR) keeps the identity of users anonymous while using the internet, *Pretty Good Privacy* (PGP) is used to encode and decode messages between market participants and cryptocurrencies hide the money trail of darknet transactions (Mounteney et al., 2016). Combined, the software enabled a growing number of cryptomarkets to emerge, either in the form of vendor shops or as two-sided marketplaces where both sellers and buyers can set up accounts. The high level of anonymity makes cryptomarkets the ideal place to sell black market goods, like illicit drugs, weapons, or pornography (Christin, 2013).

I use two exogenous shocks to production uncertainty that are unique to cryptomarkets, but can easily be transferred to other settings. These two sources of uncertainty are an increase in the number of darknet market-related arrests and an increase in price volatility of the cryptocurrency Bitcoin. The former I interpret as a proxy for holding risk, as the threat of an arrest endangers a vendor's entire operation and the current drug stock held in possession. The latter can be seen as a transaction risk where the value of all pending transactions changes with the Bitcoin price.

Using web-scraped data from eight of the largest cryptomarkets between 2014 and 2015, I generate a vendor panel of all active drug sellers. Following an event study approach, I estimate the causal dynamic effects of a shock in either type of production risk on different supply-side outcomes. Focusing on illicit substances, this unique dataset allows me to examine effects on drug quantity, drug price, vendor rating, mode of payment, as well as on decisions to enter or exit the darknet market altogether on the vendor level.

I show that both types of production risk cause similar reactions from vendors. Both risks act as entry deterrents to new vendors and established vendors pass on the added risk to buyers in the form of a risk premium. The estimated effects of the additional risk on prices are larger for volatility risk with short-term cannabis (opioid) prices increasing on average by 8.7% (9%) compared to 4.8% (4.2%) in the case of arrest shocks, all coefficients significant at the 1% level. Within one month of the shock, the expected probability of entry of cannabis (opioid) vendors decreases by 15.8% (13.7%) after Bitcoin price fluctuations and falls by around 3.3% (3.9%) after arrests. Vendors show weak reactions in terms of the amount of drugs supplied. In the case of added risk of arrest, the increased market price triggers a significant short-term quantity increase of cannabis of 29.3%. Heterogeneity analysis reveals that opioid vendors react to shocks within the first two weeks, while cannabis vendors usually only react within the first month of the shock.

Previous research on the effects of law enforcement activity on cryptomarkets focuses on the impact of the international police raid *Operation Onymous* that shut down major market platforms in November 2014. Décary-Hétu and Giommoni (2017) show that the listings remained stable in price, and the number of active vendors and listings only dropped temporarily. Vendors directly affected by the shutdown could not be deterred, with 75% of dealers in shutdown markets continuing to sell on different platforms. Van Buskirk et al. (2017) explore the effects of *Operation Onymous* and the *Evolution* exit scam on the number of vendors. They find that both shocks decreased the number of vendors temporarily, but neither affected the rate of growth in vendor numbers. Ladegaard (2018) analyses the effects of media coverage of darknet market-related police work and related court decisions. Using time series analysis, he finds that trade activity measured in seller revenues increases in times of increased media attention. Bhaskar et al. (2019) confirms that neither of the market shutdowns of *Silk Road*, *Silk Road* 2.0 or *Evolution* had long-lasting effect on listings or revenue.

Building on these works, I aim to expand the current literature in a number of ways. Making use of an event study framework, I establish a causal interpretation of the effects of police interventions and focus my analysis on dynamic paths of the shock. Furthermore, I consider all darknet-related arrests that occurred during the period, not just the major shutdowns. I look at heterogeneous effects on vendors of different types of drugs and retrieve the actual drug quantities offered in grams, rather than using the number of listings as a proxy for supply as is common in the previous literature. Finally, I am the first to distinguish different types of risks vendors face by including uncertainty from financial markets in the analysis. I show that police intervention is merely one of many potential production risks in the cryptomarket ecosystem, for which established vendors seem to have developed answers in the form of a temporary risk premium.

2 Theory and mechanisms

I contribute to two lines of literature, to the literature on production under uncertainty and to the literature on deterrence of crime, which shares common roots with the former.

2.1 Production under uncertainty

Uncertainty is a common problem for firms where production decisions have to be adjusted to a lack of information, usually about prices or costs. Modern microeconomic theory of production under uncertainty begins with Sandmo (1971) who builds his model on the concepts of expected utility and risk aversion with the main result being that under perfect competition, price uncertainty decreases the optimal output of risk-averse firms. This is the case because firms value their losses higher than their profits, which results in a market with positive profits (Wambach, 1999). Leland (1972) extends these results to a setting of imperfect competition with firms as price or quantity setters. He shows that, under demand uncertainty, firms will choose to set either quantity or prices, but not both when given the opportunity to make ex-post decisions. The risk-averse quantity-setting firm will decrease its output compared to the risk-neutral firm, while the price-setter either increases or lowers the price depending on the way uncertainty affects profits. I aim to explore whether these theoretical predictions also apply to cost shocks and to broaden understanding of agents' decision variables in this setting.

2.2 Crime and deterrence

Crime is an ideal setting to explore production under uncertainty. Besides it being an intrinsically interesting topic of research, one can find various types of risk on criminal markets. The crime literature considers risk in two ways, the risk of being arrested and the severity of punishment (Reuter and Kleiman, 1986). The popular framework under which crime is studied in economics, criminology, and related fields is the rational choice theory. In his economic model of crime, Becker (1968) describes criminal activity as a rational decision weighing benefits against costs. He explains expected utility EU_i of individual i by the probability of conviction p_i, the punishment per the offence f_i, as well as income from crime Y_i and her utility function U_i.

$$EU_i = p_i U_i(Y_i - f_i) + (1 - p_i) U_i(Y_i) \tag{1}$$

While expected utility is decreasing in both p and f, it is not clear what the appropriate reactions are going to be. The supply of crime O_i of individual i in Becker (1968) depends negatively on risk of conviction and gravity of punishment,

$$O_i = O_i(\underbrace{p_i}_{(-)}, \underbrace{f_i}_{(-)}, \underbrace{u_i}_{(\pm)}) \tag{2}$$

where O_i is the number of offenses, i.e., the supply of illicit goods, and u_i represents all other influences. I can test this relationship by replacing O_i with the amount of drugs offered by a cryptomarket vendor, assuming that outside factors u_i remain constant. From this analysis, hypotheses about entry and exit decisions can be derived, where new vendors only enter the market if expected utility is positive and vendors drop out of the market once expected utility becomes negative.

The related theory of perceptual deterrence offers an alternative model to think about crime. While, like in the economic model of crime, criminals are modeled as rational decision-makers, a distinction is made between the objectively observable risk and the subjective perception of risk (Nagin, 2013). Another insight from perceptual deterrence studies is that criminals update their subjective view of how likely it is to be arrested. Individuals who were never caught might assign a lower subjective probability of being detected than those who have been arrested before (Nagin, 1998).

In their economic analysis of drug enforcement Reuter and Kleiman (1986) address the question of the effects of increasing arrest risk on traditional drug markets and offer a theoretical foundation. They suggest that the risk of arrest leads to two different kinds of costs: the cost of avoiding law enforcement and the cost for the losses that are associated with being arrested. An increase in police efforts will, therefore, increase the avoidance cost and the replacement costs. Assuming a competitive drug market, the supply curve shifts upward, increasing drug prices. In their empirical analysis of marijuana and cocaine drug markets, demand is described as price inelastic, where an increase in market prices of drugs increases the revenues of drug dealers.

Moving from traditional drug markets to the setting of cryptomarkets, vendors face two types of production risk. In the following, I will derive theoretical predictions for the effects of holding risk and transaction risk on production decisions of drug sellers.

2.3 Holding risk

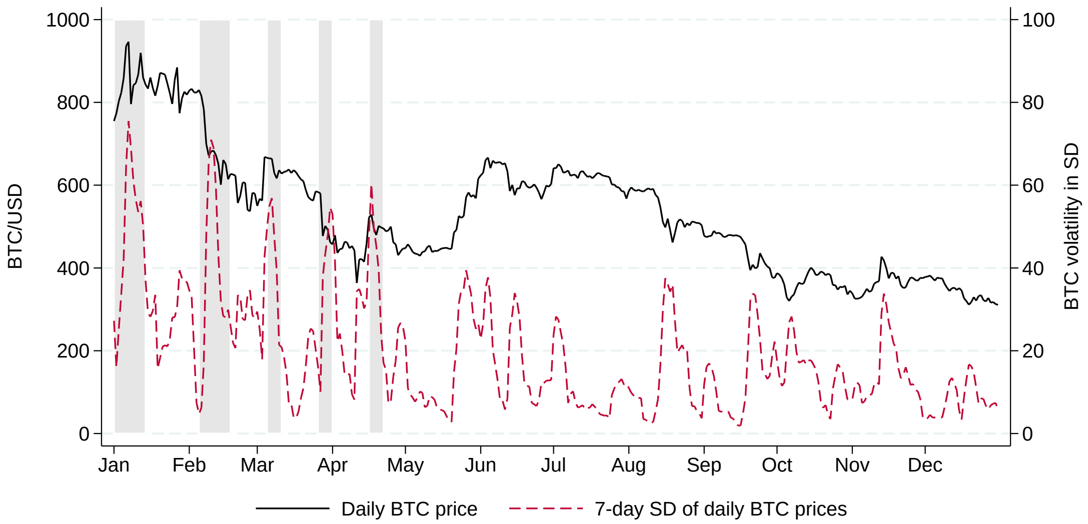
In a general way, the holding risk is the risk that is directly linked to the amount of goods held in stock. It can be thought of as the probability of losing a certain amount of the stock or the inventory cost paid for each unit stocked. While the holding risk can always be translated into a cost, the associated risk premium will depend on the producer's degree of risk aversion. These two interpretations of risk and cost are equivalent to risk-neutral producers whose utility only depends on expected costs. However, the utility of a risk-averse producer will also depend on the amount of risk and the producer's degree of risk aversion.

A profit-maximizing producer will reduce their stock when faced with an increase in holding risk, as it constitutes an inventory cost. This can be achieved by either increasing sales or by delaying restocking. The former would lead to an increase in short-term drug supply. This will result in a decrease in market price if demand is price-inelastic. Delaying restocking would keep supply and prices constant on the consumer market. Depending on whether vendors are drug producers or retailers, decreasing stock size could then translate into a decrease in wholesale demand and prices.

Like in traditional drug markets, cryptomarket sellers bear the risk of getting caught with illicit goods. Following the economic model of crime in Becker (1968), arrest risk consists of two components - the probability of detection and the severity of punishment. While on cryptomarkets the likelihood of detection varies with the level of effort of law enforcement, the level of punishment stays relatively constant. In terms of Equation (1), an increase in holding risk, i.e., arrests, only increases the chance of getting arrested, p_i, but leaves the extent of punishment unchanged. In criminal law, usually, the amount of drugs possessed determines whether an offender is treated as a user or a seller, which in turn affects the level of punishment.[1] Thus, there is an incentive to hold as little as possible of a drug at any given time. Keeping a stock of drugs can be seen as an inventory cost that depends on the current level of risk of getting arrested by law enforcement and the amount of drugs held.

[1] In the USA, penalties for drug possession, trafficking, and sale vary by state, and the severity of punishment depends, amongst other factors, on the amount of drugs confiscated (Patterson, 2021). In Germany, the penalty for a supply offense is elevated if significant amounts are traded (EMCDDA, 2020).

Figure 1a: Bitcoin price fluctuations in 2014



Notes: This graph shows the daily opening Bitcoin price in USD as a solid black line and the 7-day Bitcoin price volatility as a red dashed line. Volatility is measured as the standard deviation of opening prices within the last seven days. The weeks which will be defined as volatility shocks later in this study are shaded in grey. The corresponding price data was retrieved from CoinMarketCap (2020).

2.4 Transaction risk

Transaction risk is the risk that targets a specific transaction. Common examples are the default risk of buyers or the exchange rate risk. Again, different levels of risk aversion will yield different reactions to transaction risk.

On platforms where buyers and sellers remain anonymous, special importance comes to securing payments. Market administrators facilitate payments by acting as intermediaries in the transaction process for which they collect fees. In order to ensure anonymity, cryptocurrencies, most dominantly Bitcoins, are used to obscure payments (Bhaskar et al., 2019).[2] Most cryptomarkets offer one of two modes of payment security. First, markets can set up an escrow system, where administrators act as a neutral third party. Buyers have to finalize a transaction if they are satisfied with the delivery, and administrators decide who gets the money in case of dispute (Barratt and Aldridge, 2016). Second, in order to avoid market administrators shutting down the server and taking the money in escrow, a multi-signature system can be used. Here, payment from a cryptocurrency wallet is only confirmed when two of the three parties involved agree to the transaction (Bhaskar et al., 2019). On some markets, vendors, especially those with a good reputation, also have the option to demand payments to be finalized early (FE), i.e., the buyer has to pay before receiving the goods (Bhaskar et al., 2019). Besides the risk of getting scammed by either market operators or buyers, there exists an additional little discussed risk for vendors. As payments are made in highly volatile cryptocurrencies, the sellers also have to bear a considerable exchange rate risk. After choosing a product, the buyer converts their currency into a cryptocurrency and transfers it to their market account. Only after the product is delivered and confirmed by

[2] All eight markets in my sample utilized Bitcoin as their currency of choice.

Figure 1b: EUR/USD exchange rate fluctuations in 2014

Notes: This graph shows the daily BTC/USD price as a solid black line and the daily EUR/USD exchange rate as a red dashed line. Prices are shown relative to their values at the beginning of 2014. The EUR/USD exchange rate data was retrieved from Macrotrends LLC (2021).

the buyer, the cryptocurrency is transferred to the seller's wallet. During this period, the seller bears the risk of unfavorable exchange rate changes. This period can vary, but Janze (2017) finds that the escrow mechanism is concluded within six days on average. In order to show how high this risk is for vendors, Figure 1a depicts Bitcoin prices and volatility in 2014. During the observation period, Bitcoin prices could drop by 24% within a week and by even 21% within a day. The average 7-day volatility in 2014 was 20.8 standard deviations, with the largest spikes of around 70 standard deviations at the beginning of 2014. Figure 1b compares Bitcoin prices to the EUR/USD exchange rate in 2014. The cryptocurrency is much more volatile than the traditional currency, with EUR/USD rates never changing by more than 3.7 percent within a day in 2014.

We can use the economic model of crime in Becker (1968) to explain the effects of transaction risk, where the utility loss is caused by a simultaneous increase of f_i and p_i, and both variables are distributions over possible outcomes.[3] Note that this is different from how holding risk enters Equation (1). In the context of the economic model of crime, an increase in transaction risk will lead a risk-averse profit maximizer to reduce their quantity sold. With the aggregate supply curve shifting down, an increase in transaction risk will cause market prices to increase if market demand is inelastic.

Another transaction risk comes from currency exchanges. The fact that Bitcoin transactions are irrevocable makes it attractive for criminals to attack financial intermediaries like Bitcoin exchange platforms (Moore and Christin, 2013), which puts the money currently held in escrow at risk. Finally, I choose Bitcoin volatility as a proxy for transaction risk because exchange rate volatilities are everyday phenomena that have large impacts on the value of pending transactions, and major shocks to Bitcoin prices are observable periodically.

[3] Of course, it is also possible that f_i takes on negative values when the exchange rate changes in favor of the vendor.

I aim to expand the branches of literature discussed in this section in three ways. First, I contribute to the literature that empirically tests the rational choice theory of crime, specifically the effect of police intervention on the supply decision in Equation (2). I extend the current research by allowing for more diverse responses apart from quantity supplied. It is possible that actors on drug markets react to increases in risk with price changes, as is hypothesized in the literature of production under uncertainty (Leland, 1972). It is also conceivable that vendors react by reducing the quality, e.g., by lacing drugs with cheaper substances. Second, in these basic models of criminal activity, increasing the probability or magnitude of arrests could act as a deterrence, decreasing drug supply, ignoring the effects of competition. It seems highly unlikely that changes in risk and degree of punishment only affect one individual criminal but the market as a whole. Therefore, criminals will not only react to police intervention itself but also to the behavior of other market participants. The question is then, which paths shocks in risk and punishment take when competitors simultaneously react to these developments. The dynamic approach of analysis followed in this study helps to disentangle reactions to intervention and reactions to competing vendors. Third, it is not clear which types of uncertainties are recognized by vendors in the cryptomarket setting. In the line of thinking of perceptual deterrence theory, I determine whether arrests and Bitcoin volatility are subjective risks that vendors are aware of and warrant reactions on their part.

3 Institutional setting

Cryptomarkets are an interesting setting to observe different types of risk and test the economic theory of production under uncertainty as well as the economic model of crime and aspects of the deterrence theory. The combination of online markets and illegal drug sales gives rise to a market with a unique set of features.

3.1 Cryptomarkets

Since the launch of the first cryptomarket *SilkRoad* in 2011, countless cryptomarkets have been established and dissolved (Barratt and Aldridge, 2016). The most popular type of cryptomarket is a two-sided marketplace that facilitates the transaction of a range of licit and illicit products between a large number of sellers and buyers. The most frequently offered products are drugs and drug-related equipment (71%), illegal or delicate information material (10.3 percent), counterfeit products (4.3%), stolen data and accounts (3.8 percent), illegal services for hacking, advertising, and money laundering (2.9 percent), forgeries of documents (1.7 percent), stolen electronics (1 percent), and weapons and ammunition (0.7%).[4]

Trust plays a vital role in traditional online markets (Kim and Peterson, 2017) and illegal drug markets (Tzvetkova et al., 2016) where the potential for information asymmetry is high. This extends to cryptomarkets as they are a meeting point between the two, where the required anonymity makes it impossible to inspect goods prior to purchase and to enforce contracts in case of refusal of payment. Therefore, reputation and trust-building processes are central to maintaining business relationships in this setting. It is in the interest of market administrators to offer the necessary infrastructure to reduce information asymmetry by

[4] The percentages are based on data from *Agora* marketplace between 2014 and 2015, where I use the marketplace's pre-existing product categories. *Agora* is the market with the most available listings and the longest observation period in the dataset.

providing feedback systems that include ratings and user comments (Barratt and Aldridge, 2016), where reputation systems are readily used by market participants (Espinosa, 2019) with about three-quarters of listings receiving a feedback (Kruithof et al., 2016). Studies that analyze the effects of these reputation systems find that on darknet markets, the risk of receiving low-quality goods or being scammed is relatively low, especially for cannabis and ecstasy products (Espinosa, 2019), as sellers usually get the option to pay after receipt. Only a small number of listings receive negative feedback, and a bad reputation punishes vendors with declines in sales and subsequent market exits (Bhaskar et al., 2019). Exploring the network structure of a sizeable opioid cryptomarket, Duxbury and Haynie (2018) find that only about 70% of buyers with multiple purchases bought from the same vendor and identify reputation as being a better predictor of sales than price or product diversity. Similarly, Décary-Hétu and Quessy-Doré (2017) find that 60% of buyers' transactions are with the same vendor and that 95% of feedback is positive, with little variation across vendors. Consequently, vendors have incentives to reveal the full information on their products to build trust. In fact, the length of the product description is positively correlated with the level of sellers' trust (Décary-Hétu and Quessy-Doré, 2017).

At first glance, cryptomarkets seem highly competitive (Paquet-Clouston et al., 2018), with large numbers of active vendors and website designs that encourage comparison of price, variety, and reputation. Using data from *Alphabay* marketplace, Paquet-Clouston et al. (2018) show, however, that a few key vendors take up large market shares. Low-level vendors hardly generate any revenue, while high-level vendors use aggressive advertising techniques and spam the market with their listings, which is a behavior that proves to be popular on the markets I analyzed. Most importantly, the darknet does not suffer from the threat of physical violence from competitors evident in street sales.

When it comes to defining the direct competitors of darknet vendors, platform and geographical location should be considered to describe a vendor's market. Vendors are active on multiple servers, but it is not known to which extent and how often buyers are comparing prices and varieties across different platforms. Although cryptomarkets are accessible globally, international borders still take importance in the definition of markets. Selling drugs across country borders is more costly, time-consuming, and simply riskier for all participants, as the chance of getting one's package checked will greatly increase (Aldridge and Décary-Hétu, 2016). This makes it more attractive for customers and sellers to only operate within their borders.[5] Furthermore, cryptomarkets should not be seen as entirely separated from traditional drug markets as cryptomarket vendors supply and compete with street sellers (Barratt and Aldridge, 2016). The cost of entering cryptomarkets likely depends on the prior situation of vendors. Starting from scratch and building up the necessary supply of drugs to sell on darknet markets requires a considerable amount of prior knowledge, connections, and money. However, if we consider drug dealers switching from traditional drug markets to cryptomarkets, the direct entry costs are relatively low. On *Alphabay*, for instance, the vendor fee is only 200 USD, and the registration process is simple (Paquet-Clouston et al., 2018). The information required to conduct business anonymously via the darknet is widely available. Menu costs are low, as price changes can be made instantly and do not generate monetary cost. It is even possible to peg the price of an offer made in a cryptocurrency to the USD

[5] As shown in the summary statistics in Table 1 of Section 4, only 5.3% of vendors in my sample declare worldwide delivery, while 83% restrict delivery to their home region EU, Australia, or North America, where only the last has internal border controls between the USA and Canada.

price, although this option was not available for all markets from the beginning (Décary-Hétu and Giommoni, 2017). While direct menu costs are close to zero, other price adjustment costs, such as gathering information about customers and competitors and making pricing decisions, affect price differences in online markets (Böheim et al., 2019). The cost of collecting the necessary information is not the same for all vendors and is likely higher for vendors that are active in multiple markets or offer differentiated products (Lach and Tsiddon, 1996).

Cryptomarkets are an attractive alternative to traditional drug markets that offer some unique advantages to customers. Illicit goods and services come in greater variety, at lower prices (Phelps and Watt, 2014) and higher quality (Bhaskar et al., 2019) compared to street sales. It is easy to compare product descriptions and search costs are limited to the time invested. The main risks for buyers are the risk of getting scammed by vendors (by requiring to pay before delivery) or administrators (exit scams), and the risk of getting caught by law enforcement, which is lower than on traditional drug markets (Buxton and Bingham, 2015). To my knowledge, there is no clear conclusion in the current literature on whether the majority of darknet buyers consists of consumers or retailers of drugs. Analyzing the original *Silk Road* in 2013, Aldridge and Décary-Hétu (2014) conclude that in these early times of cryptomarkets, seller-buyer relationships can be described as business-to-business relationships, with about a third of revenues being generated by listings with high quantities and high prices, which they assume is mainly used to source local drug dealers. However, it is evident from descriptive studies that a large and growing number of drug consumers supply themselves with illicit substances from cryptomarkets (Winstock et al., 2019). Winstock et al. (2019) show in their Global Drug Survey 2019 that over 10% of participants bought drugs at least once over the darknet within the last 12 months, with shares being highest in Finland (45.2%), the United Kingdom (28.6%), and Australia (14.9%).[6] The survey shows that two-thirds of darknet buyers are male, 80% of users are younger than 40, and that the share of first-time users shows a year-by-year increase from 7.7% in 2014 to 27.1% in 2019. In case buyers are also drug consumers, the demand is likely price-inelastic due to physical and psychological addiction caused by the illicit substances sold.

3.2 Cryptocurrencies

On darknet markets, cryptocurrencies are used to obscure payment trails and ensure the anonymity of sellers and buyers. Cryptocurrencies are decentralized digital currencies that use a public ledger system, called the blockchain, where transactions are stored for the purpose of verification. The original cryptocurrency - Bitcoin (BTC) - was proposed in Nakamoto (2008) and the first Bitcoin was created in 2009 (Halaburda et al., 2020). While nowadays most cryptomarkets offer a variety of cryptocurrencies for use, in 2014 and 2015, Bitcoin was the only dominant currency. Out of the 80 cryptomarkets listed by Branwen (2013) active during my observation period, 75 allowed the use of Bitcoin, 69 of which had Bitcoin as their only currency.[7] Users store their Bitcoins in digital *wallets* that include their public *bitcoin address* and their *private key* that is used to authorize transactions (Halaburda et al., 2020). New Bitcoins are created and distributed to so-called miners, who offer their processing power

[6] The Global Drug Survey is an international online survey directed towards drug users that is conducted on a yearly basis.

[7] This information was retrieved from the extensive although possibly incomplete list of darknet markets made available by Gwern Branwen on www.gwern.net/DNM-survival.

to validate and synchronize transactions. On the demand side, individuals use Bitcoins as a method of payment or investment, where the anonymity is especially attractive for illegal trade. While the blockchain does not include user names, all transactions can be traced back to one's wallet (De Balthasar and Hernandez-Castro, 2017).

Bitcoins can be obtained in many ways at varying degrees of anonymity, explained in O'Driscoll (2018). First, one can use a Bitcoin exchange platform, which acts similar to a traditional currency exchange market. However, on Bitcoin exchanges, anonymity is hardly ensured, as online services require payment details. Second, one can get in contact with private Bitcoin users via online platforms and trade directly. Third, it is possible to use a so-called Bitcoin ATM, where cash can be exchanged anonymously for a Bitcoin wallet. Once a wallet is acquired, one can use further steps to obscure the payment path between buyer and seller. On the Tor network as well as on the clear web, there are coin mixing or coin tumbling sites that move Bitcoins from one's initial wallet to several anonymous ones until the Bitcoins end up in a final wallet that is only used to make purchases. This coin mixing process is described in detail in De Balthasar and Hernandez-Castro (2017). The wallet used to buy Bitcoins from a Bitcoin exchange is usually linked to personal information. Therefore, the user creates a second anonymous wallet that they wish to use for further transactions before sending the desired amount of Bitcoins to a wallet held by the mixing service. The service then randomly chooses one of its wallets to send the Bitcoins to the user's new wallet. Given that the service keeps this payment path secret, the wallet with which the Bitcoins were acquired should now not be traceable to the wallet used for purchases. In return, the service keeps a small fee that often consists of a variable and fixed component.

3.3 Risk reduction

At this point, it is worthwhile to discuss the potential mechanisms, tools, and techniques that criminals on cryptomarkets can use in order to mitigate or eliminate holding and transaction risks. Analyzing forum posts from sellers of stolen data, Holt et al. (2015) give valuable insights into the risk reduction strategies employed by vendors on illicit online markets.[8] They find that buyers mainly fear being scammed by vendors and, therefore, rely on the reputation system. Vendors have to fear law enforcement, as well as upset buyers and competitors that either harm their reputation or leak information. Vendors can screen their potential customers using the forums and feedback system and satisfy them with timely deliveries and high quality standards. In order to prevent police detection, vendors had to develop a wide range of tools and practices, however. They can use PGP keys to secure information exchange, the Tor network to anonymize connections, and cryptocurrencies to hide payments, but they are most vulnerable at the point of physical delivery. Some of the common practices to minimize the risks involved in sending illicit substances via mail include using return addresses with fake names, concealing products in a professionally (Rhumorbarbe et al., 2016), mixing deliveries with other goods, and making use of fake deliveries to divert police attention (Europol, 2017).

Cryptomarkets have relatively short life spans, which means that vendors are in constant fear of losing their trading platform. Branwen (2013) collects data on darknet market closures

[8] (Holt et al., 2015) point out that these strategies might be crime-specific. Although there are slight differences in the structure of data markets compared to the darknet markets explored here, the risks stay the same. The main difference seems to be in the transaction process, where data thieves refrain from using cryptocurrencies in favor of online payment systems where deposits are made from electronic accounts directly.

starting in 2011. On average, the servers were online for 33 weeks, with the longest active platform being accessible for 5.5 years (*Dream Market*) and the shortest ones being hacked within a single day. In order to mitigate the damage of platform closures, vendors operate on multiple markets at the same time. This is evident from the data, as 27.4% of vendors in my sample operate in more than one market throughout the observation period, and multi-market vendors operate in 2.6 markets on average. These numbers are likely downward biased, as user pseudonyms were used to match vendors across markets, yet some vendors might have different user handles for each market.

From the perspective of law enforcement, cryptomarkets were a relatively new phenomenon in the observation period of 2014 to mid-2015, which faced the police with new challenges. Using information from interviews with experts and law enforcement representatives, Kruithof et al. (2016) give an overview of strategies employed or planned by international, particularly Dutch, law enforcement that aim to detect and catch cryptomarket vendors, where they identify four main strategies. First, traditional investigation techniques like physical monitoring, the use of informants, and undercover work can target the production and distribution process of the vendor's supply chain. Second, the postal way from the seller to the buyer can be targeted by intercepting suspicious packages or ordering from specific vendors and tracing the mail. Third, online monitoring can involve observing darknet markets and the money trail that transactions leave behind. Fourth, online disruption aims at attacking the reputation of cryptomarkets themselves. This can be achieved by setting up fake vendor or buyer accounts or shutting down popular markets that might secure high media coverage and potentially scare away market participants. Generally, police intervention in the early period of cryptomarkets focused on taking down marketplaces and above-average buyers (Van Slobbe, 2016).

In terms of transaction risk, the most obvious answer would be to require transactions to be finalized early. This is a common suggestion or requirement made by vendors, where buyers have to make payments before the actual delivery of the good (Moeller et al., 2017). Of course, this makes buyers vulnerable to scam, which means vendors must either have an outstanding reputation or offer the buyers compensation for the higher risk in the form of lower prices (Europol, 2017). Markets also allow denominating prices in USD, which means that the actual number of Bitcoins required for the purchase fluctuates over time.[9] This mechanic takes care of fluctuations before the purchase, but as prices are fixed at the time of sale, the vendor still has to bear transaction risk for the period between sale and confirmation.

4 Data

I draw on three different data sources, where I use snapshots of cryptomarkets to construct my outcome variables of interest as well as other vendor-specific characteristics, and data on darknet market-related arrests and Bitcoin prices to define shocks in holding and transaction risk.

[9] Christin (2013) mentions this possibility for the original Silk Road. As all markets in the sample are now closed, it was not possible to retrieve this information for all platforms. However, looking at listings that are online for multiple days, it is evident that prices are changing slightly between each scrape. Once prices are converted to USD, they become stable, suggesting that setting prices in USD was the standard procedure on the servers examined in this study.

4.1 Cryptomarket data

The dataset comprising detailed listings on darknet markets was constructed by independent researcher Gwern Branwen (Branwen et al., 2015b). Branwen uses an automated scraping procedure that captures information from 89 English-language darknet markets between 2011 and 2015. As markets tend to be short-lived, I focus on eight large darknet marketplaces active between 2014 and 2015: *Abraxas*, *Agora*, *Alphabay*, *Dream Market*, *Evolution*, *Nucleus*, *Outlaw Market*, and *Silk Road* 2.0. Scraped information on listings includes the vendor's pseudonym, the date of the scrape, a broad product category that varies across markets, the vendor's product description, which is used to retrieve the amount in grams or milliliters offered, the location from which the vendor operates (often undeclared, or continent information only), the countries the vendor supplies, the price in Bitcoin, the vendor's current rating, and for some markets also an indicator for whether the vendor requires early finalization of the transaction. The general data cleaning process required some non-trivial assumptions, which are explained in detail in Appendix A. Pre-processed data is then pooled across markets, and vendors are matched by their pseudonyms in order to construct a daily vendor panel.

The scraping process can be a faulty procedure where scrapes can be incomplete for multiple reasons (Branwen et al., 2015b). E.g., the servers can be offline, or there can be connectivity problems at the time of the scrape. Different servers are online at different times, but out of the 553 days, the scraping procedure aimed to cover, on 354 days, at least one market has been successfully scraped. The presence of failed and incomplete scrapes makes it appropriate to aggregate data to weeks. As the data represent snapshots, I take the weekly mean of continuous variables across all available days, where the aggregation process takes into account on how many market scrapes a vendor was observed. The result is a weekly vendor panel with one observation for each vendor and week. Once data are aggregated on the week level, there is at least one scrape for 77 out of 79 weeks.

I focus my analysis on two drugs - cannabis and opioids. This approach allows me to address several problems. First, the scrapes only give a snapshot of offered products. Therefore, changes in outcomes can be caused by changes in either supply or demand. As I am concerned with supply-side effects, I assume demand to remain constant. The separate analysis of cannabis and opioids allows me to test, whether this assumption holds. I use the fact that opioids are substances that lead to stronger physical dependence than cannabinoids.[10] This suggests that there should be considerable differences in time preference and price elasticity between consumers of these types of drugs. Second, in the case of cannabis and opioid buyers, it is unlikely to observe switchers between the two products in the short run, making cross-price effects unlikely.[11] Third, another advantage of category-wise estimation is that the observed quantity and price effects are disentangled from the effects of moving from low to high quantity categories or cheaper to more expensive categories, and vice-versa.

Table 1 shows the summary statistics on the vendor and week level. I restrict my sample

[10] In terms of dependency, US-based studies show that approximately 10% of cannabis users develop a use disorder (Lopez-Quintero et al., 2011), while 25% of users of (medical) opioids develop a dependency (Boscarino et al., 2010). Opioids show some of the strongest (subjective) withdrawal symptoms. The side effects of using opioids are generally considered more harmful than those from using cannabinoids, which is why cannabis is often discussed as a substitute for opioids in pain-reduction (see, for example, Reiman et al. (2017)).

[11] There is potential for cross-price effects when buyers are drug retailers rather than users. In the short run, I do not expect retailers to switch between selling cannabis to opioids, as their customers are not likely to switch, and finding new customers requires time and trust.

Table 1: Summary statistics on vendor and week level

	N	Mean	Std.Dev.	Min	Max	Vendors
Cannabis						
Number of listings	43654	4.806	9.211	0	178	2193
Quantity in g	43654	301.155	1795.761	0	107163	2193
Price in USD/g	26066	16.236	25.916	0	299	2193
Rating	57027	0.998	0.047	0	1	2193
Entries	57027	0.042	0.199	0	1	2193
Exits	57027	0.049	0.216	0	1	2193
Finalize early	14339	0.289	0.453	0	1	1139
Opioids						
Number of listings	23236	3.005	5.964	0	109	1115
Quantity in g	23236	35.755	489.945	0	30903	1115
Price in USD/g	13026	446.797	484.205	0	2250	1115
Rating	30076	0.998	0.043	0	1	1115
Entries	30076	0.040	0.196	0	1	1115
Exits	30076	0.048	0.214	0	1	1115
Finalize early	7926	0.279	0.449	0	1	563
Markets						
Abraxas	57915	0.039	0.193	0	1	2978
Agora	57915	0.615	0.487	0	1	2978
Alphabay	57915	0.012	0.109	0	1	2978
Dream Market	57915	0.030	0.170	0	1	2978
Evolution	57915	0.269	0.443	0	1	2978
Nucleus	57915	0.111	0.314	0	1	2978
Outlaw Market	57915	0.056	0.229	0	1	2978
Silkroad 2.0	57915	0.099	0.299	0	1	2978
Declared region						
Europe	75837	0.345	0.475	0	1	2978
North America	75837	0.410	0.492	0	1	2978
Australia	75837	0.075	0.264	0	1	2978
Worldwide	75837	0.053	0.224	0	1	2978
Other	75837	0.117	0.321	0	1	2978
N	75837					

Notes: This table describes the vendor panel, where one observation represents a vendor at a given week. Therefore, the number of observations refers to all combinations of vendors and weeks where information is available. The mean, standard deviation, minimum, and maximum are also calculated based on vendor-week pairs. The column *vendors* shows the number of vendors for each variable in the panel. Outcome variables are shown separately for cannabis and opioid vendors, while the distribution of vendors across markets and regions is shown for the full sample. The variable *finalize early* is only available on *Evolution* and *Nucleus* markets.

to vendors who sell these categories at least once during the observation period. Cannabis and opioids are among the largest categories, where 40.5% of vendors in the original unrestricted sample are selling cannabis and 21.5% are selling opioids. There is some overlap of vendors selling both types of products, with 330 out of the 2,978 vendors in the final sample listing both products at some point in their history. The majority of vendors in the sample declare Europe and North America as their home markets, with *Agora*, *Evolution*, and *Nucleus* being the most popular markets among vendors. Note that the number of observations is higher for quantity than for prices, which directly results from the way these variables are coded. On days where vendors were not featuring any listings on servers they have been active on before and after, quantity is coded as zero, while prices necessarily retain missing values. In terms of the period of activity, there is not much difference between drug types, with cannabis vendors being active for 26 weeks and opioid vendors for 27 weeks on average.

Over the sampling period of 1.5 years, the average market was active for 52 weeks, where scraping periods range from 17 (*Alphabay*) to 78 weeks (*Agora*).[12]

4.2 Outcome variables

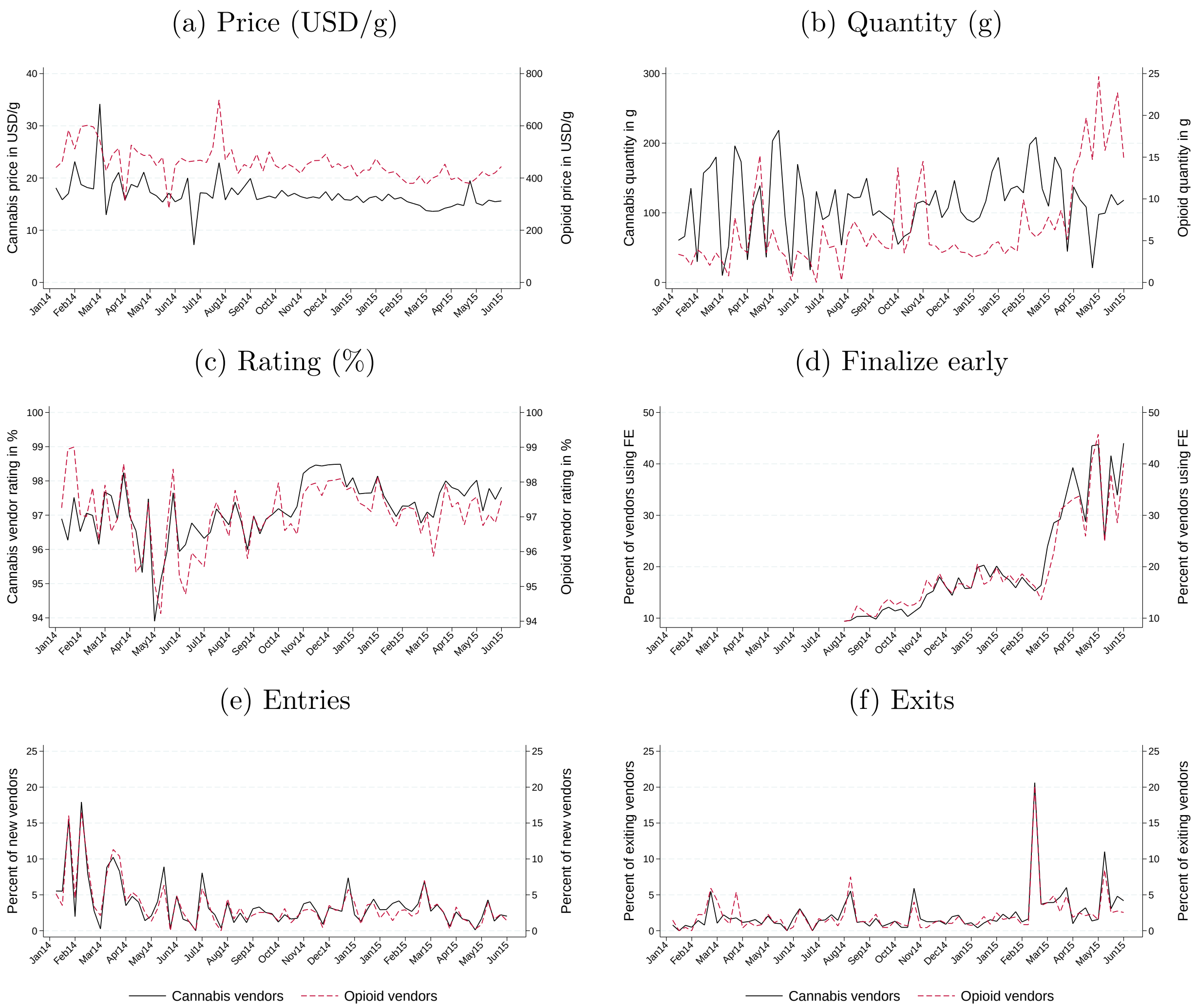
There are six important vendor-level outcome variables that can be constructed from the scraped data. The price of drugs expressed in USD per gram, the quantity in grams, the rating a vendor receives from customers, the vendor's decision to use the finalize early option, as well as the decision to enter or leave the market.[13] While price, quantity, rating, and finalize early decision can be directly observed from the market scrapes, entries and exits require an additional assumption. Entries are proxied by the share of new vendors in a given week, and exit decisions are defined in the week of the last listing in the observation period. The first and last week of observation for each market is treated as a missing value, as it is not clear whether a vendor joined or quit the market during this week or has been active outside the observation period. In order to make quantities comparable, I choose to focus only on listings that include information about quantity in weight, which are standardized to grams, and neglect listings based on volume amounts like milliliters. Considering all listings that include some sort of weight or volume information, 98.8% of cannabis listings and 99.0% of opioid listings allow for the construction of a quantity measure in grams, which justifies the choice of ignoring milliliter listings.

Figure 2 illustrates the six main dependent variables over time. Prices for both cannabis and opioids vary greatly over the course of 2014, with no clear observable trend. For prices and quantity, opioid and cannabis movements often diverge, which warrants a separate analysis of the two drug categories. The largest variability can be observed for the average quantity of drugs supplied. Ratings, on the other hand, remain remarkably stable across time. The share of vendors who finalize early can only be determined for *Evolution* and *Nucleus* markets, which is why the observation for this variable only begins in August 2014. It is worth noting that the finalize early option was more commonly used on *Nucleus*. This is why the share drastically increases from an average of 15% to above 30% after *Evolution* shuts down in March 2015. This fact is adjusted for in the regressions by adding controls for which market(s) the vendors were active in. The share of new vendors is relatively higher in the first half of 2014, with about 6% of total vendors having entered in the week of the scrape, compared to the rest of the observation period where the share is around 2.5%. The share of vendors who enter the market remains below 5% in most weeks, where the spike in exits in march 2015 can be explained by the exit scam of the administrators of the *Evolution* marketplace.

[12] For a graphical representation of scraped weeks across markets and time, please refer to Figure 11 in Section A of the Appendix.

[13] Markets either denote their listings in USD or Bitcoin. Listings that are online for multiple days and priced in Bitcoins show very slight price changes that disappear once converted to USD. This suggests that platforms peg their prices to USD even though they are displayed in Bitcoin. To establish a common currency across markets, I choose USD over Bitcoin for stability reasons. This is necessary because if prices were shown in Bitcoin, and drug prices are pegged to USD, I would not be able to disentangle changes in drug sellers' pricing behavior from Bitcoin price fluctuations.

Figure 2: Outcome variables



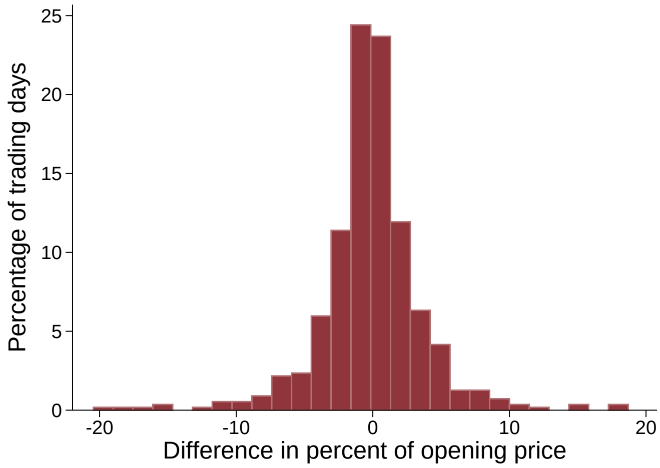
Notes: This figure depicts the dynamic changes of the six outcome variables over the observation period of January 2014 to July 2015. The sample is restricted to cannabis vendors (solid black line) and opioid vendors (dashed red line) in order to show co-movements and diverging patterns for these drug categories. Markets use different rating systems, which are standardized, where 0% is the worst possible rating and 100% is the best. Please note that axis labels do not start at zero for all variables.

4.3 Darknet market arrests and Bitcoin data

On top of vendors-specific data, I require to determine shocks in holding and transaction risk. Holding risk is represented by the number of arrests of cryptomarket participants also provided by Branwen, who published an extensive list of darknet market-related arrests between 2011 and 2015 compiled from various sources (Branwen, 2015a). The dataset contains the date of the actual arrest as well as the date the arrest was reported publicly, which often coincide. Most of the arrests are made up by buyers (226 arrests) and sellers (167 arrests), with some incidents involving market staff (18 arrests).

As I choose Bitcoin volatility as a proxy for transaction risk, I rely on historical Bitcoin price data between 2013 and 2015 published by CoinMarketCap (2020) in order to construct

Figure 3: Intra-day changes in Bitcoin prices



Notes: This figure depicts the distribution of intra-day changes in the BTC/USD price. The price changes are calculated as the difference between closing price and opening price as a percentage of opening price, where the unit of observation is a trading day.

the volatility measures. Daily opening and closing prices of Bitcoin denoted in USD are retrieved, where I select the opening prices to calculate (weekly) volatility. These opening prices are also used to standardize drug prices across markets by converting them into USD.

The cryptomarket scrapes I use are snapshots of the listings that are currently online. Unfortunately, only the date of a scrape is known, rather than its exact time. As there is potential for Bitcoin price changes within a day, using daily opening Bitcoin prices might cause problems for the construction of the price variable. Therefore, there is potentially a slight difference between my price measure of products and the actual price listed by vendors. This difference depends on the timing of the scrape and the time the opening Bitcoin price was set. To give an interpretation of how big this difference can potentially be, Figure 3 shows the difference between the daily closing and opening Bitcoin/USD price in percent of the opening price for my entire observation period. The intra-day price changes range from -20.5% to +18.7% with a mean of 0, with 50% of trading days falling between -1.6% and +1.6%. Of course, these are the worst-case scenarios of having the maximum time difference between price setting and scrape. Therefore, there exists little threat to the interpretation of the price variable, as for most days, differences are close to zero, all variables are aggregated on the week level, and the event study approach aggregates events from different periods.

5 Empirical framework

I analyze the causal effects of transaction and holding risk shocks on various vendor-specific outcomes. In order to answer these research questions in a way that allows for a causal interpretation of results, I use an event study design following the approach described in Borusyak and Jaravel (2016). In a standard event study, individuals receive treatments at different points in time and stay treated until the end of the estimation period, where the estimated model is arranged in time relative to the treatment rather than in absolute time. The main idea of an event study design is to use the pre-treatment period as a counterfactual for the post-treatment period and observe how outcome variables are changing in periods after the treatment. The identifying assumption, therefore, requires that the trend of an outcome variables would have continued in the absence of the shock.

In these difference-in-difference settings with differential event timings, effects are estimated using panel regression methods that include individual and time fixed-effects (Borusyak and Jaravel, 2016). The set-up of this study slightly deviates from this standard event study set-up in two ways. First, all vendors receive a treatment, i.e., the shock to the transaction or holding risk at the same time, where the timing of the event itself is unpredictable. Second, vendors potentially receive multiple shocks during the estimation period. This implies that for the same vendor, it is possible that an observation from a post-event period might be used as a counterfactual for a different event.

As discussed in Borusyak and Jaravel (2016) the event study approach follows three objectives. As a first step, the dynamic treatment effects relative to the event timing are estimated. To give credibility to this research design, there should not be any pre-event trends. Therefore in a second step, the results from the dynamic estimation are used to analyze the pre-event window. The identifying assumption is supported if coefficients in the pre-event periods remain insignificant, meaning the post-event effects observed only begin after a shock and have no pre-trends. Finally, the average treatment effects are estimated for a time window chosen based on the results of the first step, where the window is narrowed down to an average period in which dynamic effects are observable.

Using the vendor panel, I estimate fixed-effects models in order to determine the average treatment effect and the dynamic treatment effect. Equation (3) determines the dynamic treatment effects β_k in week k relative to the event. Y_{it} are outcome variables that include drug price, drug quantity, vendor rating, use of finalize early option, market entry, and market exit of vendor i in time t. α_i indicates vendor fixed-effects, X_{it} are control variables, and ϵ_{it} is an error term. Control variables include the market the vendor was active in, the mean price of the other vendors, the mean quantity of the other vendors, the number of active competitors, as well as binary indicators for whether there have been shocks in transaction (holding) risk in the pre-event period of holding (transaction) risk events.

$$Y_{it} = \alpha_i + \sum_{k=-7, k\neq -4}^{7} \beta_k D_k + X_{it} + \epsilon_{it} \tag{3}$$

The estimation window spans seven weeks before and after the event, where the week in the middle of the pre-event period serves as the base period. Additionally, this specification also allows for the analysis of patterns in the pre-event period and checking for the assumption of no pre-trends.

Equation (4) shows the model that estimates the average treatment effect γ, comparing the four weeks before the event to the four weeks after the event. $POST_{it}$ is a binary indicator for post-treatment periods, and the same controls are used as in the estimation of dynamic treatment effects. The window was chosen based on the results to Equation (3) that indicate that most effects occur during this period.

$$Y_{it} = \alpha_i + \gamma POST_{it} + X_{it} + \epsilon_{it} \tag{4}$$

As the data are subject to seasonality, outcome variables are replaced by fitted values from a regression of the outcome on calendar month and week of the month. Binary outcomes are estimated using a Linear Probability Model with fixed-effects.[14] A causal interpretation of β_k and γ as the effects of shocks to transaction and holding risk requires that the event timing is uncorrelated with market outcomes, conditional on vendor fixed-effects and the controls included in the regression model (Borusyak and Jaravel, 2016). This assumption of no pre-trends is tested in the dynamic Equation (3).

5.1 Event definitions

In the next step, events need to be formally defined. Events have to represent significant exogenous shocks to production risk and cannot be anticipated. Therefore, I experimented with different event definitions that fulfill both goals.[15] The definition that works best for both types of production risk is to declare an event every week where a certain threshold level of arrests or Bitcoin price volatility is exceeded. I chose the threshold levels only based on how stable coefficients are in pre-event periods. In the main specification, a shock in holding risk is defined whenever there had been seven or more darknet-market-related arrests within a calendar week, resulting in six events during the observation period.

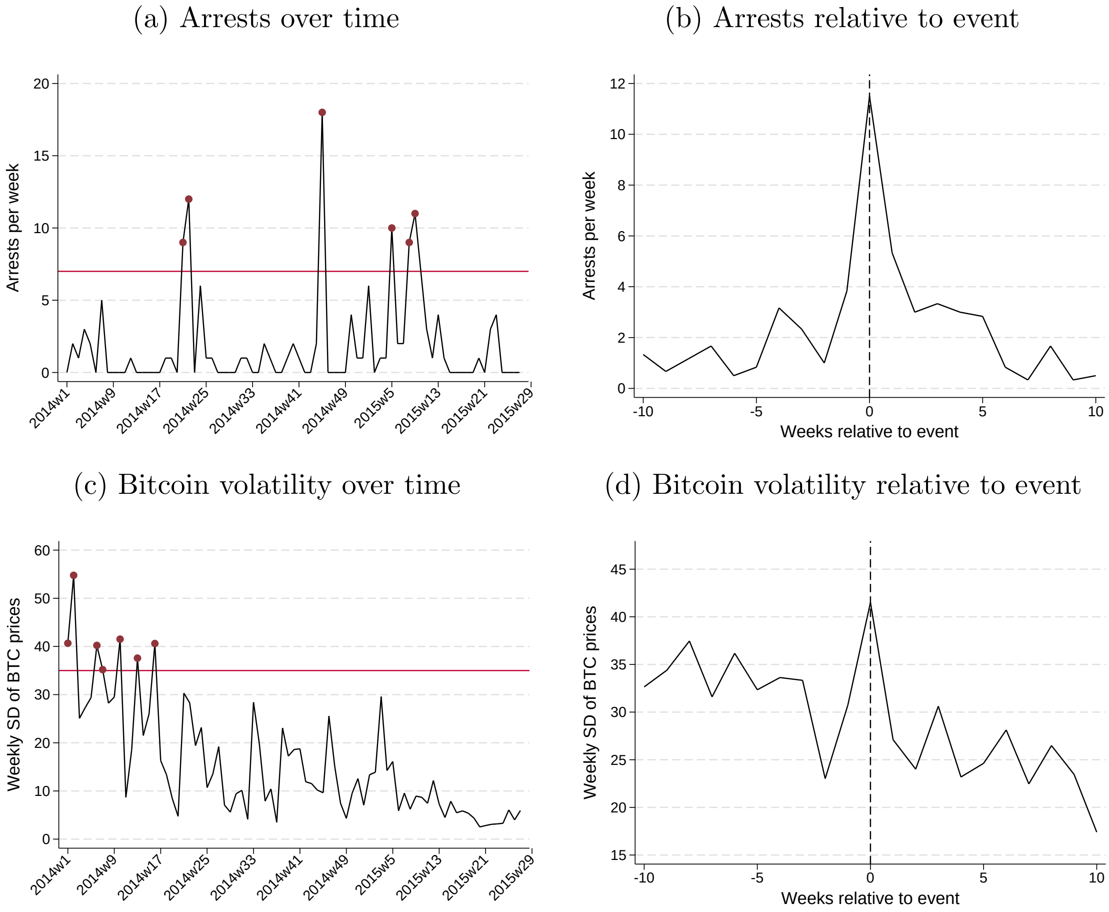
Panel (a) of Figure 4 depicts the number of arrests over the observation period, showing that holding risk events are spread out across the period. Panel (b) shows the number of arrests relative to the event timing, where the six events are pooled together. This representation aims to give an image of the relative strength of the impulse and its dynamic. One can see that this event definition leads to a strong increase in arrests at the event week, with low and steady numbers of arrests directly before and after the event. Among these events are also the arrests following the international police intervention *Operation Onymous* on 5th and 6th November 2014 that targeted large cryptomarkets resulting in the arrest of 17 individuals in the U.S. and Europe (Décary-Hétu and Giommoni, 2017).

Shocks to transaction risk are identified when Bitcoin volatility surpasses 35 standard deviations. Again, the value was chosen based on the stability of pre-event coefficients. Volatility is calculated in two steps, where first, the standard deviation of daily opening Bitcoin prices for the last seven days is determined. Then, these standard deviations are aggregated on a weekly basis by taking their mean. This procedure allows transforming daily fluctuations into weekly fluctuations accurately. The definition results in seven events during the observation period, shown in Panel (c) of Figure 4. In 5 out of 7 event weeks, the Bitcoin price declined over the course of the week. Bitcoin prices dropped by 20.64 USD or 3.7% on average (first day to last) in event weeks. On a daily level, Bitcoin prices dropped by 5.97 USD (0.9%) with daily changes varying between -144.49 USD and +75 USD or -18% and +10% of the opening price. In contrast to holding risk, these events are more concentrated around the first four months of 2014. This period saw some significant events destabilizing the price of Bitcoins. On 5th December 2013, China forbids financial institutions the exchange of cryptocurrencies (Ju et al., 2016). On 28th January, the CEO of the Bitcoin trading platform BitInstant was arrested due to allegations of money laundering in connections with cryptomarket *Silk Road* (Hill, 2014). In late February 2014, MtGox, a Bitcoin exchange where 70% of all Bitcoins had been traded until then, filed bankruptcy following the loss of Bitcoins worth more than 500 million USD, with MtGox already suspending their withdrawal

[14] In a robustness check, I use a conditional logistic regression with fixed-effects, the results of which can be found in Tables 30 - 31 in Section C of the Appendix.

[15] The results of these experiments can be found in Tables 24 - 29 in Section C of the Appendix.

Figure 4: Event definitions



Notes: This figure visualizes the criteria for the event definitions. Panels (a) and (c) show the development of arrests and Bitcoin volatility over the observation period. Using the cut-off levels shown as red lines, I define six shocks to holding risk and seven shocks to transaction risk. Panels (b) and (d) then aggregate these events by taking the mean over arrests and volatility relative to the event timing for a period of seven weeks before and after the shock.

service earlier that month (Decker and Wattenhofer, 2014). Each of these events had its impacts on Bitcoin prices, leading to unstable prices in early 2014. Panel (d) of Figure 4 depicts the relative strength of the impact of the shock in transaction risk over time relative to the event. Again, the figure indicates a significant increase in volatility around the event timing, with low levels directly before and after the shock, although pre-event volatility levels are less stable as after the event.[16]

[16] The event definitions are identical for the analysis of all outcome variables with the only exception of finalize early. As this variable is only observed on *Evolution* and *Nucleus*, which are not scraped over the same period as the rest of the markets, different threshold levels are used. I use five arrests for holding risk events and twenty standard deviations for transaction risk events. This is done in order to achieve an event study with a similar number of events as for the rest of the outcome variables. The corresponding event definition graphs can be found in Section B of the Appendix.

5.2 Exogeneity of shocks

In order to support the causality of results, it is required to assume that shocks are exogenous to the cryptomarket system. This section briefly discusses possible threats to the exogeneity of arrest shocks and volatility shocks. There are some potential channels through which cryptomarket activity can affect arrests, leading vendors to anticipate police interventions. First, increasing drug supply might induce law enforcement to increase their efforts. In this case of endogeneity of police activity, I expect to find pre-trends in the dynamic regressions, especially with regard to pre-event drug quantities. I do not find significant pre-trends in the drug supply in the dynamic regressions, which supports the assumption of exogenous shocks. Second, prime targets might anticipate that they are on top of the priority list. However, measures taken by law enforcement are lengthy and do not yield results immediately. The most prominent law enforcement interventions have targeted marketplaces, rather than specific vendors. The major operations were the shutdown of the original *Silk Road* in October 2013 and *Operation Onymous* in November 2014 (Décary-Hétu and Giommoni, 2017). Moreover, traditional investigation methods are not ideal for targeting individual vendors or buyers as the costs of surveillance likely exceed the benefits of catching small offenders (Kruithof et al., 2016). Arrests require lengthy preparation and often rely on mistakes made by sellers, buyers, or market operators. Furthermore, decisions about how many resources are used in darknet-market investigations are not made on a daily basis. Law enforcement has first to develop the necessary infrastructure and skills to conduct online detection of criminals (Kruithof et al., 2016), making reverse-causality in the short-run implausible. On top of that, it remains unclear for vendors which markets and which vendors will be targeted, which supports the assumption of random events.

For the relationship between Bitcoin prices and darknet activity, the direction of causality might also be unclear initially. This is the case because if darknet sales increase, the number of Bitcoin transactions will necessarily increase, which is publicly available information due to the design of the blockchain technology. I put forward three arguments as to why volatility shocks are exogenous, and reverse-causality does not pose a problem to the research design. First, the link between darknet sales and transactions within the blockchain can also be shown empirically as done by Janze (2017), where the author finds that there is a lagged correlation between the two variables that is strongest after six days of the sale, which can be interpreted as the average time transactions take to be concluded. If it were the case that only sales activity affects Bitcoin price and not vice-versa, one would expect to observe large changes in listings one week before an event, which is not evident from the data. Second, given that cryptomarket sales cause Bitcoin transactions to increase, the question is whether this increase can have a short-run effect on the Bitcoin price. If this is the case, then the shock is not exogenous, and the effects of transaction risk cannot be interpreted causally.

There is a growing literature on the factors that influence Bitcoin prices and its volatility described in Halaburda et al. (2020). Like traditional currencies, the Bitcoin price is based on how many people buy and sell the currency. The two main reasons for buying Bitcoins are to use them for transactions (which includes darknet use) and as an investment object. If the latter dominates, this means that volatility shocks have a strong exogenous component. In the financial literature, media attention is often linked to speculative behavior, and the effect of media on Bitcoin prices is a well-researched relationship. For the early periods, it was shown that Bitcoins were used as investment tools rather than as a medium of exchange, especially by uninformed buyers (Glaser et al., 2014). The authors find that the exchange volume of Bitcoins recorded by exchange platforms by far exceeds the transaction volume of Bitcoins measured by the blockchain. Furthermore, Halaburda et al. (2020) summarize findings from the empirical literature that show that after 2013 Google searches caused price increases (Kristoufek, 2015). Combined with the fact that Bitcoin was historically showing signs of a bubble that burst multiple times throughout its history, this supports the conclusion that price formation is dominated by speculative behavior. Third, Halaburda et al. (2020) note that the early Bitcoin market was still an emerging one that cannot be studied with the same tools as regular established currencies. Early Bitcoin prices are often described as erratic and unpredictable, which also extends to the observation period of this study, as is evident from the intra-day Bitcoin price differences shown earlier, ranging from price falls of 20% to price increases of 19% within a single day.[17] These facts combined imply that Bitcoin price formation is subject to random movements that could not be predicted in the short-run.

6 Main results

In this section, I present the main study's main results and analyze the dynamic paths that the shocks cause by estimating Equation (3), and I discuss the interdependencies of different reactions. I focus on two categories of drugs, cannabis, and opioids. As these drugs vary in their degree of dependence, this dual analysis allows to determine whether the observed reactions are supply-side or demand-side effects. While the average treatment effects for the first month of the shock are reported in the following figures, the analysis in this section focuses on the dynamic paths of shocks.

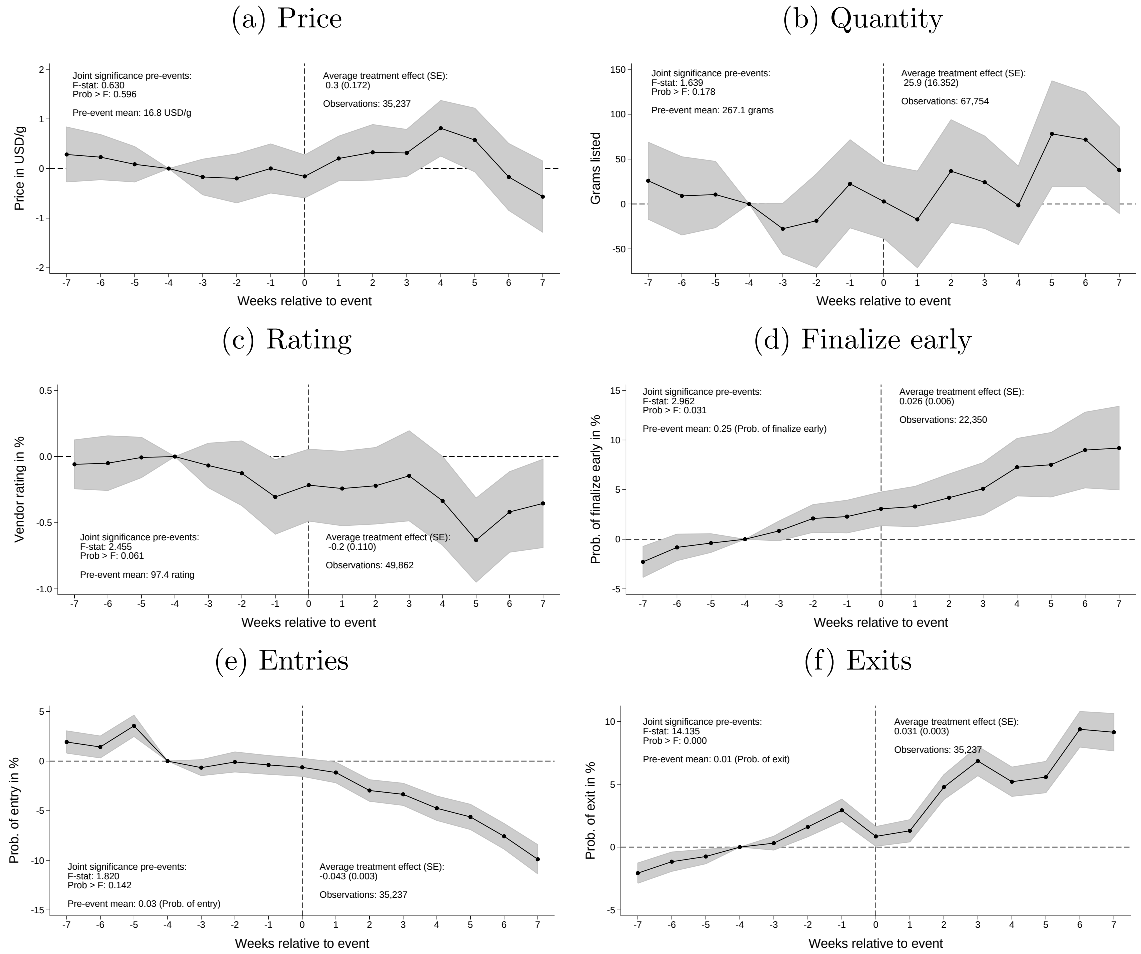
6.1 Holding risk and cannabis vendors

I estimate dynamic effects of an increase in holding risk on cannabis vendors from Equation (3). The results are reported in Columns (1) - (6) of Table 2 and are visualized in Figure 5. Examining the vendors' reactions chronologically, market exits are the first response to the shock. Throughout the entire estimation period, there exists an upward trend that begins to fluctuate around the event period. In the first two weeks of the event, market exits decrease relative to the week before the event. After the event, market exits again begin to increase in weeks two and three, and by week three, the expected probability of market exit has increased by 6.8 percentage points compared to the base period. While the short term increase in exits is consistent with the previous literature on the deterrent effect of police interventions, the event study shows that this desired effect does not come immediately but rather after an adjustment period. This implies that vendors not only react to the increased probability of arrest, but also sequential changes in market structure, e.g., number and composition of competitors, market prices, and supply. As expected, arrests have a deterrent effect on market entry. Beginning in the second week after the shock to holding risk, the number of market entries of new cannabis suppliers decreases steadily until the end of the estimation period, where the average treatment effect within one month is a decrease in the expected probability of entry of 4.3 percentage points.

Further market reactions can be observed in the fourth week after the shock in the form of price and vendor ratings. Cannabis prices increase on average by 0.81 USD/g (4.8%) with

[17] Please refer to Figure 3 and the corresponding discussion in Section 4 for a description of Bitcoin price volatility in the sampling period.

Figure 5: Effects of shocks to holding risk on cannabis vendors



Notes: This is a graphical representation of the estimated effects of shocks to holding risk on different outcome variables relative to the event time. Areas shaded in grey represent 95% confidence intervals. The estimates to the corresponding fixed-effects models are tabulated in Table 2. All estimates include controls for markets and seasonality. The Linear Probability Model used for the binary response variables in Panels (d) - (f) also includes controls for price, quantity, and number of competitors, as well as controls for shocks to transaction risk up to three weeks prior to the event. Pre-event means refer to the base period four weeks before the shock. Joint significance of pre-trends are based on a F-test for joint significance of the coefficients in three leading periods.

the coefficient being significant at the 1% level, and the price effect only vanishes by week six. One possible explanation for this price spike could be that with the decreased number of competitors, individual vendors gain more market power, which they translate into price changes. However, adding a control for the number of competitors in a region does not change the coefficients of interest, and the coefficient for the number of competitors is insignificant, as can be seen in Table 12 of Section C.2 in the Appendix. Therefore it seems appropriate to interpret the price changes as reactions to the increased number of arrests.

Simultaneously, ratings of cannabis vendors significantly decrease and remain below the level of the base week until the end of the estimation period. These changes are small in terms of magnitude, however, with the mean ratings dropping only by half a percentage point. Customers can change their ratings for several reasons. First, the quality of the product received might be sub-par. Lacing drugs with different substances is a constant threat for buyers, regardless of drug-type. Second, the goods might have arrived later than expected. Third, the rating might reflect disapproval of increased prices. Fourth, Décary-Hétu and Quessy-Doré (2017) point out that ratings depend on how long a transaction relationship is maintained, and changes in rating might therefore signify a shift to new vendors. The fact that changes in price and rating coincide suggests two possible paths. If the rating is seen as a proxy for quality, then the decrease in ratings suggests that vendors are producing drugs at inferior quality or vendors are lacing drugs. While this would mean a cost reduction, it is not clear why vendors simultaneously increase prices. The more likely explanation is, therefore, that ratings are a reaction to increased prices. In week five, after the event, vendors increase their supply by 78.1 grams on average, which is a 29.3% increase. The fact that this increase occurs just one week after the increase in prices could mean that it is now more attractive for vendors to sell cannabis online, leading them to increase supply.

The question might arise how vendors can increase their supply so fast and why vendors do not supply all their available stock in the first place. This might be the case because vendors keep some drugs for their own consumption, have designated amounts for street and online sales or they simply want to avoid getting in the focus of the police. Also, the increase in supply occurs one week after the increase in prices. It might be possible that vendors are increasing orders from their suppliers, which takes some time. Controlling for market prices, that is, prices of the other vendors active on the market, indeed shows a highly significant and positive coefficient, as can be seen in Table 13 in the Appendix. In the same specification, the dynamic effect of supplies remains positive and significant at the 10% level, which suggests that at least part of the quantity reaction can be traced back to an increase in holding risk directly. The use of finalize early as an alternative payment option increases steadily throughout the estimation period with no observable change around the event timing. This reveals that requiring customers to finalize transactions early is not a typical response to an increased risk of being arrested. In order to test the for pre-trends, T-tests of joint significance of three leading periods before the event are conducted, the results of which can be found in Figure 5. In the case of price, quantity, and entries, the null hypothesis of insignificant pre-event coefficients cannot be rejected at conventional significance levels, giving strong support to the causal interpretation of the findings presented in this study. For ratings, there is one small yet significant coefficient for the week before the event. There are significant coefficients before the event in terms of market exits, but the fluctuation observed is much larger in terms of magnitude in the post-event period.

6.2 Holding risk and opioid vendors

Although opioid sellers, very much like cannabis sellers, reacted with higher prices, more market exits and fewer entries, and received lower ratings, the dynamics vary quite a lot, as can be seen in Figure 6 and Columns (7) - (12) of Table 2. The first response of opioid vendors is a decrease in market exits relative to the week before the shock, followed by an adjustment period. By week two, coefficients for market exits have exceeded pre-event levels. Entry deterrence seems to take effect in week one already, one week earlier than for cannabis vendors. In the period one to two weeks of the shocks, opioid sellers significantly increase prices by 4.2%, only to drop back to pre-event levels in the third week, suggesting that holding risk is translated into a short-term risk premium.

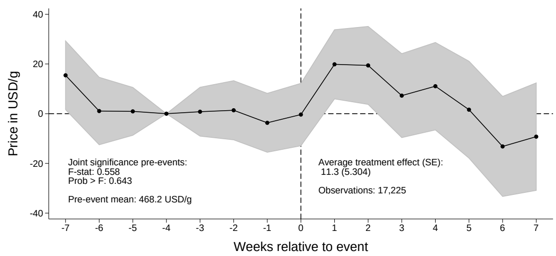
I offer three potential explanations as to why opioid sellers react faster than cannabis vendors who only adapt their prices to these shocks by week four. First, it is possible that opioid sellers are more likely associated with larger crime organizations, while it might be more common for cannabis vendor accounts to be run by a single person. Larger organizations mean access to a more extensive network, and opioid dealers might therefore have better and faster insight into who gets arrested and when. Indeed judging from the summary statistics reported in Table 1, we see that the average opioid vendor has products worth around 18,000 USD listed, while the average cannabis seller's offer sums up to approximately 7,700 USD. Second, opioid vendors might expect to be higher on the priority list of law enforcement agencies, as their product is widely considered more dangerous for the general public. The perceived risk from an increased level of arrests might therefore be relatively higher for opioid sellers, explaining the faster responses. Third, the summary statistics reveal that there are almost twice as many cannabis sellers as opioid vendors. Together with inelastic demand due to the physical dependence caused by opioids, opioid vendors likely have higher degrees of market power than cannabis vendors. This, in turn, makes it easier for them to pass on the added risk via prices. Indeed, Table 12 in Section C.2 of the Appendix shows that the number of competitors is positively correlated with opioid prices, where the coefficient is weakly significant at the 10% level. However, the main coefficient of interest stays positive and significant, which suggests that part of the price effect observed in weeks one and two can be directly traced back to the increased number of arrests.

Interestingly, a drop in user ratings by half a percentage point occurs around the same time as in the case of cannabis. In the case of opioids, it is unlikely to be linked to the increase in prices as the ratings fall three weeks after the prices spikes. Although there appears to be a drop in quantity supplied in week one, the coefficient is statistically insignificant, suggesting that in contrast to cannabis vendors, opioid sellers do not respond to more holding risk with quantity changes.

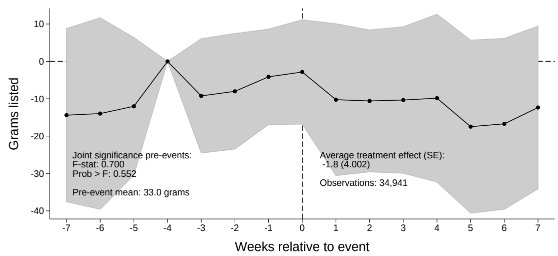
I offer three explanations for these differences. First, it could be the case that it is more likely to find only a single person behind a cannabis seller's account. Such people might have some part of their stock reserved for their own consumption or local sales that they now want to sell as fast as possible, while for opioid sellers this might be less common. Second, there might be differences in risk aversion, where opioid sellers are less risk-averse and therefore do not change their offers. Third, the quantity reactions observed might actually come from changes on the demand side. Buyers might become hesitant to use cryptomarkets whenever news about arrests become available. Then the increase in scraped cannabis listings could in part be explained by lower demand. This is because fewer sales result in fewer listings getting removed from platforms. As opioids are substances that cause physical addiction, consumers will have a much higher time preference. This means they are much less willing to wait another week to see if the arrest risk goes down again, compared to cannabis buyers who can more easily delay their purchase decision. In this sense, cannabis buyers will reduce demand, explaining the positive coefficients after the shock, while the demand for opioids remains constant. Finally, the finalize early option increases over time with a small increase around the event timing, and the general trend is hardly interrupted. Inspecting the weeks before the shock, it is evident that most estimates have insignificant pre-trends, with the only exception of market exits and finalize early, which show some upward trends before the event. Generally, the insignificant pre-event coefficients give weight to a causal interpretation of these findings.

Figure 6: Effects of shocks to holding risk on opioid vendors

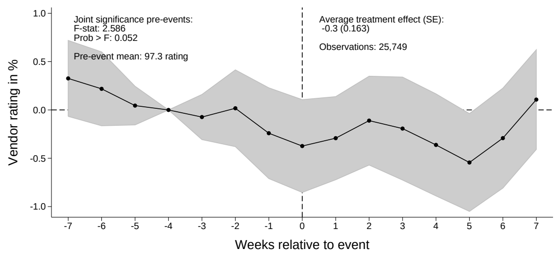
(a) Price



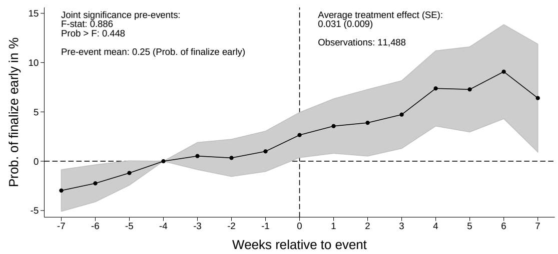
(b) Quantity



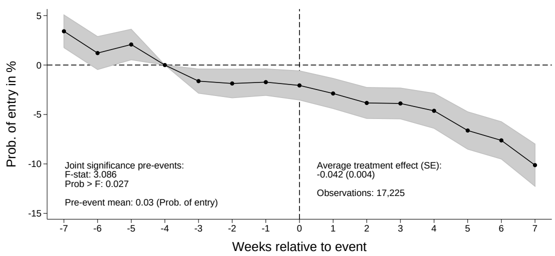
(c) Rating



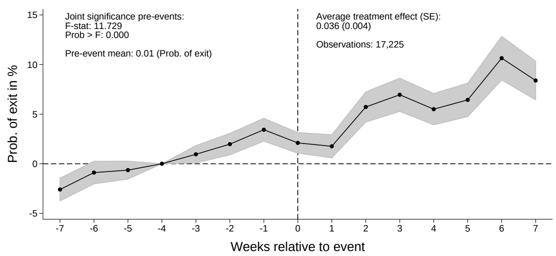
(d) Finalize early



(e) Entries



(f) Exits



Notes: This is a graphical representation of the estimated effects of shocks to holding risk on different outcome variables relative to the event time. Areas shaded in grey represent 95% confidence intervals. The estimates to the corresponding fixed-effects models are tabulated in Table 2. All estimates include controls for markets and seasonality. The Linear Probability Model used for the binary response variables in Panels (d) - (f) also includes controls for price, quantity, and number of competitors, as well as controls for shocks to transaction risk up to three weeks prior to the event. Pre-event means refer to the base period four weeks before the shock. Joint significance of pre-trends are based on a F-test for joint significance of the coefficients in three leading periods.

Table 2: Dynamic effects of shocks to holding risk

	Cannabis						Opioids					
	(1) Price USD/g	(2) Quantity Grams	(3) Rating Percent	(4) Finalize early Probability	(5) Entry Probability	(6) Exit Probability	(7) Price USD/g	(8) Quantity Grams	(9) Rating Percent	(10) Finalize early Probability	(11) Entry Probability	(12) Exit Probability
Pre-event weeks:												
-7	0.283	25.928	-0.059	-0.023***	0.019***	-0.021***	15.441**	-14.390	0.326	-0.030***	0.034***	-0.026***
	(0.282)	(21.870)	(0.094)	(0.008)	(0.006)	(0.004)	(7.045)	(11.810)	(0.200)	(0.011)	(0.008)	(0.006)
-6	0.229	9.031	-0.050	-0.008	0.014**	-0.012***	1.066	-13.966	0.218	-0.022**	0.012	-0.009
	(0.232)	(22.223)	(0.105)	(0.007)	(0.006)	(0.004)	(6.911)	(13.057)	(0.195)	(0.010)	(0.009)	(0.006)
-5	0.085	10.528	-0.007	-0.004	0.036***	-0.007**	0.937	-12.018	0.045	-0.012*	0.021***	-0.006
	(0.182)	(18.836)	(0.078)	(0.005)	(0.005)	(0.003)	(4.907)	(9.378)	(0.102)	(0.006)	(0.008)	(0.005)
-3	-0.170	-27.575*	-0.068	0.008*	-0.007	0.003	0.793	-9.238	-0.074	0.005	-0.016***	0.010**
	(0.183)	(14.379)	(0.086)	(0.005)	(0.004)	(0.003)	(5.004)	(7.794)	(0.119)	(0.007)	(0.006)	(0.004)
-2	-0.199	-18.623	-0.126	0.021***	-0.001	0.016***	1.376	-8.013	0.017	0.003	-0.019**	0.020***
	(0.252)	(26.573)	(0.125)	(0.007)	(0.005)	(0.004)	(6.056)	(7.875)	(0.202)	(0.010)	(0.007)	(0.006)
-1	0.001	22.493	-0.306**	0.023***	-0.004	0.029***	-3.665	-4.128	-0.241	0.010	-0.017**	0.034***
	(0.252)	(25.035)	(0.144)	(0.008)	(0.005)	(0.005)	(6.037)	(6.500)	(0.239)	(0.010)	(0.007)	(0.006)
Post-event weeks:												
0	-0.159	2.817	-0.216	0.031***	-0.006	0.009**	-0.346	-2.840	-0.374	0.027**	-0.021***	0.021***
	(0.221)	(20.986)	(0.138)	(0.009)	(0.005)	(0.004)	(6.398)	(7.113)	(0.245)	(0.012)	(0.008)	(0.005)
1	0.203	-17.168	-0.242*	0.033***	-0.012**	0.013***	19.867***	-10.246	-0.292	0.036**	-0.029***	0.018***
	(0.230)	(27.457)	(0.143)	(0.010)	(0.005)	(0.005)	(7.085)	(10.352)	(0.219)	(0.014)	(0.008)	(0.006)
2	0.326	36.614	-0.221	0.042***	-0.030***	0.048***	19.424**	-10.584	-0.110	0.039**	-0.038***	0.057***
	(0.286)	(29.206)	(0.147)	(0.012)	(0.006)	(0.005)	(7.989)	(9.670)	(0.234)	(0.017)	(0.008)	(0.008)
3	0.314	24.217	-0.145	0.051***	-0.033***	0.068***	7.267	-10.340	-0.193	0.047***	-0.039***	0.070***
	(0.242)	(26.257)	(0.174)	(0.013)	(0.006)	(0.006)	(8.602)	(9.988)	(0.271)	(0.017)	(0.008)	(0.009)
4	0.812***	-1.482	-0.335*	0.073***	-0.048***	0.052***	11.058	-9.848	-0.362	0.074***	-0.046***	0.055***
	(0.285)	(22.261)	(0.171)	(0.015)	(0.006)	(0.006)	(8.961)	(11.444)	(0.269)	(0.019)	(0.009)	(0.008)
5	0.575*	78.124***	-0.632***	0.075***	-0.056***	0.056***	1.612	-17.468	-0.544**	0.073***	-0.066***	0.064***
	(0.327)	(30.078)	(0.162)	(0.017)	(0.006)	(0.006)	(9.933)	(11.791)	(0.258)	(0.022)	(0.010)	(0.009)
6	-0.170	71.672***	-0.419***	0.090***	-0.076***	0.094***	-13.178	-16.714	-0.292	0.091***	-0.076***	0.106***
	(0.344)	(26.789)	(0.155)	(0.019)	(0.007)	(0.007)	(10.248)	(11.657)	(0.263)	(0.024)	(0.010)	(0.011)
7	-0.567	37.718	-0.354**	0.092***	-0.099***	0.091***	-9.241	-12.349	0.107	0.064**	-0.101***	0.084***
	(0.366)	(24.628)	(0.170)	(0.021)	(0.008)	(0.008)	(11.015)	(11.095)	(0.263)	(0.028)	(0.011)	(0.010)
Constant	1.422***	-228.897**	0.162	0.073	0.105***	-0.016	5.938	-18.971	-0.557	0.049	0.118***	0.023
	(0.483)	(116.506)	(0.278)	(0.089)	(0.017)	(0.022)	(11.700)	(13.500)	(0.954)	(0.130)	(0.029)	(0.028)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market price	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Market supply	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Number competitors	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Volatility shocks	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	35,237	67,754	49,862	22,350	35,237	35,237	17,225	34,941	25,749	11,488	17,225	17,225
Mean of dep. var.	16.79	267.12	97.38	0.25	0.03	0.01	468.20	32.98	97.27	0.25	0.03	0.01
R-squared	0.004	0.005	0.003	0.089	0.034	0.055	0.006	0.011	0.008	0.084	0.034	0.054

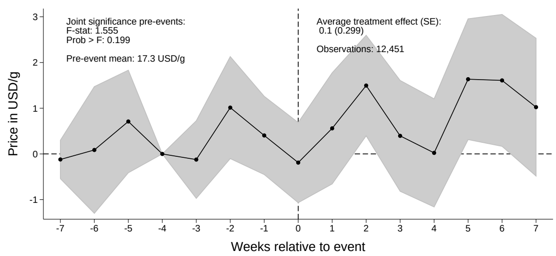
Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. *Volatility shocks* are four control variables for the weekly standard deviation of Bitcoin prices in the weeks 0 to -3. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

6.3 Transaction risk and cannabis vendors

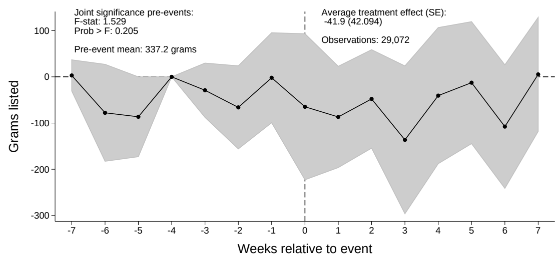
Turning to transaction risk shocks, i.e., increases in Bitcoin price volatility, the estimated effects on the cannabis market can be observed in Figure 7 and Columns (1) - (6) of Table 3. Transaction risk has an immediate effect on entries and exits of cannabis vendors. The average treatment effects are a decrease of expected entry probability by 6.4 percentage points and an increase in exit probability by two percentage points. Although both market entries and exits show some trend throughout the estimation period, there are significant jumps after the shock.

Figure 7: Effects of shocks to transaction risk on cannabis vendors

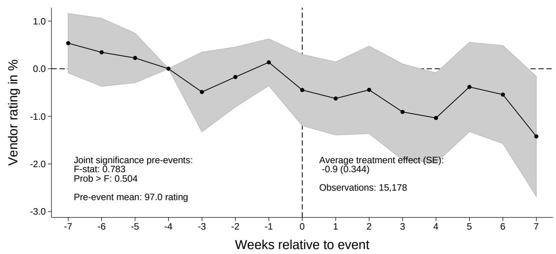
(a) Price



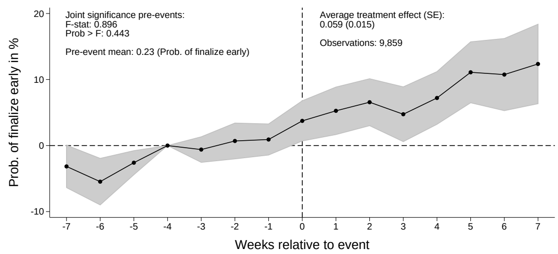
(b) Quantity



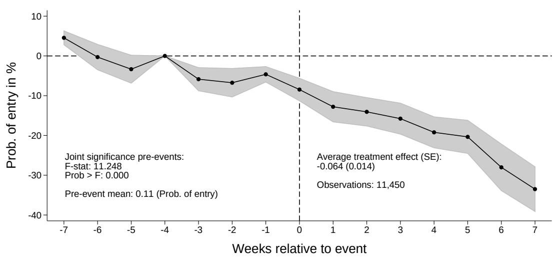
(c) Rating



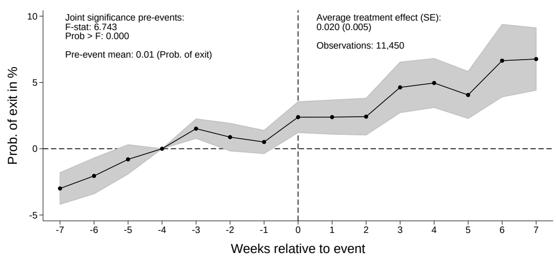
(d) Finalize early



(e) Entries



(f) Exits



Notes: This is a graphical representation of the estimated effects of shocks to transaction risk on different outcome variables relative to the event time. Areas shaded in grey represent 95% confidence intervals. The estimates to the corresponding fixed-effects models are tabulated in Table 3. All estimates include controls for markets and seasonality. The Linear Probability Model used for the binary response variables in Panels (d) - (f) also includes controls for price, quantity, and number of competitors, as well as controls for shocks to holding risk up to three weeks prior to the event. Pre-event means refer to the base period four weeks before the shock. Joint significance of pre-trends are based on a F-test for joint significance of the coefficients in three leading periods.

After two weeks of an increase in transaction risk, cannabis vendors react with an increase in prices. This spike vanishes in the third week but again becomes significant in weeks five and six after the event, suggesting that the market goes through an adjustment process after the shock in uncertainty. In terms of magnitude, the prices increased between 8.7 and 9.5%, making them almost twice as large as the price reactions to arrest shocks. Again, the likely explanation is that vendors pass the risk on to the buyer with a risk premium.

The expected probability of making use of the finalize early requirement again shows an upward trend with a small spike at the event timing compared with the three leading periods. This increase amounts to 5.9 percentage points on average, which is a sizeable increase. It is likely that vendors use early finalization as a tool to mitigate Bitcoin volatility. However, the vendors' favored option seems to be an increase in price.

As observed for shocks in holdings risk, one week after prices increase, there are significant reductions in vendor ratings of 0.9 percentage points in week three and 1.4 in week seven. As ratings are given after the transaction was finalized, the one week delay observed corresponds with the average transaction duration of six days reported by Janze (2017). Therefore, it seems likely that the drops in rating are responses to price premiums.

Quantities of cannabis offered are, on average, lower in the post-event period and show a large variation. The corresponding post-event coefficients are insignificant, except for a decrease of 136 grams in week three, which is significant at the 10% level. After inspecting the pre-event periods, one sees that pre-trends for the price, quantity, and rating are again insignificant, market entries and exits behave stable in the three weeks leading up to the event and only finalize early shows an obvious pre-trend.

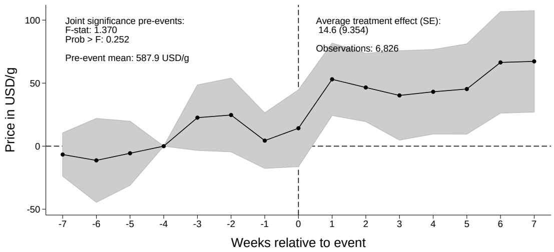
6.4 Transaction risk and opioid vendors

Figure 8 and Columns (7) - (12) of Table 3 illustrate the effects of price volatility shocks on the opioid market. Chronologically, the first reaction to an increase in transaction risk can be seen in entry deterrence and market exits of opioid vendors. With clear jumps in the event week, market entries are on average lower by 4.8% and exits increase by 2.3% when comparing the month before and after the event. Vendor ratings decrease by half a percentage point compared to the base period, yet the effect is statistically insignificant. One week after the Bitcoin price shock, opioid vendors react by increasing their prices by 9% on average, with corresponding coefficients being significant at the 1% level. Interestingly, this risk premium is not accompanied by a strong adjustment process, like in the case of cannabis, and persists through the entire estimation period.

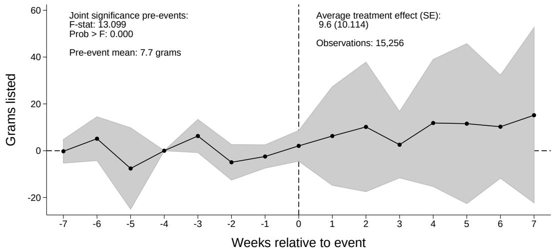
While the mean opioid quantity is unaffected by volatility shocks, it is noticeable that the standard errors of post-event coefficients are increasing. The use of the finalize early requirement shows a general upward trend, without a kink after the shock to transaction risk. Considering pre-trends, the weeks leading up to the event do not show significant coefficients for the price, quantity or ratings. Coefficients for entries and exits are statistically significant in some periods. Overall, a break of the trend is evident after the shock in both cases.

Figure 8: Effects of shocks to transaction risk on opioid vendors

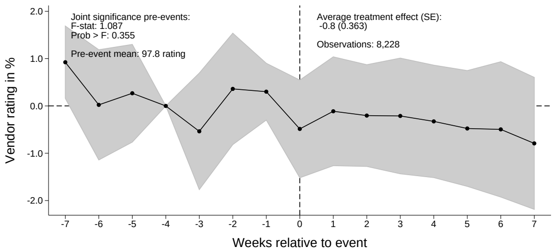
(a) Price



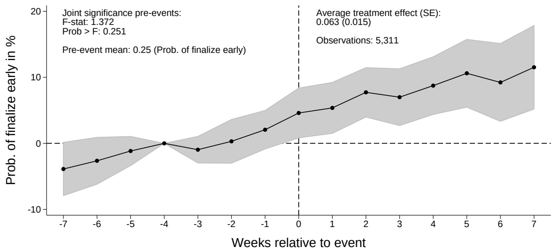
(b) Quantity



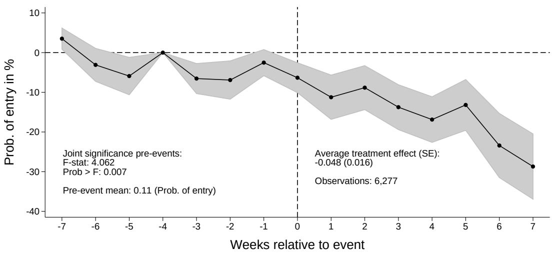
(c) Rating



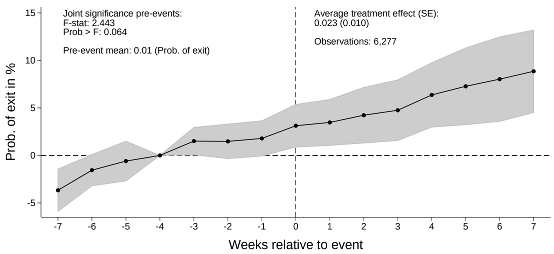
(d) Finalize early



(e) Entries



(f) Exits



Notes: This is a graphical representation of the estimated effects of shocks to transaction risk on different outcome variables relative to the event time. Areas shaded in grey represent 95% confidence intervals. The estimates to the corresponding fixed-effects models are tabulated in Table 3. All estimates include controls for markets and seasonality. The Linear Probability Model used for the binary response variables in Panels (d) - (f) also includes controls for price, quantity, and number of competitors, as well as controls for shocks to holding risk up to three weeks prior to the event. Pre-event means refer to the base period four weeks before the shock. Joint significance of pre-trends are based on a F-test for joint significance of the coefficients in three leading periods.

Table 3: Dynamic effects of shocks to transaction risk

	Cannabis						Opioids					
	(1) Price USD/g	(2) Quantity Grams	(3) Rating Percent	(4) Finalize early Probability	(5) Entry Probability	(6) Exit Probability	(7) Price USD/g	(8) Quantity Grams	(9) Rating Percent	(10) Finalize early Probability	(11) Entry Probability	(12) Exit Probability
Pre-event weeks:												
-7	-0.121	3.027	0.536*	-0.032*	0.046***	-0.030***	-6.642	-0.237	0.924**	-0.039*	0.035***	-0.037***
	(0.214)	(17.193)	(0.317)	(0.016)	(0.009)	(0.006)	(8.728)	(2.564)	(0.389)	(0.021)	(0.014)	(0.011)
-6	0.087	-77.815	0.344	-0.055***	-0.003	-0.021***	-11.282	5.135	0.023	-0.026	-0.031	-0.016*
	(0.706)	(53.433)	(0.363)	(0.018)	(0.016)	(0.007)	(16.903)	(4.760)	(0.592)	(0.018)	(0.021)	(0.008)
-5	0.710	-86.449**	0.226	-0.026***	-0.033*	-0.008	-5.625	-7.582	0.268	-0.012	-0.059**	-0.006
	(0.571)	(44.007)	(0.265)	(0.009)	(0.018)	(0.006)	(12.899)	(8.835)	(0.525)	(0.011)	(0.024)	(0.011)
-3	-0.124	-29.024	-0.489	-0.006	-0.059***	0.015***	22.610*	6.291*	-0.536	-0.010	-0.065***	0.015**
	(0.432)	(29.951)	(0.426)	(0.010)	(0.015)	(0.004)	(13.193)	(3.595)	(0.626)	(0.010)	(0.019)	(0.007)
-2	1.014*	-66.091	-0.175	0.007	-0.067***	0.009*	24.717*	-4.945	0.360	0.003	-0.069***	0.015
	(0.568)	(45.774)	(0.321)	(0.014)	(0.018)	(0.005)	(14.856)	(3.853)	(0.599)	(0.017)	(0.025)	(0.009)
-1	0.405	-2.008	0.135	0.009	-0.046***	0.005	4.393	-2.463	0.301	0.021	-0.025	0.018*
	(0.436)	(49.617)	(0.250)	(0.012)	(0.010)	(0.004)	(11.182)	(2.519)	(0.305)	(0.015)	(0.017)	(0.009)
Post-event weeks:												
0	-0.190	-64.773	-0.447	0.037**	-0.085***	0.024***	14.218	2.071	-0.486	0.046**	-0.063***	0.031***
	(0.447)	(80.536)	(0.381)	(0.015)	(0.014)	(0.006)	(15.473)	(3.320)	(0.525)	(0.019)	(0.019)	(0.011)
1	0.560	-86.775	-0.625	0.053***	-0.128***	0.024***	53.046***	6.282	-0.113	0.054***	-0.112***	0.035***
	(0.619)	(55.815)	(0.390)	(0.018)	(0.019)	(0.007)	(14.577)	(10.716)	(0.585)	(0.020)	(0.028)	(0.012)
2	1.496***	-47.798	-0.444	0.066***	-0.141***	0.024***	46.563***	10.165	-0.204	0.077***	-0.088***	0.042***
	(0.560)	(54.281)	(0.467)	(0.018)	(0.018)	(0.007)	(13.769)	(14.075)	(0.547)	(0.019)	(0.028)	(0.015)
3	0.395	-136.303*	-0.907*	0.047**	-0.158***	0.046***	40.256**	2.561	-0.212	0.070***	-0.137***	0.048***
	(0.617)	(81.492)	(0.513)	(0.021)	(0.020)	(0.010)	(18.009)	(7.204)	(0.622)	(0.022)	(0.029)	(0.016)
4	0.023	-40.651	-1.034**	0.072***	-0.192***	0.050***	43.141**	11.848	-0.327	0.087***	-0.169***	0.064***
	(0.602)	(75.037)	(0.481)	(0.020)	(0.020)	(0.009)	(17.024)	(13.813)	(0.604)	(0.022)	(0.029)	(0.017)
5	1.635**	-12.616	-0.383	0.111***	-0.204***	0.041***	45.344**	11.557	-0.477	0.106***	-0.132***	0.073***
	(0.673)	(67.249)	(0.477)	(0.024)	(0.021)	(0.009)	(18.189)	(17.385)	(0.622)	(0.026)	(0.033)	(0.021)
6	1.609**	-107.646	-0.543	0.108***	-0.280***	0.066***	66.442***	10.259	-0.496	0.092***	-0.234***	0.080***
	(0.735)	(68.093)	(0.524)	(0.028)	(0.030)	(0.014)	(20.456)	(11.193)	(0.727)	(0.030)	(0.041)	(0.023)
7	1.024	5.307	-1.421**	0.124***	-0.335***	0.068***	67.266***	15.160	-0.792	0.115***	-0.287***	0.089***
	(0.767)	(62.820)	(0.641)	(0.031)	(0.029)	(0.012)	(20.430)	(19.050)	(0.709)	(0.032)	(0.042)	(0.022)
Constant	0.054	-72.001	-0.838	0.002	0.351***	0.004	-14.039	-11.845	-2.069*	0.112	0.269***	0.043**
	(0.958)	(96.728)	(0.829)	(0.126)	(0.037)	(0.012)	(36.102)	(9.195)	(1.250)	(0.137)	(0.046)	(0.021)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market price	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Market supply	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Number competitors	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Arrest shocks	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	12,451	29,072	15,178	9,859	11,450	11,450	6,826	15,256	8,228	5,311	6,277	6,277
Mean of dep. var.	17.25	337.20	96.99	0.23	0.11	0.01	587.87	7.70	97.80	0.25	0.11	0.01
R-squared	0.008	0.002	0.007	0.046	0.123	0.038	0.017	0.002	0.010	0.066	0.103	0.032

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. *Arrest shocks* are four control variables for the weekly number of arrests in the weeks 0 to -3. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

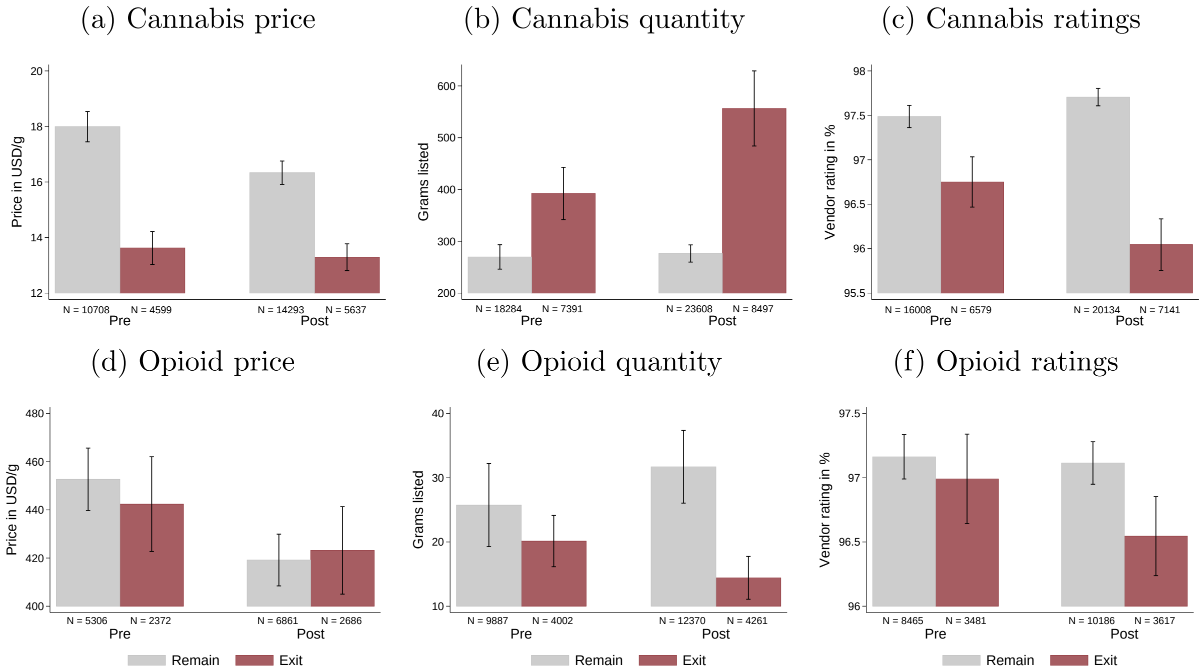
7 Heterogeneity analysis

The main results show the dynamic effects of production shocks and the responses of cannabis and opioid vendors. This section aims to further look into heterogeneous treatment effects that go beyond the division into drug categories by examining the differences between exiting and remaining vendors, determining regional effects, and presenting heterogeneous effects for different vendor sizes.

7.1 Exiting vendors

When analyzing the deterrent effects of police intervention, it is worthwhile to determine which types of vendors are deterred and how they differ from those who remain in the market. The previous section shows that holding risk leads to a break in the previous trend in the probability of market exits. After the shock, the expected probability of leaving the market continues to increase but fluctuates heavily throughout the following weeks.

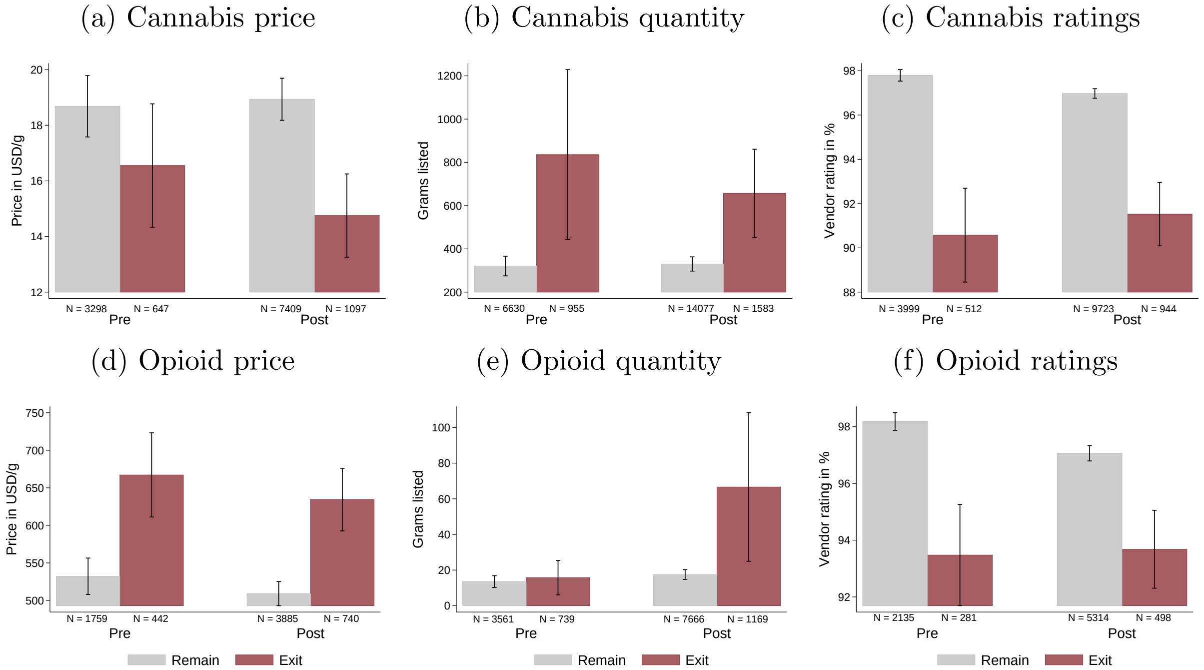
Figure 9: Holding risk: characteristics of exiting vendors



Notes: The figures compare vendors that leave the market after a shock to holding risk to those who remain in the market. The variables are shown separately for the pre-event and post-event period to give an interpretation of whether the difference between remaining and exiting vendors has been prevalent before the event or occurred thereafter. Error bars indicate 95% confidence intervals. One observation accounts for one vendor and week.

Figure 9 shows the average prices, quantities, and ratings of vendors that leave the market within the seven weeks of a shock and compares it to the vendors who remain in the market during this period. The figure also shows the average characteristics of these vendors before and after the event to show whether differences have been prevalent before the shock or developed as a potential reaction to the shock. For cannabis vendors, it is evident from Panels (a) - (c) that, on average, exiting vendors have significantly lower prices, sell at higher quantities, and gain lower ratings than remaining cannabis vendors. The remaining cannabis vendors do not significantly change their supply after the shock, but deterred cannabis vendors greatly increase their average quantity from 390 to 560 grams. This suggests that the late supply effect observed after a shock to holding risk indeed comes from exiting vendors clearing their stock before they go out of business. Still, it is astonishing that the average deterred vendor has a significantly larger amount of cannabis on offer. As expected, vendors with lower ratings have a harder time adjusting to the increased risk, because arrest risk might also reduce demand. In times of high uncertainty, it is reasonable for customers to stick to known and well-reputed vendors. Exiting vendors even lose rating after events, which might be a response to announcing or observing the exit, or it might reflect the fact that some vendors commit exit scams. Exiting opioid vendors in Panels (d) - (f), on the other hand, do not significantly vary in terms of price, but they have significantly lower quantities on offer and have lower ratings. Exiting opioid vendors seem to behave quite differently to cannabis vendors, as they reduce quantities before leaving the market. This could mean that they are more likely to possess the means to shift distribution to street sales.

Figure 10: Transaction risk: characteristics of exiting vendors



Notes: The figures compare vendors that leave the market after a shock to transaction risk to those who remain in the market. The variables are shown separately for the pre-event and post-event period to give an interpretation of whether the difference between remaining and exiting vendors has been prevalent before the event or occurred thereafter. Error bars indicate 95% confidence intervals. One observation accounts for one vendor and week.

The main results show that transaction risk significantly increases market exits in the week of the shock. Panels (a) - (c) of Figure 10 show the characteristics of cannabis vendors that quit in the period after a shock to transaction risk. Exiting vendors have lower prices, supply more, and have lower ratings than remaining sellers. All these differences existed before the shock, but the gap between the two groups has increased for quantity and ratings. This implies that whether a vendor leaves after an arrest shock or a volatility shock, there is no difference in the exiting dynamics. Cannabis vendors increase the supply to get rid of all their stock, although their ratings do not drop compared to the pre-event period like it was the case for holding risk.

Opioid vendors are described in Panels (d) - (f). On average, they charge significantly higher prices than remaining vendors, have higher quantities, and lower reputation. Mean quantities sharply increase from 16 to 67 grams in the post-event period. This result contrasts with the earlier finding of decreasing quantities in the case of holding risk. The transaction risk might induce vendors to quit because costs are exceeding revenues, and therefore a slow exit with selling remaining quantities is possible. In case of arrests, opioid vendors might fear that there are long-lasting consequences as they move up on the priority list of law enforcement agencies, and hence an immediate reduction in quantity is preferred.

7.2 Regional effects

Tables 4 and 5 in Section C.1 summarize the heterogeneous effects of shocks to holding risk, where I divide the sample into regions based on the location vendors ship to and from. While some vendors choose to disclose which country they are active in, most vendors can only be traced to their continent. As the sample only includes English language markets, vendors are divided into European, North American, Australian, and worldwide.

After a shock in arrests, the increase in cannabis prices in the baseline model is driven by the European region, with positive but insignificant post-event coefficients for North America and Australia. Vendors who claim to supply worldwide significantly decrease their prices after the event, with the two leading periods also being significant. The increases in cannabis supply also mainly come from Europe and North America, where the coefficients in North America stay insignificant, however. Europe, North America, and Australia show increasing prices in the post-event period, that peak in the fourth week after the event, although coefficients are only significant at the 5% level for Europe. These regions all show positive quantity reactions one to two weeks later, which supports the interpretation that short-term cannabis supply reactions follow price changes rather than being a delayed reaction to the police intervention.

In terms of opioid prices, vendors in Europe, North America, and Australia increase prices in a similar time frame. Price increases happen clearly after the event, and most pre-event coefficients are insignificant throughout regions. Vendors in these regions increase prices one week after the event, where the increase is strongest and sustained for longer in Australia. Again, worldwide vendors react with a decrease in price, where the coefficients are lowest in weeks two and three after the event and significance levels of 5%. Worldwide sellers differ in some characteristics. As indicating the countries the vendor ships to is a trust-building measure that likely benefits sales, not revealing one's country of operation might imply some sort of risk-aversion. Observing the means of dependent variables in these regressions reveals that worldwide vendors are on average selling lower quantities at lower prices and have a lower reputation. The negative price reaction to arrests could be explained by a higher degree of risk-aversion or the fact that worldwide sellers are at greater risk of being detected as their goods pass through border customs more frequently. Finally, these vendors could anticipate a decline in demand. Judging from the fact that these are, on average, small vendors that have few regular customers and low ratings, their only chance to stay competitive is by lowering their prices. When it comes to opioid quantities, coefficients are negative but insignificant across all regions. This is at odds with the findings for cannabis, which could imply that opioid supply can not be adjusted to price stimuli as easily as it is the case for cannabis products.

Heterogeneous effects of shocks to transaction risk for geographic subsamples are shown in Tables 6 and 7. The increases in cannabis price in the baseline model are driven by increases in Europe and North America. In the European subsample, coefficients are positive and highly significant for the whole post-event period. Vendors from Australia and worldwide sellers significantly decrease their prices after the Bitcoin shock, although some pre-trends exist in both cases. Regarding the quantity of cannabis products supplied, the negative coefficient in week three found in the full sample is strongest in North America. Australia proves again to be an outlier in these estimates. While the other regions yield negative coefficients after an increase in Bitcoin volatility, coefficients in Australia are positive throughout the post-event period, which can be explained by a general growth trend in cannabis listings in Australia. European, North American, and Australian opioid sellers increase their prices sharply after an increase in Bitcoin volatility, while the grams of opioids listed remain largely constant in all regions.

7.3 Vendor size

The heterogeneous responses to shocks in holding risk by vendor size are shown in Tables 8 and 9. The Tables report the results of sub-sample regressions, where vendors are divided into quartiles based on the distribution of the mean amount of drugs they offered in a week. The increase in cannabis price is strongest for small vendors in the first quartile of the distribution. Here, the increase in price relative to the pre-event period peaks at 14.3% in week four, significant at the 1% level. Post-event coefficients remain positive yet mostly insignificant in the second and third quartile. The responses in terms of cannabis supply vary greatly across quartiles. While vendors in quartiles two through four significantly increase their supply after a shock to holding risk, vendors in the first quartile significantly decrease the quantity of cannabis offered.

For opioids, the estimated price effects are also strongest for vendors in the lower two quartiles of vendor size. The coefficients of weeks one to four remain positive across all size categories, yet only significant in quartiles one and two. While there were no significant quantity responses after a shock in holding risk in the baseline specification, there are negative post-event coefficients for vendors in quartiles two through four. Timing-wise, medium-sized vendors significantly reduce their supply in weeks one and four, with some fluctuations in the whole estimation period, suggesting an adjustment process. The largest vendors reduce their supply throughout the whole period, with coefficients becoming significant at the 10% level in week five. While in the main specification estimated effects on opioid quantities are insignificant across the estimation period, medium-sized vendors reduce their supply one week after their event. This finding might suggest that smaller opioid vendors pass on the added risk to consumers in the form of a risk premium, while larger opioid sellers may have the infrastructure to move sales to traditional distribution channels, i.e., street sales. There also seems to exist a systematic difference in reactions to police intervention between cannabis and opioid vendors, where cannabis vendors generally increase supply, while opioid vendors reduce supply.

Tables 10 and 11 tabulate the effects of volatility shocks by vendor size. In terms of cannabis price, the estimated effects are again strongest in the first quartile. The smallest vendors increased prices by 14.7% on average, while larger vendors showed insignificant responses. The decreases in cannabis supply are uniform across vendor sizes.

After volatility shocks, opioid vendors increase their prices throughout all quartiles. Only for the vendors in the first quartile, the estimated price response is negative yet insignificant. Larger vendors increased their prices in response to the higher transaction risk, where estimated coefficients are statistically significant at the 5% level. As for the quantity responses to increases in transaction risk, coefficients remain insignificant across all quartiles, supporting the main result that volatility only affects opioid prices but not the quantity listed. Analyzing responses by vendor size generally reveals that price reactions mainly stem from smaller vendors, which indicates that the added risk is a less credible threat to larger vendors who might have a more diversified operation that is not as dependent on one distribution channel.

8 Robustness

In a first robustness check to the main findings, I add different control variables to the dynamic model in Equation (3). Tables 12 - 23 in Section C.2 of the Appendix tabulate the estimation results. The added controls include the level of market prices, market supply, number of competitors, as well as controls for Bitcoin volatility in standard deviations in case of holding risk events and number of arrests in case of transaction risk events for the event week and the three leading weeks. These last variables have the purpose of disentangling the effects in situations where holding risk and transaction risk events are close to each other.

Columns (2) and (9) represent the specifications reported in the main findings for cannabis and opioids, while baseline specifications for binary variables are shown in Columns (7) and (14). Using different sets of control variables does not change the signs of post-event coefficients for any outcome variable or production risk. Only in the case of cannabis quantity, the coefficient for week five after shocks to holding risk becomes insignificant if controls for the supply of other vendors and number of competitors are added. The general results are not changed in either direction of effect or timing of reactions.

As a second robustness check to the main results, the baseline models are estimated with varying event definitions. In terms of holding risk, I vary the threshold level at which I define an event, the results of which can be found in Tables 24 - 26 in Appendix C.2. Price reactions remain positive and similar in timing for both cannabis and opioid vendors. The magnitude of the effect also increases the higher the threshold is set. This makes intuitive sense, as stronger shocks should also have stronger responses. Alternatively, this could also mean that the effects observed are driven by events with the highest number of arrests. Estimated quantity reactions remain positive for cannabis users and coefficients for the fifth event week remain significant at least at the 5% level. Again higher thresholds come with higher coefficients, supporting the main findings, as stronger impulses translate into stronger responses. For opioids, changing the threshold level for arrest shocks does not change the signs of coefficients, which are negative in all specifications and periods except for a negative week six coefficient that is significant at the 10% level when specifying an event threshold of five arrests. The low significance and late timing suggest that these effects can hardly be traced back to the event. In terms of ratings, again, varying thresholds does not change the signs or significance of coefficients for cannabis sellers. For opioid sellers, the directions of effects are the same, but higher cut-off levels see higher levels of significance. In both cases, increasing the threshold also increases the window in which significant coefficients can be found. Importantly this analysis shows that pre-event coefficients are consistently insignificant, giving credibility to the event study design.

Tables 27 - 29 show the differences in event definitions for the transaction risk. The first four model definitions of Bitcoin volatility use the standard deviations of the Bitcoin price within a week, varying only in the threshold level that defines an event. $Peak \geq 25$ looks at all local maxima in Bitcoin volatility, where volatility is defined in standard deviations of the Bitcoin price. Each maximum that is larger than 25 standard deviations is chosen as an event. This definition aims to rule out events in adjacent periods. The last definition uses four exogenous shocks in Bitcoin volatility that are compiled from media reports.[18] The price increase following a volatility shock is observable across all possible event definitions for cannabis and opioids. The only specification which yields insignificant post-event coefficients for cannabis prices is the one where events are defined by newspaper articles. The declines in cannabis supply around week three are mainly driven by weeks with very high volatility, which again supports the link between price volatility and vendor responses shown in this study. For the $Peak \geq 25$ and the *Exogenous* definitions, there is a significant increase in quantity in the week of the event. As in both cases, there are significant coefficients within the three leading weeks before the event, I do not interpret this as a threat to the main findings. Quantity responses of opioid vendors are insignificant across all definitions, which shows that the main findings are robust in terms of event definition. In vendors' ratings, varying the event definition does not change signs of coefficients in 11 out of 12 specifications.

The third robustness check identifies whether results change significantly if a conditional logistic regression model is used instead of the linear probability model for estimating the effects on the binary outcome variables market-entry, market-exit, and requirement of early finalization. Table 30 shows that for shocks to holding risk, finalize early, entry and exit decisions coefficients do not change the direction of effect across models and the general trends are comparable. For transaction risk, Table 31 confirms that the choice of the model does not greatly alter signs, although in the logistic regression model, finalize early coefficients remain insignificant throughout. These robustness checks give weight to the main findings discussed in this study. The findings in this section show that the models have been correctly specified and are not sensitive to the addition of further controls. It was shown that the choice of event definition does not significantly change the signs of effects as well as the timings of reactions. Furthermore, this gives support to the choice of event definitions used in the main findings, where the only choice criterion has been that pre-trends remain stable.

[18] One of the largest Bitcoin exchanges *Mt. Gox* suspended exchanges due to security issues on 07.02.2014 (Hajdarbegovic, 2014). Mt. Gox released news about filing for bankruptcy and stolen Bitcoins on 28.02.2014 (British Broadcasting Corporation, 2014). The U.S. tax agency IRS released news that cryptocurrencies are to be treated as property instead of currencies on 25.03.2014 (Internal Revenue Service, 2014). The U.S. Consumer Financial Protection Bureau issued a warning concerning the risks of cryptocurrencies on 11.08.2014 (Consumer Financial Protection Bureau, 2014).

9 Conclusion

I analyze the supply-side responses of production risk in a cryptomarket setting, where two primary sources of risk are established. Holding risk depends on the amount of goods currently held in stock, and transaction risk affects the value of all pending transactions. While reactions to both types of risk are generally similar, I find that only for holding risk there are significant quantity responses while the added risk premium and entry deterrence is higher for transaction risk.

I confirm results from previous studies that cryptomarket vendors significantly react to increased police activity, where I extend the literature by some novel contributions. Previous research focuses on the effects of single international police interventions like *Operation Onymous*. In contrast, I observe general police activity in the form of darknet market-related arrests in an event study design that supports a causal interpretation of results. Exploring multiple possible outcomes and their dynamic paths, I show that police intervention does not merely act as an entry deterrent but that the market significantly responds by an increase in price and quantity, with ratings dropping likely as a result of higher prices. Heterogeneity analysis for cannabis and opioid vendors provides evidence that sellers of these categories react differently in terms of response timing. While opioid vendors react faster than cannabis vendors, cannabis sellers show a delayed increase in quantity sold, which is interpreted as a reaction to the prior increase in market price.

My analysis broadens the understanding of cryptomarkets by identifying another source of risk for cryptomarket vendors that has, to my knowledge, not been discussed in the academic literature before. I show that darknet vendors change behavior after an increase in volatility of Bitcoin prices, the main currency used at the time on cryptomarkets. Following an increase in Bitcoin volatility, vendors are more likely to leave a market, and new vendors are effectively deterred. Interestingly, high levels of transaction risk are a stronger entry deterrent than holding risk, while for existing vendors, an increase in police activity leads to a higher share of market exits than Bitcoin volatility. After a shock to transaction risk, vendors respond with a price increase, where opioid vendors act one week faster than cannabis vendors and keep the prices on a higher level for an extended period. The finalize early tool is not a viable solution to either of these risks, as vendors do not significantly increase their use after a shock. I explain this by the fact that finalizing early requires high levels of trust by consumers, limiting the use to established and trusted vendors.

The results of this study may apply outside the setting of cryptomarkets. As the structure of markets and websites are similar to clear web marketplaces, this work also provides insights into how vendors react to holding and transaction risk in these markets. Results may even be applied to general economic activity where holding risk can be replaced with inventory cost and transaction risk with exchange rate volatility.

It is important to discuss two limitations to this study. First, in 2014-2015, cryptomarktes were a relatively recent phenomenon with platforms in their current form operating since 2011, which places the observation period of this thesis in the early period of cryptomarkets that goes together with strong growth trends and learning periods. While cryptomarket use is still growing, the learning effects might have led to vendors' adjustment to the setting-specific risk, which warrants further research with newer data. Second, the most crucial assumption made is that demand remains constant after a shock in holding or transaction risk, for which there does not exist a satisfactory way of validation given the available data.

Policymakers might be interested in this thesis's findings to learn about the effects and possible negative externalities of police intervention. There exists a deterring short-run effect of police intervention, yet against the backdrop of generally increasing numbers of sellers and buyers in the cryptomarket system, this means that police interventions fail to shut down long term growth trends. I show that increasing the level of arrests also leads to short-run increases in price. As vendors are effectively passing on the added risk to buyers in the form of higher prices, consumers' welfare will go down. As the substances sold have varying degrees of physical dependence, consumers might not be able to decrease demand, leaving remaining vendors unaffected, which implies that police intervention fails to hit the intended target. Furthermore, the data suggest that police interventions are just one of several comparable sources of risks on darknet markets that vendors are well aware of and are constantly adjusting to. The immediate price reactions hint towards the fact that criminals have found a way to pass on the increased risk, while the intended decrease in vendor-level quantity is not observable, where in the case of cannabis arrests even lead to a short-run increase.

My research can easily be extended to more recent years by starting one's own scraping procedures, given that cryptomarkets can be accessed by everyone. As this study focuses on short-run responses, a more extended observation period could give valuable information on the long-term effects of production risk on cryptomarkets.

References

Aldridge, J. and Décary-Hétu, D. (2014). Not an 'Ebay for drugs': The cryptomarket 'Silk Road' as a paradigm shifting criminal innovation. Available at SSRN 2436643 (2014).

Aldridge, J. and Décary-Hétu, D. (2016). Cryptomarkets and the future of illicit drug markets. *Internet and drug markets*, *EMCDDA insights*, Publications Office of the European Union, Luxembourg, 23-30.

Barratt, M. and Aldridge, J. (2016). Everything you always wanted to know about drug cryptomarkets* (*but were afraid to ask), *International Journal of Drug Policy* **35**: 1–6.

Becker, G. S. (1968). Crime and punishment: An economic approach, *Journal of Political Economy* **76**(2): 169–217.

Bhaskar, V., Linacre, R. and Machin, S. (2019). The economic functioning of online drugs markets, *Journal of Economic Behavior & Organization* **159**: 426–441.

Böheim, R., Hackl, F. and Leitner, M. (2019). The impact of price adjustment costs on price dispersion in e-commerce, CESifo Working Paper Series, Vol. 7510 .

Borusyak, K. and Jaravel, X. (2016). Revisiting event study designs. Available at SSRN 2826228 (2017).

Boscarino, J. A., Rukstalis, M., Hoffman, S. N., Han, J. J., Erlich, P. M., Gerhard, G. S. and Stewart, W. F. (2010). Risk factors for drug dependence among out-patients on opioid therapy in a large US health-care system, *Addiction* **105**(10): 1776–1782.

Branwen, G. (2013). Darknet market mortality risks, `https://www.gwern.net/DNM-survival`. 09.04.2020.

Branwen, G. (2015a). Darknet market arrests, 2011–2015, `https://www.gwern.net/DNM-arrests`. 08.01.2020.

Branwen, G., Christin, N., Décary-Hétu, D., Andersen, R. M., StExo, Presidente, E., Anonymous, Lau, D., Sohhlz, D. K., Cakic, V., Buskirk, V., Whom, McKenna, M. and Goode, S. (2015b). Dark Net Market archives, 2011-2015, `https://www.gwern.net/DNM-archives`. (2019-09-01).

British Broadcasting Corporation (2014). MtGox bitcoin exchange files for bankruptcy, `https://www.bbc.com/news/technology-25233230`. 05.01.2020.

Buxton, J. and Bingham, T. (2015). The rise and challenge of dark net drug markets. *Global Drug Policy Observatory*, Swansea.

Christin, N. (2013). Traveling the Silk Road: A measurement analysis of a large anonymous online marketplace, Proceedings of the 22nd International Conference on World Wide Web, WWW '13, Association for Computing Machinery, New York, 213–224.

CoinMarketCap (2020). Historical data for Bitcoin, `https://coinmarketcap.com/currencies/bitcoin`. 24.02.2020.

Consumer Financial Protection Bureau (2014). CFPB warns consumers about bitcoin, https://www.consumerfinance.gov/about-us/newsroom/cfpb-warns-consumers-about-bitcoin. 05.01.2020.

De Balthasar, T. and Hernandez-Castro, J. (2017). An analysis of Bitcoin laundry services, in H. Lipmaa, A. Mitrokotsa and R. Matulevičius (eds), Secure IT Systems. NordSec 2017. Lecture Notes in Computer Science, Vol. 10674, Springer. 297-312.

Décary-Hétu, D. and Giommoni, L. (2017). Do police crackdowns disrupt drug cryptomarkets? A longitudinal analysis of the effects of Operation Onymous, *Crime, Law and Social Change* **67**(1): 55–75.

Décary-Hétu, D. and Quessy-Doré, O. (2017). Are repeat buyers in cryptomarkets loyal customers? Repeat business between dyads of cryptomarket vendors and users, *American Behavioral Scientist* **61**(11): 1341–1357.

Decker, C. and Wattenhofer, R. (2014). Bitcoin transaction malleability and MtGox, in M. Kutyłowski and J. Vaidya (eds), Computer Security - ESORICS 2014. Lecture Notes in Computer Science, Vol. 8713, Springer.

Duxbury, S. W. and Haynie, D. L. (2018). The network structure of opioid distribution on a darknet cryptomarket, *Journal of Quantitative Criminology* **34**: 921–941.

EMCDDA (2020). Penalties for drug law offences in europe at a glance. European monitoring centre for drugs and drug addiction., https://www.emcdda.europa.eu/publications/topic-overviews/content/drug-law-penalties-at-a-glance_en. 27.07.2020.

Espinosa, R. (2019). Scamming and the reputation of drug dealers on darknet markets, *International Journal of Industrial Organization* **67**: 102523.

Europol (2017). Drugs and the darknet. perspectives for enforcement, research and policy, https://www.europol.europa.eu. 03.10.2020.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C. and Siering, M. (2014). Bitcoin - asset or currency? Revealing users' hidden intentions, *ECIS* 2014, Tel Aviv.

Hajdarbegovic, N. (2014). Price drops as Mt. Gox blames bitcoin flaw for withdrawal delays, https://www.coindesk.com/price-drops-mt-gox-blames-bitcoin-flaw-withdrawal-delays. 04.01.2020.

Halaburda, H., Haeringer, G., Gans, J. S. and Gandal, N. (2020). The microeconomics of cryptocurrencies, NBER Working Paper 27477.

Hill, K. (2014). Winklevosses, Bitcoin community shocked by arrest of BitInstant CEO Charlie Shrem, https://www.forbes.com/sites/kashmirhill/2014/01/27/winklevosses-bitcoin-community-shocked-by-arrest-of-bitinstant-ceo-charlie-shrem/?sh=419c80bd242d. 04.08.2020.

Holt, T. J., Smirnova, O., Chua, Y. T. and Copes, H. (2015). Examining the risk reduction strategies of actors in online criminal markets, *Global Crime* **16**(2): 81–103.

Internal Revenue Service (2014). IRS virtual currency guidance: Virtual currency is treated as property for U.S. federal tax purposes, `https://www.irs.gov/newsroom/irs-virtual-currency-guidance`. 05.01.2020.

Janze, C. (2017). Are cryptocurrencies criminals best friends? Examining the co-evolution of Bitcoin and darknet markets, *Americas Conference on Information Systems (AMCIS)*, August 2017 .

Ju, L., Lu, T. J. and Tu, Z. (2016). Capital flight and Bitcoin regulation, *International Review of Finance* **16**(3): 445–455.

Kim, Y. and Peterson, R. A. (2017). A meta-analysis of online trust relationships in e-commerce, *Journal of Interactive Marketing* **38**: 44–54.

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis., PLoS ONE 10(4): e0123923 .

Kruithof, K., Aldridge, J., Décary-Hétu, D., Sim, M., Dujso, E. and Hoorens, S. (2016). Internet-facilitated drugs trade: An analysis of the size, scope and the role of the Netherlands, RAND Corporation. `https://www.rand.org/pubs/research_reports/RR1607.html`. 07.01.2020.

Lach, S. and Tsiddon, D. (1996). Staggering and synchronization in price-setting: Evidence from multiproduct firms, *American Economic Review* **86**: 1175–96.

Ladegaard, I. (2018). We know where you are, what you are doing and we will catch you: Testing deterrence theory in digital drug markets, *The British Journal of Criminology* **58**(2): 414–433.

Leland, H. E. (1972). Theory of the firm facing uncertain demand, *American Economic Review* **62**(3): 278–291.

Lopez-Quintero, C., de los Cobos, J. P., Hasin, D. S., Okuda, M., Wang, S., Grant, B. F. and Blanco, C. (2011). Probability and predictors of transition from first use to dependence on nicotine, alcohol, cannabis, and cocaine: Results of the national epidemiologic survey on alcohol and related conditions (nesarc), *Drug and Alcohol Dependence* **115**(1): 120 – 130.

Macrotrends LLC (2021). Euro dollar exchange rate (eur usd) - historical chart, `https://www.macrotrends.net/2548/euro-dollar-exchange-rate-historical-chart`. 09.03.2021.

Moeller, K., Munksgaard, R. and Demant, J. (2017). Flow my FE the vendor said: Exploring violent and fraudulent resource exchanges on cryptomarkets for illicit drugs, *American Behavioral Scientist* **61**(11): 1427–1450.

Moore, T. and Christin, N. (2013). Beware the middleman: Empirical analysis of Bitcoin-exchange risk, in A.-R. Sadeghi (ed.), Financial Cryptography and Data Security, Springer, Berlin, Heidelberg, pp. 25–33.

Mounteney, J., Oteo, A. and Griffiths, P. (2016). The internet and drug markets: Shining a light on these complex and dynamic systems, in: The internet and drug markets, European Monitoring Centre for Drugs and Drug Addiction (EMCDDA), Lisbon.

Nagin, D. S. (1998). Criminal deterrence research at the outset of the twenty-first century, *Crime and Justice* **23**: 1–42.

Nagin, D. S. (2013). Deterrence in the twenty-first century, *Crime and Justice* **42**: 199–263.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system, https://pdos.csail.mit.edu/6.824/papers/bitcoin.pdf.

O'Driscoll, A. (2018). How to buy and pay with Bitcoin anonymously, `https://www.comparitech.com/crypto/buy-pay-with-bitcoin-anonymously`. 02.09.2020.

Paquet-Clouston, M., Décary-Hétu, D. and Morselli, C. (2018). Assessing market competition and vendors' size and scope on AlphaBay, *International Journal of Drug Policy* **54**: 87 – 98.

Patterson, E. (2021). Penalties and sentencing, `https://drugabuse.com/addiction/drug-abuse/penalties/`. 08.03.2021.

Phelps, A. and Watt, A. (2014). I shop online – recreationally! Internet anonymity and Silk Road enabling drug use in Australia, *Digital Investigation* **11**(4): 261 – 272.

Reiman, A., Welty, M. and Solomon, P. (2017). Cannabis as a substitute for opioid-based pain medication: Patient self-report, *Cannabis and Cannabinoid Research* **2**(1): 160–166.

Reuter, P. and Kleiman, M. A. R. (1986). Risks and prices: An economic analysis of drug enforcement, *Crime and Justice* **7**: 289–340.

Rhumorbarbe, D., Staehli, L., Broséus, J., Rossy, Q. and Esseiva, P. (2016). Buying drugs on a darknet market: A better deal? Studying the online illicit drug market through the analysis of digital, physical and chemical data, *Forensic Science International* **267**: 173–182.

Sandmo, A. (1971). On the theory of the competitive firm under price uncertainty, *American Economic Review* **61**(1): 65–73.

Tzvetkova, M., Pardal, M., Disley, E., Rena, A., Talic, S. and Forberger, S. (2016). Strategies for a risky business: How drug dealers manage customers, suppliers and competitors in italy, slovenia and germany, *International Journal of Drug Policy* **31**: 90–98.

Van Buskirk, J., Bruno, R., Dobbins, T., Breen, C., Burns, L., Naicker, S. and Roxburgh, A. (2017). The recovery of online drug markets following law enforcement and other disruptions, *Drug and Alcohol Dependence* **173**: 159–162.

Van Slobbe, J. (2016). The drug trade on the deep web: a law enforcement perspective, in: The internet and drug markets, European Monitoring Centre for Drugs and Drug Addiction (EMCDDA), Lisbon.

Wambach, A. (1999). Bertrand competition under cost uncertainty, *International Journal of Industrial Organization* **17**(7): 941 – 951.

Winstock, A., Barratt, M., Maier, L., Aldridge, A., Zhuparris, A., Davies, E., Hughes, C., Johnson, M., Kowalski, M. and Ferris, J. (2019). Global Drug Survey (GDS) 2019 Key findings report, `https://www.globaldrugsurvey.com/gds-2019`.

Appendices

A Data Pre-processing

The data provided by Branwen et al. (2015b) offers a unique look into the supply side of the online drug trade, and I am grateful that the authors made the dataset publicly available for research purposes. Still, the raw data required an extensive amount of pre-processing in order to be useable for this study. This section describes how data was cleaned, explains how variables were constructed, and discusses the relevant assumptions made in the process.

A.1 Data cleaning

The dataset contains several outliers that need to be accounted for. First, flooding the market with countless identical offers is a common advertising practice observed on the eight markets. This behavior potentially leads to an overestimation of supplied quantities. In order to address this problem, I aggregate the number of listings at the vendor-day level, mark vendor-days above the 99th percentile of listings as spam, and omit these observations.

Second, vendors sometimes used listings purely to inform their customers. The description would then include a message about new products or information about when vendors are on holiday. In many cases, vendors used unrealistically high prices, presumably so that no one can remove the message by starting a transaction or in order to appear on top of the listings when sorting for price in descending order. I address both of these issues by omitting vendor-days where prices are above their 99th percentile. Some vendors seem to confuse microgram with milligram, resulting in absurdly high USD/g prices, or vendors ask outright unbelievably high prices compared to street prices.

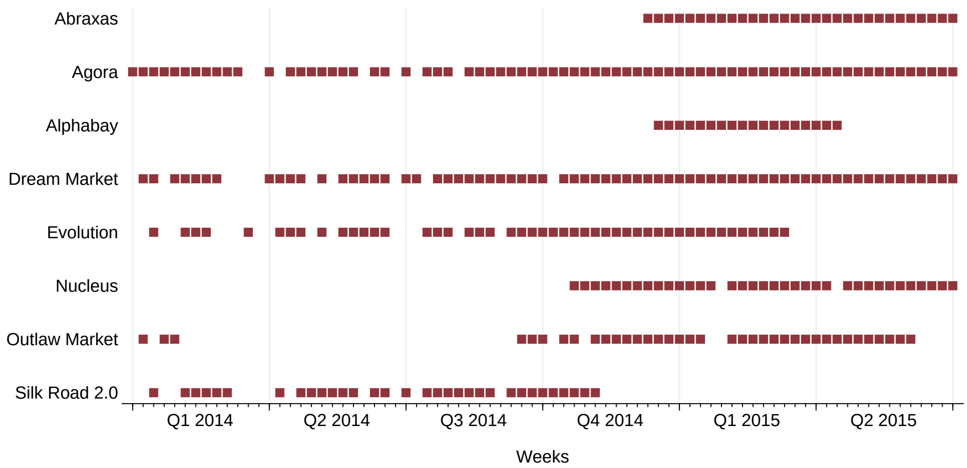
In order to further detect outliers in terms of price, I use data on retail prices of drugs between 2014 and 2015 provided by the United Nations Office on Drugs and Crime (2015) as a rough guideline.[19] Maximum prices for cannabis-type drugs in 2015 are reported as 63.5 USD/g (USA, 2015), 49.5 USD/g (Western and Central Europe, 2014), and 45.1 USD/g (Oceania, 2014). Maximum prices for opioids are 450 USD/g (USA, 2014), 266.3 USD/g (Western and Central Europe, 2014), and 827.81 USD/g (Oceania, 2014). Taking the US prices as the basic level, I allow for additional headroom by multiplying this threshold by five in order to set a limit for reasonable prices. Therefore, 300 USD/g for cannabis and 2250 USD/g for opioids are chosen as upper price limits. All prices above these thresholds are considered outliers and are treated as missing values. Inspecting the descriptions of these products confirms that these are mostly messages, sold-out listings, or outright unrealistic prices that hint towards an error on the side of the vendor.

Third, the scraping process was incomplete on some days. The scraping process can stop due to multiple reasons, most likely because the internet connection or the market server timed out (Branwen et al., 2015b), where the latter is a common occurrence for darknet markets. Even though I am mostly interested in vendor level data, this is important because, on days where markets have been successfully scraped, a quantity of 0 is assigned if a vendor was not listing any products. I assume that incomplete scrapes occur randomly and that the scraped

[19] The price data from was retrieved from the United Nations' *Retail drug price and purity level* available at https://dataunodc.un.org/data/drugs/Retail drug price and purity level.

listings I retrieve are also selected randomly, rather than in a specific order. Therefore, price and rating are still representative, but a missing value must be assigned to quantity for days of incomplete scrapes. I identify incomplete scrapes by looking at the number of listings per day and market. A market-day combination counts as an incomplete scrape if the number of listings is at least 15% lower than the average amount over a window of ± 15 days.

Figure 11: Scraped weeks



Notes: This figure shows availability of samples across markets and weeks, where red squares indicate that there exists at least one scrape of a certain market in this week.

Another related problem was that scrapes do not exist for each market-day combination, which can be a major issue in analyzing a vendor panel. To see why, suppose a vendor is active on two markets, where she offers consistently high quantities on market A and low quantities on market B and her real supply amounts to the sum quantities sold on A and B. However, if only market B is scraped on a particular day, it would seem as if she now reduced supply even though, in reality, she offered the same amount. The best tool available to tackle this issue is to aggregate data on week level in order to mitigate the impact of these fluctuations and to control for which market was scraped in each week. Figure 11 shows the weeks for which there exists at least one scrape per server. While *Agora* and *Dream Market* are active across the entirety of the observation period, *Evolution* and *Silk Road* 2.0 are closed within the sampling period, and the rest only enters the darknet (or starts getting scraped) in the last quarter of 2014.

A.2 Construction of variables

Section 4 describes the general construction of outcome variables in the dataset, while this section gives additional information that went into the design of the vendor panel. In order to estimate category-wise treatment effects, it was necessary to construct drug categories that are applicable across markets. Unfortunately, there are no uniform categories across markets, so I choose the eleven categories from *Alphabay*, which happen to be the most common ones across markets. I divide the listings into benzodiazepine, cannabis, dissociatives, ecstasy, opioids, fentanyl, prescription drugs, psychedelics, steroids, stimulants, weight loss, and other, although in the final study, I only analyze cannabis and opioids. Most other categories are too small and show too much variance across time to be considered here. Fentanyl was removed from the opioid category as amounts were consistently listed for unreasonably high prices given the amount sold. In order to classify listings the same way across markets, I generate a dictionary with keywords that occur most frequently in product descriptions. To classify products, this process is repeated for each category, and keywords are checked manually for relevance before the list is applied to each marketplace.

Similar to categories, I establish a dictionary of country names for each region. I choose the location of the vendor as the definition of region. In case there is no information on the vendor's home country, I use information on the accepted countries of destination. Constructing a vendor panel of multiple markets makes it necessary to match vendors across servers. I use the vendor's online pseudonym and apply case insensitive matching. Ignoring differences between lower and upper case characters is a strong choice that I take because different servers might allow for different naming rules or conventions. Finally, I remove all # characters from names, as they are sometimes used to format names.

As far as quantities are concerned, I choose not to use the standard approach in the literature of using the number of listings as a proxy. The more accurate way is to use the exact amount of grams or milliliters that a listing contains. This approach allows for more accurate analysis because vendors often vary the weight of drugs on the listing level rather than making new listings. In any case, if the vendor chooses to increase listings, she automatically increases the amount of grams as well, which results in a more reliable measure of quantity.

Unfortunately, the scraping procedure does not extract this weight information. I extract information about quantity measured in gram or milliliter units from the descriptions of listings. An exemplary listing description would read "50 Pills Xanax x 1 mg". I first search for regular expressions that contain a number as well as a related keyword, where the algorithm would find, in this case, "1" and "Mg". I then search for common quantity multipliers like "50 Pills" in order to correctly assign a quantity of 0.05 grams. I used different methods to check whether this algorithm works as intended.

For most markets, about 80% of cannabis and 90% of opioid listings have information about quantity in their product description. *Outlaw Market* and *Silkroad* 2.0 are outliers for both categories with cannabis rates of 10% and 21%, and opioid rates of 57% and 51%, respectively. Markets use different ways to express vendor ratings by either giving 1 out of 5 points or a percentage. To construct a variable that can be used in the aggregated sample, I normalize all ratings between 0 and 1 in each market.

B Event definitions finalize early

The finalize early variable is only available on *Evolution* and *Nucleus* markets and can only be observed as of August 2014 (2014w33), which requires different event definitions compared to the other outcome variables that are spread out over the observation period. Using threshold values of seven weekly arrests and a Bitcoin volatility of 35 standard deviations would only leave four out of six holding risk events and zero transaction risk events as Bitcoin volatility was highest in early 2014. To make the analysis comparable, I lower the threshold for holding risk events to five arrests and the threshold for transaction risk events to 20 standard deviations. This procedure leads to six arrest events and four volatility events, shown in Panels (a) and (c) of Figure 12, where grey-dashed lines indicate periods where the finalize early variable cannot be observed. The interpretation of Panels (b) and (d) is analogous to the discussion in Section 5.

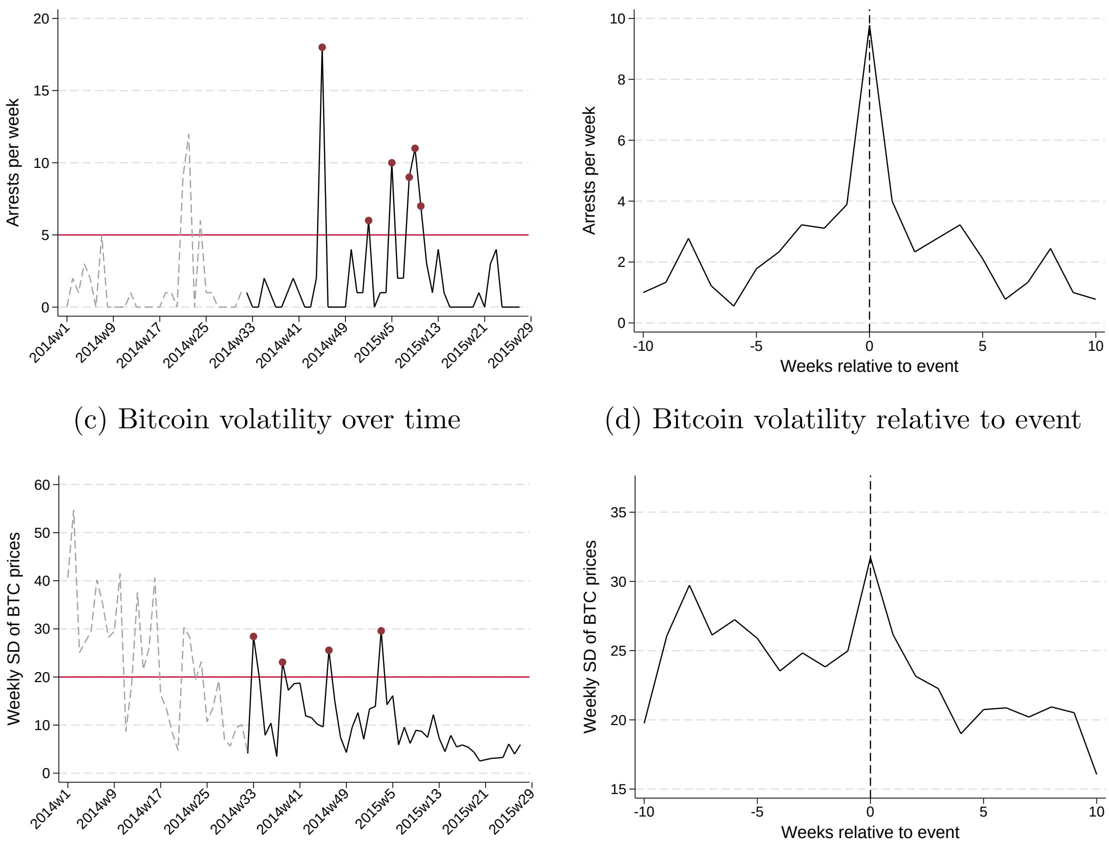
Figure 12: Event definitions for finalize early

(a) Arrests over time

(b) Arrests relative to event

(c) Bitcoin volatility over time

(d) Bitcoin volatility relative to event



Notes: This figure visualizes the criteria for the event definitions. Panels (a) and (c) show the development of arrests and Bitcoin volatility over the observation period. Using the cut-off levels shown as red lines, I define six shocks to holding risk and four shocks to transaction risk. Panels (b) and (d) aggregate these events by taking the mean over arrests and volatility relative to the event timing for a period of seven weeks before and after the shock.

C Additional tables and graphs

C.1 Heterogeneous effects

Table 4: Heterogeneous effects of shocks to holding risk by region. Dep.var.: Price in USD/g

	Cannabis					Opioids				
	(1) Baseline	(2) Europe	(3) N.America	(4) Australia	(5) Worldwide	(6) Baseline	(7) Europe	(8) N.America	(9) Australia	(10) Worldwide
Pre-event weeks:										
-7	0.283	0.133	-0.257	2.848*	0.269	15.441**	11.592	17.934	-4.147	56.670***
	(0.282)	(0.305)	(0.491)	(1.494)	(1.149)	(7.045)	(10.562)	(11.857)	(29.318)	(15.199)
-6	0.229	0.069	-0.281	3.232**	1.190	1.066	-7.649	9.207	-21.096	35.725**
	(0.232)	(0.280)	(0.377)	(1.285)	(0.941)	(6.911)	(10.738)	(12.431)	(31.518)	(14.289)
-5	0.085	-0.013	0.025	0.673	0.611	0.937	2.388	2.755	-50.064**	27.657***
	(0.182)	(0.244)	(0.264)	(0.928)	(1.199)	(4.907)	(7.400)	(8.283)	(22.699)	(9.592)
-3	-0.170	-0.219	-0.125	1.886*	-1.451	0.793	-11.449	8.804	-0.367	2.967
	(0.183)	(0.234)	(0.265)	(1.134)	(1.527)	(5.004)	(7.430)	(8.603)	(20.556)	(14.384)
-2	-0.199	-0.290	-0.365	0.915	-1.978***	1.376	-17.745*	15.482	15.348	-3.867
	(0.252)	(0.281)	(0.478)	(1.247)	(0.670)	(6.056)	(9.494)	(9.630)	(30.470)	(13.629)
-1	0.001	-0.041	0.080	0.634	-1.956***	-3.665	-3.236	8.476	15.389	-9.956
	(0.252)	(0.311)	(0.457)	(1.236)	(0.505)	(6.037)	(8.913)	(11.031)	(22.770)	(10.708)
Post-event weeks:										
0	-0.159	-0.077	-0.082	0.989	-3.847***	-0.346	8.032	-0.090	23.894	-8.641
	(0.221)	(0.331)	(0.365)	(1.219)	(0.760)	(6.398)	(9.706)	(11.306)	(30.183)	(16.224)
1	0.203	-0.145	0.351	1.343	-3.425***	19.867***	22.403*	19.779*	63.040*	-13.166
	(0.230)	(0.255)	(0.417)	(1.140)	(1.261)	(7.085)	(11.600)	(11.874)	(33.465)	(19.820)
2	0.326	0.096	0.332	-0.042	-2.292*	19.424**	15.020	25.078*	72.826**	-39.961**
	(0.286)	(0.427)	(0.500)	(1.119)	(1.215)	(7.989)	(12.049)	(15.168)	(34.725)	(15.697)
3	0.314	0.159	0.077	0.453	-1.536	7.267	15.131	4.392	59.192	-43.244**
	(0.242)	(0.265)	(0.455)	(1.158)	(1.179)	(8.602)	(11.792)	(16.769)	(37.131)	(20.231)
4	0.812***	0.783**	0.502	1.246	-1.860	11.058	22.288*	-4.836	95.323**	-41.200
	(0.285)	(0.323)	(0.523)	(1.312)	(1.329)	(8.961)	(12.140)	(16.621)	(41.132)	(25.052)
5	0.575*	0.081	0.632	0.438	-1.298	1.612	0.324	-10.817	61.359	-30.321
	(0.327)	(0.289)	(0.632)	(1.448)	(1.691)	(9.933)	(14.530)	(18.726)	(46.094)	(21.937)
6	-0.170	-0.557*	-0.022	-0.177	-2.625	-13.178	-16.164	-25.733	0.425	-33.205
	(0.344)	(0.296)	(0.696)	(1.469)	(1.669)	(10.248)	(12.313)	(20.273)	(51.162)	(26.675)
7	-0.567	-0.144	-1.276*	-2.924*	-1.237	-9.241	-5.716	-9.300	-24.888	-42.795
	(0.366)	(0.390)	(0.734)	(1.495)	(1.583)	(11.015)	(11.964)	(20.606)	(66.999)	(26.385)
Constant	1.422***	0.834	2.883**	-0.552	4.263**	5.938	11.476	-18.484	51.974	-15.293
	(0.483)	(0.514)	(1.127)	(1.405)	(1.949)	(11.700)	(11.063)	(27.454)	(47.521)	(35.259)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,237	13,463	14,229	2,145	2,324	17,225	5,347	6,982	1,367	1,311
Mean of dep. var.	16.79	13.79	19.18	20.94	16.37	468.20	330.44	567.98	782.77	303.90
R-squared	0.004	0.006	0.010	0.068	0.050	0.006	0.020	0.011	0.057	0.225

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 5: Heterogeneous effects of shocks to holding risk by region. Dep.var.: Quantity in grams

	Cannabis					Opioids				
	(1) Baseline	(2) Europe	(3) N.America	(4) Australia	(5) Worldwide	(6) Baseline	(7) Europe	(8) N.America	(9) Australia	(10) Worldwide
Pre-event weeks:										
-7	25.928	38.966**	20.373	6.911	48.199	-14.390	-26.509	-15.850	-1.511	-10.391
	(21.870)	(18.148)	(49.555)	(5.510)	(37.226)	(11.810)	(27.367)	(19.101)	(1.035)	(11.462)
-6	9.031	24.720	-39.333	-6.190	81.181*	-13.966	-16.739	-16.901	-0.608	-17.181
	(22.223)	(20.944)	(48.807)	(4.347)	(46.368)	(13.057)	(27.264)	(23.212)	(0.659)	(20.183)
-5	10.528	31.640***	-27.909	-1.397	57.564	-12.018	-19.865	-10.986	0.064	-9.042
	(18.836)	(11.051)	(41.587)	(2.672)	(44.607)	(9.378)	(26.943)	(12.753)	(0.270)	(5.507)
-3	-27.575*	-53.036**	-34.847	-5.656*	114.846	-9.238	-37.290	1.236	0.290	-1.925
	(14.379)	(26.071)	(23.374)	(3.112)	(97.746)	(7.794)	(28.817)	(3.020)	(0.246)	(19.533)
-2	-18.623	-47.555	-22.001	-10.876***	192.919*	-8.013	-18.117	-3.402	0.054	-0.018
	(26.573)	(38.890)	(50.440)	(3.315)	(101.442)	(7.875)	(20.605)	(10.795)	(0.294)	(18.021)
-1	22.493	20.113	23.833	-2.888	114.449**	-4.128	1.927	-7.938	-0.463**	4.158*
	(25.035)	(20.428)	(57.122)	(5.881)	(57.307)	(6.500)	(13.353)	(10.700)	(0.200)	(2.220)
Post-event weeks:										
0	2.817	-5.972	1.850	-3.377	65.272	-2.840	10.370	-7.865	-0.460	0.726
	(20.986)	(17.420)	(49.096)	(9.312)	(53.036)	(7.113)	(16.720)	(10.282)	(0.349)	(10.245)
1	-17.168	-27.864	-42.916	-4.307	149.600*	-10.246	-19.159	-5.964	0.233	13.217*
	(27.457)	(22.212)	(62.439)	(11.530)	(80.770)	(10.352)	(33.682)	(9.883)	(0.475)	(7.689)
2	36.614	29.638	34.063	3.367	176.511**	-10.584	-31.344	0.398	0.307	10.002
	(29.206)	(34.771)	(61.328)	(13.221)	(88.375)	(9.670)	(30.879)	(9.808)	(0.393)	(8.305)
3	24.217	26.321	8.248	4.662	187.184*	-10.340	-26.665	-1.285	-0.773	8.275
	(26.257)	(31.663)	(54.007)	(16.531)	(106.880)	(9.988)	(31.097)	(10.640)	(0.882)	(7.880)
4	-1.482	-17.198	-13.807	-10.514	100.863	-9.848	-16.553	-5.366	-0.648	7.541
	(22.261)	(23.447)	(46.805)	(19.102)	(116.648)	(11.444)	(34.731)	(12.016)	(0.432)	(10.016)
5	78.124***	59.055	70.597	-5.321	253.213	-17.468	-36.654	-6.666	0.199	8.359
	(30.078)	(41.611)	(56.953)	(20.213)	(178.210)	(11.791)	(38.264)	(11.948)	(0.453)	(7.704)
6	71.672***	74.562**	86.475	0.720	10.315	-16.714	-38.327	-11.033	0.512	5.398
	(26.789)	(29.804)	(56.582)	(18.853)	(116.582)	(11.657)	(38.035)	(11.566)	(0.694)	(10.574)
7	37.718	44.305**	67.836	-0.261	-156.973	-12.349	-15.941	-10.784	0.976	-1.338
	(24.628)	(19.383)	(46.297)	(21.908)	(247.740)	(11.095)	(33.193)	(13.050)	(0.706)	(12.568)
Constant	-228.897**	-135.907***	-464.476	-33.300	-115.038	-18.971	10.036	-15.494***	-0.696	-33.440*
	(116.506)	(48.374)	(369.063)	(33.926)	(83.865)	(13.500)	(27.572)	(5.624)	(0.702)	(17.893)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,754	23,971	26,237	4,429	4,519	34,941	8,944	15,678	2,821	2,504
Mean of dep. var.	267.12	198.32	404.73	60.47	101.04	32.98	51.30	30.03	4.35	31.28
R-squared	0.005	0.003	0.018	0.024	0.009	0.011	0.007	0.004	0.063	0.040

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 6: Heterogeneous effects of shocks to transaction risk by region. Dep.var.: Price in USD/g

	Cannabis					Opioids				
	(1) Baseline	(2) Europe	(3) N.America	(4) Australia	(5) Worldwide	(6) Baseline	(7) Europe	(8) N.America	(9) Australia	(10) Worldwide
Pre-event weeks:										
-7	-0.121	-0.938**	0.264	2.947**	-3.360	-6.642	-11.777	-10.986	-92.044***	-43.034
	(0.214)	(0.407)	(0.305)	(1.432)	(2.474)	(8.728)	(16.121)	(12.314)	(20.211)	(30.805)
-6	0.087	-0.042	0.112	2.469	0.399	-11.282	-12.818	-2.753	1.677	-163.115***
	(0.706)	(0.906)	(1.176)	(4.330)	(4.553)	(16.903)	(35.660)	(24.976)	(53.623)	(38.954)
-5	0.710	1.350**	0.974	0.672	-8.794***	-5.625	-5.673	-21.713	4.467	-204.429**
	(0.571)	(0.658)	(1.027)	(1.808)	(2.205)	(12.899)	(17.920)	(22.395)	(62.751)	(82.601)
-3	-0.124	0.569	-0.989	2.011	2.940	22.610*	29.180	24.198	108.009***	-109.302***
	(0.432)	(0.612)	(0.656)	(3.304)	(3.761)	(13.193)	(29.030)	(19.498)	(28.581)	(36.425)
-2	1.014*	1.536**	1.798*	-3.063	-4.833	24.717*	32.886	15.796	64.027	-132.634*
	(0.568)	(0.625)	(1.021)	(2.215)	(3.128)	(14.856)	(24.969)	(26.480)	(49.943)	(75.131)
-1	0.405	1.151*	0.964	-2.897**	-0.599	4.393	49.141**	3.765	21.926	22.100
	(0.436)	(0.631)	(0.739)	(1.224)	(1.134)	(11.182)	(20.190)	(17.997)	(30.645)	(18.289)
Post-event weeks:										
0	-0.190	1.242*	-0.002	-4.426***	-5.561***	14.218	48.343*	16.574	105.192***	-47.076
	(0.447)	(0.732)	(0.748)	(1.397)	(1.625)	(15.473)	(27.201)	(23.555)	(29.491)	(37.898)
1	0.560	3.017***	0.406	-5.230**	-5.373	53.046***	77.897***	32.252	168.721***	-123.037*
	(0.619)	(0.979)	(0.979)	(2.261)	(5.291)	(14.577)	(26.466)	(23.907)	(49.218)	(70.367)
2	1.496***	3.225***	1.123	-1.592	3.666	46.563***	64.155***	38.905*	189.141***	53.034
	(0.560)	(0.870)	(0.894)	(1.856)	(5.007)	(13.769)	(22.844)	(22.259)	(49.214)	(56.303)
3	0.395	2.447***	0.727	-7.120	-1.696	40.256**	91.620***	28.640	219.709***	116.290*
	(0.617)	(0.910)	(0.992)	(4.421)	(3.345)	(18.009)	(32.783)	(28.131)	(36.433)	(55.690)
4	0.023	1.919*	0.317	-5.110	-5.573	43.141**	101.300***	18.678	261.702***	-29.972
	(0.602)	(1.033)	(0.932)	(3.148)	(4.866)	(17.024)	(33.473)	(25.631)	(35.094)	(57.318)
5	1.635**	3.755***	1.418	-2.828	-0.486	45.344**	83.307***	28.439	291.769***	33.602
	(0.673)	(1.136)	(1.029)	(3.433)	(6.029)	(18.189)	(29.408)	(28.627)	(53.202)	(53.918)
6	1.609**	4.013***	1.029	-2.059	-1.573	66.442***	92.114**	49.763	368.043***	-39.492
	(0.735)	(1.054)	(1.198)	(5.463)	(3.872)	(20.456)	(35.482)	(31.401)	(45.830)	(103.753)
7	1.024	3.379***	0.529	-0.878	-1.335	67.266***	107.500***	33.404	382.247***	51.389
	(0.767)	(1.133)	(1.296)	(4.152)	(3.427)	(20.430)	(40.064)	(30.794)	(35.431)	(78.621)
Constant	0.054	-0.826	-1.564	7.306*	2.744	-14.039	-60.493	-41.172	0.993	-52.640
	(0.958)	(1.736)	(1.256)	(4.336)	(2.176)	(36.102)	(60.516)	(68.416)	(128.053)	(59.755)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,451	4,104	6,011	733	416	6,826	1,977	3,099	441	246
Mean of dep. var.	17.25	17.76	17.66	13.50	21.06	587.87	476.00	654.81	1363.56	454.26
R-squared	0.008	0.020	0.007	0.148	0.034	0.017	0.043	0.015	0.375	0.265

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 7: Heterogeneous effects of shocks to transaction risk by region. Dep.var.: Quantity in grams

	Cannabis					Opioids				
	(1) Baseline	(2) Europe	(3) N.America	(4) Australia	(5) Worldwide	(6) Baseline	(7) Europe	(8) N.America	(9) Australia	(10) Worldwide
Pre-event weeks:										
-7	3.027	-16.665	6.807	-17.357**	-15.479	-0.237	-4.732	0.436	0.344***	-0.659
	(17.193)	(23.542)	(31.927)	(7.468)	(32.628)	(2.564)	(5.214)	(4.739)	(0.072)	(1.643)
-6	-77.815	-130.019	-94.665	4.580	71.204	5.135	-1.088	12.660	0.342**	3.689**
	(53.433)	(114.812)	(84.388)	(23.461)	(79.141)	(4.760)	(8.330)	(8.180)	(0.150)	(1.517)
-5	-86.449**	-107.373	-143.320**	11.552*	84.413***	-7.582	4.472	-16.731	0.624***	2.109
	(44.007)	(105.429)	(59.046)	(6.656)	(23.729)	(8.835)	(6.645)	(17.166)	(0.134)	(2.890)
-3	-29.024	-45.654	-32.910	27.031*	42.405	6.291*	1.786	16.262***	0.090	3.816***
	(29.951)	(43.407)	(59.896)	(15.841)	(65.395)	(3.595)	(8.872)	(5.755)	(0.108)	(1.075)
-2	-66.091	-29.368	-119.014**	32.504***	54.885*	-4.945	6.387	-6.953	0.288**	1.986*
	(45.774)	(119.091)	(53.429)	(9.900)	(30.571)	(3.853)	(6.742)	(6.306)	(0.112)	(0.989)
-1	-2.008	40.205	-20.718	25.530***	-1.672	-2.463	3.848	-3.642	-0.127	0.141
	(49.617)	(130.294)	(56.336)	(8.723)	(67.599)	(2.519)	(4.725)	(4.798)	(0.092)	(0.566)
Post-event weeks:										
0	-64.773	-104.130	-42.430	51.563***	-150.177*	2.071	2.178	7.469	0.097	0.924
	(80.536)	(226.939)	(39.343)	(15.543)	(76.781)	(3.320)	(8.570)	(5.049)	(0.142)	(1.164)
1	-86.775	-88.246	-103.002	50.717***	-121.613***	6.282	4.890	14.337	0.098	4.156
	(55.815)	(141.925)	(63.784)	(10.475)	(42.578)	(10.716)	(11.052)	(21.381)	(0.197)	(3.501)
2	-47.798	-40.504	-54.662	31.732***	34.067	10.165	8.453	20.851	-0.188	0.034
	(54.281)	(140.847)	(56.092)	(8.368)	(63.634)	(14.075)	(13.049)	(29.022)	(0.247)	(0.778)
3	-136.303*	-112.863	-185.865***	61.867***	-115.048	2.561	4.226	11.808	-0.468	-0.379
	(81.492)	(226.335)	(60.404)	(20.770)	(69.179)	(7.204)	(12.380)	(14.335)	(0.285)	(1.095)
4	-40.651	-9.677	-36.830	85.950***	-99.832	11.848	8.227	26.185	-0.230	4.854
	(75.037)	(194.873)	(75.852)	(20.024)	(72.736)	(13.813)	(17.024)	(27.406)	(0.280)	(3.502)
5	-12.616	69.372	-78.299	53.604***	-5.746	11.557	0.895	29.063	-0.170	0.786
	(67.249)	(132.884)	(115.460)	(11.283)	(77.301)	(17.385)	(13.662)	(35.484)	(0.304)	(0.941)
6	-107.646	-17.213	-188.800*	68.289***	-60.673	10.259	3.271	27.930	0.012	2.512
	(68.093)	(147.341)	(108.902)	(10.221)	(41.165)	(11.193)	(14.454)	(22.444)	(0.367)	(1.923)
7	5.307	68.768	1.662	89.993***	-62.389	15.160	13.804	31.303	-0.623	4.503
	(62.820)	(140.085)	(92.928)	(19.938)	(52.059)	(19.050)	(20.865)	(38.180)	(0.403)	(4.127)
Constant	-72.001	-131.703	-114.193	-62.594*	-5.089	-11.845	-19.310	-21.621	0.114	-3.559**
	(96.728)	(173.993)	(186.240)	(33.812)	(31.164)	(9.195)	(17.382)	(22.783)	(0.166)	(1.391)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,072	10,134	12,117	1,926	852	15,256	3,870	7,347	1,214	497
Mean of dep. var.	337.20	405.74	450.67	74.78	18.05	7.70	9.09	9.47	0.91	3.62
R-squared	0.002	0.003	0.003	0.086	0.031	0.002	0.008	0.003	0.153	0.043

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 8: Heterogeneous effects of shocks to holding risk by vendor size. Dep.var.: Price in USD/g

	Cannabis					Opioids				
	(1) Baseline	(2) 1. quartile	(3) 2. quartile	(4) 3. quartile	(5) 4. quartile	(6) Baseline	(7) 1. quartile	(8) 2. quartile	(9) 3. quartile	(10) 4. quartile
Pre-event weeks:										
-7	0.283	-0.095	0.641	0.915*	-0.368	15.441**	0.715	0.659	32.871**	15.937**
	(0.282)	(0.975)	(0.521)	(0.478)	(0.496)	(7.045)	(18.701)	(19.190)	(14.876)	(7.301)
-6	0.229	0.094	0.288	0.936**	-0.295	1.066	-7.745	-18.447	21.455	12.613*
	(0.232)	(0.880)	(0.487)	(0.403)	(0.361)	(6.911)	(24.284)	(13.951)	(15.448)	(6.593)
-5	0.085	-0.008	0.199	0.343	-0.335*	0.937	9.348	4.093	6.394	8.700*
	(0.182)	(0.827)	(0.402)	(0.264)	(0.194)	(4.907)	(15.265)	(11.284)	(10.644)	(4.836)
-3	-0.170	-1.801**	0.375	-0.109	0.119	0.793	47.248***	-26.215**	-0.351	-6.987
	(0.183)	(0.860)	(0.382)	(0.278)	(0.235)	(5.004)	(16.461)	(10.276)	(12.195)	(5.188)
-2	-0.199	-1.840**	0.199	0.572	-0.223	1.376	48.495***	-11.357	14.487	-13.178*
	(0.252)	(0.793)	(0.528)	(0.588)	(0.272)	(6.056)	(17.411)	(11.471)	(15.430)	(6.886)
-1	0.001	-1.526*	0.436	0.537	-0.133	-3.665	10.257	-3.781	9.335	-15.561***
	(0.252)	(0.853)	(0.412)	(0.647)	(0.243)	(6.037)	(14.225)	(14.808)	(15.281)	(5.079)
Post-event weeks:										
0	-0.159	-0.281	0.469	-0.203	-0.055	-0.346	22.334	10.300	2.955	-10.005
	(0.221)	(0.943)	(0.411)	(0.450)	(0.234)	(6.398)	(14.604)	(13.184)	(16.685)	(7.284)
1	0.203	0.734	1.023**	0.073	0.277	19.867***	83.804***	41.622**	17.547	1.328
	(0.230)	(0.992)	(0.516)	(0.430)	(0.218)	(7.085)	(18.165)	(16.131)	(17.732)	(6.647)
2	0.326	1.995**	0.775	0.795	-0.268	19.424**	99.830***	50.417***	18.098	4.031
	(0.286)	(0.866)	(0.616)	(0.656)	(0.301)	(7.989)	(17.486)	(16.852)	(21.335)	(6.957)
3	0.314	3.325***	0.494	0.202	-0.181	7.267	77.807***	42.693**	4.620	6.785
	(0.242)	(0.896)	(0.554)	(0.408)	(0.367)	(8.602)	(15.831)	(18.379)	(22.721)	(8.119)
4	0.812***	4.932***	0.813	0.642	-0.051	11.058	87.099***	47.157**	15.034	4.575
	(0.285)	(1.072)	(0.678)	(0.462)	(0.416)	(8.961)	(19.063)	(18.888)	(22.811)	(9.187)
5	0.575*	2.276**	1.276	0.830*	-0.329	1.612	56.788**	29.494	-2.697	-1.954
	(0.327)	(1.104)	(0.872)	(0.476)	(0.480)	(9.933)	(26.108)	(21.194)	(23.220)	(11.255)
6	-0.170	-0.166	1.062	0.527	-0.611	-13.178	50.024*	19.712	-27.129	-6.654
	(0.344)	(1.184)	(0.905)	(0.460)	(0.527)	(10.248)	(26.227)	(20.855)	(25.683)	(9.855)
7	-0.567	-1.307	0.089	-0.102	-0.662	-9.241	47.111*	-5.571	-28.642	6.693
	(0.366)	(1.567)	(0.914)	(0.461)	(0.539)	(11.015)	(28.518)	(24.378)	(27.875)	(8.831)
Constant	1.422***	4.256**	0.024	3.079***	-0.173	5.938	-27.043	-6.008	-15.438	24.653**
	(0.483)	(2.122)	(0.809)	(1.064)	(0.563)	(11.700)	(32.689)	(37.564)	(25.565)	(10.417)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,237	5,474	8,696	10,334	10,733	17,225	2,685	4,105	4,845	5,590
Mean of dep. var.	16.79	34.59	17.56	13.72	10.41	468.20	1015.82	689.95	344.47	166.89
R-squared	0.004	0.058	0.009	0.012	0.006	0.006	0.044	0.025	0.013	0.023

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 9: Heterogeneous effects of shocks to holding risk by vendor size. Dep.var.: Quantity in grams

	Cannabis					Opioids				
	(1) Baseline	(2) 1. quartile	(3) 2. quartile	(4) 3. quartile	(5) 4. quartile	(6) Baseline	(7) 1. quartile	(8) 2. quartile	(9) 3. quartile	(10) 4. quartile
Pre-event weeks:										
-7	25.928	0.307	1.315	4.715	89.764	-14.390	-0.001	-0.001	0.001	-61.449
	(21.870)	(0.187)	(0.878)	(4.211)	(109.265)	(11.810)	(0.002)	(0.028)	(0.142)	(50.436)
-6	9.031	-0.321**	-1.300	-6.424	27.075	-13.966	-0.004**	-0.077***	-0.376*	-55.414
	(22.223)	(0.146)	(0.860)	(4.269)	(116.505)	(13.057)	(0.002)	(0.026)	(0.192)	(56.205)
-5	10.528	-0.205**	-1.186**	-1.914	15.349	-12.018	-0.001	-0.011	-0.237	-48.205
	(18.836)	(0.101)	(0.471)	(2.537)	(102.176)	(9.378)	(0.001)	(0.013)	(0.168)	(39.657)
-3	-27.575*	-0.133	-0.080	0.973	-117.878*	-9.238	0.000	0.004	-0.179	-37.786
	(14.379)	(0.100)	(0.482)	(2.733)	(68.550)	(7.794)	(0.001)	(0.020)	(0.119)	(32.608)
-2	-18.623	-0.382***	-1.134	-7.906**	-82.131	-8.013	-0.002	-0.037	-0.396**	-34.394
	(26.573)	(0.125)	(0.782)	(3.474)	(127.340)	(7.875)	(0.002)	(0.029)	(0.179)	(33.071)
-1	22.493	-0.126	1.638**	3.617	104.431	-4.128	-0.002	-0.017	-0.004	-20.813
	(25.035)	(0.130)	(0.770)	(3.458)	(117.582)	(6.500)	(0.002)	(0.021)	(0.269)	(27.432)
Post-event weeks:										
0	2.817	-0.174	0.724	4.947	5.454	-2.840	-0.002	-0.019	-0.102	-15.739
	(20.986)	(0.153)	(0.732)	(3.709)	(103.073)	(7.113)	(0.002)	(0.019)	(0.193)	(28.111)
1	-17.168	-0.465***	-1.478	-5.245	-115.080	-10.246	-0.003	-0.088***	-0.477**	-49.071
	(27.457)	(0.174)	(0.919)	(4.718)	(136.723)	(10.352)	(0.002)	(0.024)	(0.239)	(42.708)
2	36.614	0.016	2.850**	12.876**	120.206	-10.584	0.001	0.025	0.123	-55.300
	(29.206)	(0.188)	(1.192)	(5.688)	(142.207)	(9.670)	(0.003)	(0.062)	(0.246)	(40.825)
3	24.217	0.039	3.920***	16.477***	45.367	-10.340	0.002	0.058	0.061	-51.318
	(26.257)	(0.208)	(1.194)	(5.375)	(127.333)	(9.988)	(0.003)	(0.071)	(0.278)	(41.750)
4	-1.482	-0.605***	-0.899	-3.264	-70.536	-9.848	-0.001	-0.091**	-0.509*	-48.407
	(22.261)	(0.219)	(1.016)	(4.728)	(109.889)	(11.444)	(0.003)	(0.038)	(0.269)	(48.448)
5	78.124***	-0.180	1.747	12.583**	318.992**	-17.468	0.003	-0.043	0.064	-83.954*
	(30.078)	(0.204)	(1.133)	(5.632)	(148.546)	(11.791)	(0.004)	(0.035)	(0.291)	(50.177)
6	71.672***	0.261	4.859***	26.130***	292.929**	-16.714	0.003	0.097	0.223	-76.019
	(26.789)	(0.245)	(1.459)	(6.500)	(129.116)	(11.657)	(0.004)	(0.085)	(0.333)	(49.845)
7	37.718	-0.290	0.926	6.974	124.888	-12.349	-0.002	-0.013	-0.148	-48.060
	(24.628)	(0.212)	(1.298)	(5.393)	(124.126)	(11.095)	(0.003)	(0.045)	(0.295)	(46.394)
Constant	-228.897**	-0.842**	-2.166	-33.912***	-943.282**	-18.971	0.003	0.104	-0.812**	-54.344
	(116.506)	(0.379)	(1.783)	(9.382)	(451.856)	(13.500)	(0.005)	(0.147)	(0.327)	(45.716)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,754	13,310	14,257	14,630	13,616	34,941	6,471	7,072	7,403	7,934
Mean of dep. var.	267.12	1.76	13.42	63.13	1204.66	32.98	0.02	0.24	2.11	137.15
R-squared	0.005	0.018	0.015	0.023	0.020	0.011	0.012	0.017	0.020	0.043

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * p < 0.10 ** p < 0.05 *** p < 0.01.

Table 10: Heterogeneous effects of shocks to transaction risk by vendor size. Dep.var.: Price in USD/g

	Cannabis					Opioids				
	(1) Baseline	(2) 1. quartile	(3) 2. quartile	(4) 3. quartile	(5) 4. quartile	(6) Baseline	(7) 1. quartile	(8) 2. quartile	(9) 3. quartile	(10) 4. quartile
Pre-event weeks:										
-7	-0.121	-0.591	0.010	-0.218	0.022	-6.642	14.897	-20.560	-35.107*	-0.370
	(0.214)	(0.809)	(0.315)	(0.451)	(0.231)	(8.728)	(15.891)	(19.748)	(20.627)	(9.799)
-6	0.087	1.743	0.541	-0.878	0.140	-11.282	4.642	-41.654	20.465	-9.586
	(0.706)	(2.787)	(0.954)	(1.465)	(0.393)	(16.903)	(46.881)	(47.301)	(24.290)	(15.379)
-5	0.710	3.453*	-1.061	1.724	0.741	-5.625	-19.653	-37.836	33.213	-21.008
	(0.571)	(1.917)	(0.711)	(1.335)	(0.450)	(12.899)	(25.924)	(33.862)	(23.460)	(15.349)
-3	-0.124	2.573	0.344	-1.382**	-0.221	22.610*	20.428	14.726	31.761*	8.870
	(0.432)	(1.869)	(0.522)	(0.646)	(0.361)	(13.193)	(37.045)	(35.602)	(16.880)	(13.272)
-2	1.014*	8.521***	-0.112	0.476	0.339	24.717*	-19.185	-5.720	50.101*	3.780
	(0.568)	(2.158)	(0.488)	(1.115)	(0.467)	(14.856)	(29.183)	(39.287)	(29.769)	(16.297)
-1	0.405	2.641**	-0.064	0.876	0.105	4.393	-51.694***	8.522	18.289	-2.132
	(0.436)	(1.233)	(0.419)	(1.177)	(0.333)	(11.182)	(17.521)	(21.487)	(24.584)	(17.558)
Post-event weeks:										
0	-0.190	-0.156	0.194	0.525	0.209	14.218	-42.625	-13.297	22.883	-2.153
	(0.447)	(1.481)	(0.638)	(1.041)	(0.341)	(15.473)	(35.198)	(38.687)	(30.060)	(18.040)
1	0.560	6.454***	0.501	0.968	0.409	53.046***	-0.359	43.558	32.707	25.655**
	(0.619)	(1.936)	(0.532)	(1.529)	(0.421)	(14.577)	(28.225)	(41.781)	(27.025)	(12.582)
2	1.496***	8.036***	-0.154	0.883	0.104	46.563***	-1.898	64.743*	60.528**	17.523
	(0.560)	(2.190)	(0.521)	(1.076)	(0.395)	(13.769)	(27.764)	(34.608)	(28.045)	(13.682)
3	0.395	2.900	0.010	0.695	0.063	40.256**	-30.715	53.394	73.803**	23.472
	(0.617)	(2.581)	(0.646)	(1.170)	(0.514)	(18.009)	(29.586)	(49.920)	(33.971)	(18.900)
4	0.023	3.438	0.006	0.786	0.392	43.141**	-44.935	52.266	31.091	21.076
	(0.602)	(2.160)	(0.603)	(1.384)	(0.464)	(17.024)	(33.799)	(44.949)	(37.122)	(15.950)
5	1.635**	6.767***	0.151	1.726	0.218	45.344**	-26.293	59.108	58.578	14.213
	(0.673)	(2.511)	(0.801)	(1.379)	(0.508)	(18.189)	(40.041)	(42.483)	(43.989)	(19.716)
6	1.609**	8.967***	0.084	2.496*	0.650	66.442***	29.029	72.911	94.645**	31.060
	(0.735)	(3.083)	(0.754)	(1.404)	(0.576)	(20.456)	(32.225)	(55.561)	(44.178)	(21.722)
7	1.024	8.280***	0.256	1.376	0.284	67.266***	-12.129	95.278*	76.749	28.164
	(0.767)	(2.882)	(0.709)	(1.755)	(0.622)	(20.430)	(40.081)	(55.513)	(47.899)	(19.332)
Constant	0.054	-5.835	0.426	0.735	0.542	-14.039	158.435	-102.396	-95.756	-1.089
	(0.958)	(3.583)	(1.175)	(2.070)	(0.907)	(36.102)	(165.998)	(92.149)	(77.905)	(26.307)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,451	2,490	2,275	3,542	4,144	6,826	1,192	1,748	1,594	2,292
Mean of dep. var.	17.25	43.88	13.46	12.56	8.30	587.87	1025.57	857.61	385.86	230.89
R-squared	0.008	0.054	0.024	0.008	0.013	0.017	0.072	0.038	0.065	0.015

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 11: Heterogeneous effects of shocks to transaction risk by vendor size. Dep.var.: Quantity in grams

	Cannabis					Opioids				
	(1) Baseline	(2) 1. quartile	(3) 2. quartile	(4) 3. quartile	(5) 4. quartile	(6) Baseline	(7) 1. quartile	(8) 2. quartile	(9) 3. quartile	(10) 4. quartile
Pre-event weeks:										
-7	3.027	0.383***	1.458*	3.895*	25.967	-0.237	0.001	0.017	0.102	-1.135
	(17.193)	(0.145)	(0.774)	(2.336)	(72.977)	(2.564)	(0.002)	(0.012)	(0.171)	(12.243)
-6	-77.815	0.070	-0.769	-3.608	-413.366	5.135	-0.005	0.034	0.237	22.558
	(53.433)	(0.496)	(1.485)	(5.280)	(263.840)	(4.760)	(0.003)	(0.036)	(0.420)	(22.604)
-5	-86.449**	-0.147	-0.060	-4.866	-493.413**	-7.582	-0.003	0.031	0.479**	-39.294
	(44.007)	(0.311)	(1.315)	(4.840)	(222.113)	(8.835)	(0.003)	(0.021)	(0.183)	(41.983)
-3	-29.024	0.038	-0.062	0.154	-220.970	6.291*	-0.004	0.018	0.136	26.883
	(29.951)	(0.378)	(1.028)	(3.906)	(142.239)	(3.595)	(0.003)	(0.024)	(0.378)	(16.361)
-2	-66.091	-0.327	-0.699	0.483	-422.665*	-4.945	-0.004	0.037	0.427	-27.565
	(45.774)	(0.314)	(1.645)	(5.264)	(239.985)	(3.853)	(0.003)	(0.025)	(0.283)	(19.397)
-1	-2.008	0.050	0.375	1.877	-10.440	-2.463	-0.001	0.011	0.242	-11.431
	(49.617)	(0.292)	(1.655)	(3.921)	(249.450)	(2.519)	(0.002)	(0.017)	(0.162)	(11.189)
Post-event weeks:										
0	-64.773	-0.497	-2.856*	-7.226	-380.214	2.071	-0.002	0.012	0.040	9.799
	(80.536)	(0.476)	(1.718)	(5.108)	(411.153)	(3.320)	(0.003)	(0.023)	(0.382)	(14.547)
1	-86.775	-0.596	-2.366*	-7.014	-580.844**	6.282	-0.002	0.005	0.215	24.734
	(55.815)	(0.379)	(1.319)	(5.147)	(274.963)	(10.716)	(0.003)	(0.023)	(0.369)	(47.214)
2	-47.798	-0.192	0.027	-1.383	-323.525	10.165	-0.005	-0.001	0.154	40.896
	(54.281)	(0.296)	(1.361)	(5.241)	(268.709)	(14.075)	(0.004)	(0.023)	(0.251)	(62.991)
3	-136.303*	-0.781*	-3.553**	-13.406**	-727.732*	2.561	-0.006*	-0.015	-0.109	6.839
	(81.492)	(0.403)	(1.791)	(5.907)	(409.022)	(7.204)	(0.004)	(0.026)	(0.327)	(28.830)
4	-40.651	-0.462	-0.995	3.955	-329.670	11.848	0.001	0.004	0.438	48.775
	(75.037)	(0.502)	(1.808)	(6.803)	(377.281)	(13.813)	(0.004)	(0.029)	(0.487)	(61.039)
5	-12.616	-0.640	-0.869	-0.499	-165.493	11.557	-0.003	-0.006	0.197	45.547
	(67.249)	(0.498)	(2.001)	(7.430)	(340.839)	(17.385)	(0.004)	(0.028)	(0.506)	(76.373)
6	-107.646	-1.108**	-4.335**	-16.539**	-786.791**	10.259	-0.006	-0.024	-0.008	32.996
	(68.093)	(0.454)	(1.959)	(7.085)	(351.747)	(11.193)	(0.005)	(0.028)	(0.496)	(47.104)
7	5.307	-0.588	-1.004	3.854	-137.287	15.160	-0.000	-0.018	0.332	59.508
	(62.820)	(0.484)	(2.065)	(8.329)	(317.269)	(19.050)	(0.005)	(0.034)	(0.451)	(85.206)
Constant	-72.001	-0.980	-3.946**	-4.996	-259.350	-11.845	0.003	-0.057	0.078	-31.213
	(96.728)	(0.696)	(1.930)	(8.217)	(460.122)	(9.195)	(0.006)	(0.036)	(0.385)	(36.615)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,072	4,787	4,073	5,176	5,548	15,256	2,242	2,949	2,325	3,230
Mean of dep. var.	337.20	2.30	11.65	58.72	1617.84	7.70	0.03	0.16	1.68	36.04
R-squared	0.002	0.031	0.018	0.014	0.010	0.002	0.014	0.010	0.008	0.006

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

C.2 Robustness checks

Table 12: Dynamic effects of shocks to holding risk. Dep.var.: Price in USD/g

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	0.320	0.283	0.273	0.287	0.288	0.483	0.450	16.241**	15.441**	14.091**	21.427***	20.853***	16.404**	29.515***
	(0.284)	(0.282)	(0.280)	(0.284)	(0.286)	(0.299)	(0.294)	(7.254)	(7.045)	(7.160)	(7.613)	(7.118)	(6.984)	(6.829)
-6	0.240	0.229	0.167	0.135	0.219	0.280	0.226	1.943	1.066	-2.690	7.849	4.669	-0.693	6.246
	(0.231)	(0.232)	(0.226)	(0.232)	(0.233)	(0.245)	(0.242)	(7.105)	(6.911)	(6.735)	(7.349)	(7.067)	(6.955)	(6.421)
-5	0.056	0.085	0.006	0.001	0.056	0.014	0.029	1.545	0.937	-0.508	5.411	1.720	-2.740	1.112
	(0.183)	(0.182)	(0.185)	(0.181)	(0.183)	(0.161)	(0.167)	(4.985)	(4.907)	(4.904)	(5.066)	(4.986)	(4.998)	(4.738)
-3	-0.184	-0.170	-0.224	-0.248	-0.179	-0.099	-0.135	0.827	0.793	-1.022	4.251	0.007	3.554	5.464
	(0.185)	(0.183)	(0.177)	(0.183)	(0.189)	(0.174)	(0.178)	(5.040)	(5.004)	(4.837)	(5.094)	(5.008)	(5.256)	(5.117)
-2	-0.243	-0.199	-0.292	-0.256	-0.226	-0.032	0.005	1.632	1.376	0.009	6.233	-0.179	6.044	9.712
	(0.250)	(0.252)	(0.243)	(0.248)	(0.259)	(0.252)	(0.270)	(6.065)	(6.056)	(5.952)	(6.293)	(6.126)	(6.212)	(6.430)
-1	-0.019	0.001	-0.012	0.150	0.007	0.281	0.477*	-3.792	-3.665	-5.752	-0.829	-5.945	2.393	2.748
	(0.253)	(0.252)	(0.254)	(0.277)	(0.272)	(0.233)	(0.270)	(6.009)	(6.037)	(6.082)	(6.137)	(6.227)	(6.055)	(6.481)
Post-event weeks:														
0	-0.215	-0.159	-0.207	-0.105	-0.184	0.034	0.210	-0.414	-0.346	-1.278	0.750	-3.116	1.824	-0.035
	(0.225)	(0.221)	(0.226)	(0.232)	(0.247)	(0.218)	(0.234)	(6.483)	(6.398)	(6.525)	(6.519)	(6.654)	(6.784)	(6.850)
1	0.155	0.203	0.139	0.221	0.194	0.354	0.486*	20.144***	19.867***	19.362***	22.448***	16.035**	22.308***	20.561***
	(0.231)	(0.230)	(0.230)	(0.237)	(0.266)	(0.229)	(0.259)	(7.167)	(7.085)	(7.177)	(7.395)	(7.573)	(7.383)	(7.785)
2	0.283	0.326	0.361	0.591*	0.330	0.463*	0.825**	19.886**	19.424**	20.165**	23.092***	15.229*	22.705***	23.187**
	(0.284)	(0.286)	(0.302)	(0.333)	(0.342)	(0.278)	(0.363)	(7.945)	(7.989)	(7.939)	(8.345)	(8.747)	(8.209)	(9.245)
3	0.234	0.314	0.304	0.447*	0.276	0.478*	0.757**	6.866	7.267	8.350	10.629	3.107	12.082	17.238*
	(0.250)	(0.242)	(0.254)	(0.262)	(0.306)	(0.261)	(0.320)	(8.521)	(8.602)	(8.411)	(9.024)	(9.203)	(9.230)	(10.134)
4	0.723**	0.812***	0.720**	0.750**	0.741**	1.073***	1.168***	9.708	11.058	9.350	10.514	8.330	18.181*	19.071*
	(0.298)	(0.285)	(0.298)	(0.298)	(0.321)	(0.299)	(0.319)	(8.935)	(8.961)	(8.952)	(9.054)	(9.171)	(9.630)	(10.079)
5	0.505	0.575*	0.463	0.737**	0.517	0.908***	1.298***	-0.062	1.612	-2.591	1.458	-0.475	9.308	9.515
	(0.319)	(0.327)	(0.315)	(0.332)	(0.335)	(0.325)	(0.360)	(9.783)	(9.933)	(9.795)	(10.005)	(9.828)	(10.422)	(10.923)
6	-0.233	-0.170	-0.176	0.081	-0.218	0.173	0.584	-15.086	-13.178	-14.958	-13.438	-16.282	-8.690	-4.577
	(0.323)	(0.344)	(0.327)	(0.333)	(0.346)	(0.349)	(0.385)	(10.042)	(10.248)	(10.033)	(10.332)	(10.372)	(10.665)	(11.276)
7	-0.617*	-0.567	-0.678*	-0.606*	-0.621*	-0.148	-0.064	-12.009	-9.241	-14.023	-10.380	-10.604	-1.717	3.145
	(0.367)	(0.366)	(0.370)	(0.367)	(0.363)	(0.398)	(0.406)	(11.009)	(11.015)	(11.090)	(11.271)	(10.681)	(11.673)	(11.709)
Market price			-0.117				0.088			-0.170**				-0.286***
			(0.081)				(0.124)			(0.072)				(0.080)
Market supply				-0.003**			-0.004**				0.378*			0.731***
				(0.001)			(0.002)				(0.194)			(0.182)
Competitors					-0.002		0.001					0.452*		0.623**
					(0.004)		(0.005)					(0.256)		(0.279)
7-day SD of BTC						0.008	0.009						0.371	0.290
						(0.009)	(0.009)						(0.240)	(0.245)
7-day SD of BTC lag 1						0.016*	0.012						0.273	0.336
						(0.009)	(0.009)						(0.213)	(0.217)
7-day SD of BTC lag 2						0.016	0.015						0.515**	0.576***
						(0.011)	(0.012)						(0.204)	(0.205)
7-day SD of BTC lag 3						0.004	0.006						-0.277	-0.274
						(0.009)	(0.010)						(0.271)	(0.270)
Constant	-0.071	1.422***	0.837	0.587*	0.386	-0.840**	0.636	-3.496	5.938	30.677**	-14.084*	-67.622*	-17.699*	-61.076
	(0.180)	(0.483)	(0.622)	(0.301)	(1.165)	(0.345)	(1.403)	(5.486)	(11.700)	(15.299)	(8.132)	(35.333)	(10.428)	(38.867)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	35,237	35,237	35,237	35,237	35,237	35,237	35,237	17,225	17,225	17,225	17,225	17,225	17,225	17,225
Mean of dep. var.	16.79	16.79	16.79	16.79	16.79	16.79	16.79	468.20	468.20	468.20	468.20	468.20	468.20	468.20
R-squared	0.002	0.004	0.002	0.002	0.002	0.002	0.005	0.005	0.006	0.006	0.005	0.006	0.006	0.013

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 13: Dynamic effects of shocks to holding risk. Dep.var.: Quantity in grams

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	14.233	25.928	25.412	19.926	20.050	20.585	31.279	-16.511	-14.390	-33.545	-25.838*	-12.218	-17.167	-36.522
	(26.732)	(21.870)	(52.824)	(31.172)	(27.767)	(22.110)	(44.194)	(11.686)	(11.810)	(24.207)	(13.900)	(10.946)	(13.085)	(25.432)
-6	-7.764	9.031	3.824	7.950	-4.069	-4.451	21.625	-15.662	-13.966	-31.063	-26.376*	-13.163	-15.240	-35.212
	(26.490)	(22.223)	(51.238)	(30.450)	(27.002)	(22.033)	(34.243)	(13.172)	(13.057)	(25.900)	(15.588)	(12.594)	(14.604)	(28.612)
-5	6.866	10.528	20.078	16.166	7.064	7.988	20.138	-11.597	-12.018	-24.832	-18.877*	-11.471	-10.687	-32.428
	(20.340)	(18.836)	(37.998)	(23.618)	(20.390)	(16.789)	(29.437)	(9.353)	(9.378)	(19.658)	(11.244)	(9.329)	(9.643)	(21.533)
-3	-35.623**	-27.575*	-5.008	-26.622	-36.757**	-36.097**	0.247	-8.803	-9.238	-13.092	-14.833	-9.600	-9.758	-23.959
	(15.400)	(14.379)	(25.530)	(16.574)	(15.667)	(15.334)	(26.381)	(7.691)	(7.794)	(16.805)	(9.427)	(7.670)	(7.951)	(18.487)
-2	-28.376	-18.623	-4.295	-24.916	-31.367	-26.161	1.242	-5.843	-8.013	-12.733	-13.326	-7.627	-7.779	-29.868
	(29.374)	(26.573)	(55.643)	(34.227)	(29.519)	(25.886)	(38.595)	(7.680)	(7.875)	(15.341)	(9.372)	(7.965)	(8.342)	(19.658)
-1	17.891	22.493	29.563	-1.055	13.385	23.752	33.176	-1.731	-4.128	-4.353	-6.425	-3.880	-4.257	-17.491
	(26.837)	(25.035)	(43.881)	(29.867)	(26.663)	(18.929)	(28.576)	(6.512)	(6.500)	(12.619)	(7.692)	(6.943)	(8.173)	(17.708)
Post-event weeks:														
0	1.654	2.817	8.222	-11.057	-3.841	9.120	23.001	-0.251	-2.840	-0.022	-1.545	-2.838	-1.750	-6.544
	(20.477)	(20.986)	(30.746)	(23.517)	(20.297)	(16.710)	(38.897)	(8.097)	(7.113)	(15.757)	(9.270)	(8.278)	(10.474)	(21.139)
1	-23.883	-17.168	-5.510	-30.258	-30.737	-18.125	22.543	-6.629	-10.246	-11.260	-10.321	-9.982	-7.811	-22.358
	(28.625)	(27.457)	(53.801)	(33.676)	(27.997)	(23.102)	(38.995)	(11.682)	(10.352)	(23.166)	(13.739)	(11.545)	(12.397)	(25.191)
2	29.642	36.614	31.347	-2.085	21.595	32.607	31.512	-6.978	-10.584	-17.188	-12.331	-10.835	-8.333	-33.104
	(30.345)	(29.206)	(57.489)	(36.229)	(28.895)	(27.963)	(44.395)	(10.687)	(9.670)	(20.650)	(12.883)	(10.716)	(11.103)	(24.849)
3	13.950	24.217	-23.425	-8.597	6.562	16.233	-15.039	-5.274	-10.340	-19.857	-11.276	-8.772	-7.420	-40.815
	(30.017)	(26.257)	(59.946)	(35.912)	(29.009)	(28.594)	(47.750)	(10.917)	(9.988)	(21.136)	(13.215)	(10.878)	(11.657)	(27.328)
4	-19.460	-1.482	-28.720	-20.372	-22.891	-14.660	-0.688	-2.072	-9.848	-7.696	-3.368	-3.170	-5.255	-25.073
	(29.550)	(22.261)	(58.767)	(34.601)	(29.409)	(27.289)	(46.807)	(14.046)	(11.444)	(25.098)	(16.203)	(13.913)	(14.795)	(26.821)
5	57.791*	78.124***	139.477**	40.302	55.688	63.734*	126.329*	-8.430	-17.468	-16.664	-11.727	-8.286	-11.927	-37.709
	(34.761)	(30.078)	(68.408)	(41.754)	(34.360)	(33.130)	(67.627)	(13.223)	(11.791)	(22.681)	(15.525)	(13.226)	(14.796)	(28.574)
6	53.954*	71.672***	79.642	28.447	51.067*	61.168**	66.039	-7.741	-16.714	-27.106	-11.128	-8.064	-10.966	-50.353
	(30.485)	(26.789)	(58.757)	(36.807)	(30.452)	(28.750)	(68.946)	(12.649)	(11.657)	(22.293)	(14.789)	(12.610)	(14.101)	(31.007)
7	15.565	37.718	79.562	25.776	16.077	23.220	91.986	-2.294	-12.349	-13.803	-4.980	-0.171	-6.332	-35.236
	(29.794)	(24.628)	(59.396)	(34.908)	(29.785)	(28.391)	(61.795)	(10.865)	(11.095)	(19.201)	(12.639)	(11.013)	(12.665)	(26.448)
Market price			62.066***				40.463**			0.212				0.241
			(14.563)				(17.308)			(0.228)				(0.219)
Market supply				0.438***			0.415*				-0.461***			-0.775***
				(0.118)			(0.235)				(0.119)			(0.195)
Competitors					0.355		-0.848					0.453**		0.548
					(0.353)		(0.900)					(0.214)		(0.451)
7-day SD of BTC						-0.205	-1.717						-0.108	-0.380
						(0.758)	(1.370)						(0.177)	(0.312)
7-day SD of BTC lag 1						0.296	-0.316						-0.148	-0.369
						(0.850)	(1.876)						(0.169)	(0.404)
7-day SD of BTC lag 2						0.360	1.363						-0.148	0.128
						(0.867)	(1.384)						(0.193)	(0.410)
7-day SD of BTC lag 3						0.275	0.179						0.031	-0.164
						(1.027)	(2.042)						(0.237)	(0.473)
Constant	-6.353	-228.897**	-243.303**	-65.479*	-86.953	-19.904	-216.270	6.388	-18.971	-2.864	23.887**	-54.079*	12.654	-62.657
	(20.809)	(116.506)	(114.394)	(36.645)	(86.001)	(26.597)	(267.630)	(8.816)	(13.500)	(44.112)	(12.076)	(29.543)	(14.874)	(77.885)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	67,754	67,754	35,237	57,780	67,754	67,754	35,237	34,941	34,941	17,225	30,520	34,941	34,941	17,225
Mean of dep. var.	267.12	267.12	267.12	267.12	267.12	267.12	267.12	32.98	32.98	32.98	32.98	32.98	32.98	32.98
R-squared	0.001	0.005	0.003	0.001	0.001	0.001	0.011	0.000	0.011	0.002	0.001	0.001	0.001	0.011

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 14: Dynamic effects of shocks to holding risk. Dep.var.: Rating in percentage points

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	-0.079	-0.059	-0.083	-0.076	-0.077	-0.119	0.107	0.331*	0.326	0.337	0.341*	0.257	0.346*	0.368
	(0.088)	(0.094)	(0.113)	(0.089)	(0.091)	(0.109)	(0.180)	(0.199)	(0.200)	(0.268)	(0.185)	(0.200)	(0.200)	(0.293)
-6	-0.055	-0.050	0.079	-0.045	-0.054	-0.116	0.126	0.232	0.218	0.451**	0.243*	0.196	0.144	0.373**
	(0.105)	(0.105)	(0.118)	(0.102)	(0.106)	(0.128)	(0.151)	(0.187)	(0.195)	(0.193)	(0.146)	(0.190)	(0.198)	(0.188)
-5	-0.015	-0.007	0.022	-0.010	-0.015	-0.079	0.059	0.031	0.045	0.113	0.039	0.029	-0.029	0.132
	(0.076)	(0.078)	(0.087)	(0.075)	(0.076)	(0.090)	(0.104)	(0.100)	(0.102)	(0.095)	(0.092)	(0.100)	(0.118)	(0.093)
-3	-0.079	-0.068	-0.158	-0.075	-0.080	0.058	0.049	-0.072	-0.074	-0.074	-0.065	-0.056	-0.039	0.062
	(0.084)	(0.086)	(0.111)	(0.086)	(0.084)	(0.092)	(0.123)	(0.117)	(0.119)	(0.100)	(0.087)	(0.116)	(0.140)	(0.121)
-2	-0.146	-0.126	-0.393**	-0.144	-0.147	0.028	0.007	-0.014	0.017	-0.015	-0.005	0.025	0.106	0.330**
	(0.124)	(0.125)	(0.183)	(0.125)	(0.126)	(0.120)	(0.159)	(0.207)	(0.202)	(0.176)	(0.152)	(0.204)	(0.224)	(0.157)
-1	-0.322**	-0.306**	-0.561***	-0.335**	-0.324**	-0.194	-0.059	-0.290	-0.241	-0.277	-0.285	-0.247	-0.165	0.061
	(0.144)	(0.144)	(0.206)	(0.135)	(0.148)	(0.128)	(0.168)	(0.251)	(0.239)	(0.211)	(0.217)	(0.245)	(0.240)	(0.154)
Post-event weeks:														
0	-0.208	-0.216	-0.353*	-0.216	-0.209	-0.177	0.001	-0.361	-0.374	-0.315*	-0.359	-0.314	-0.328	-0.136
	(0.138)	(0.138)	(0.201)	(0.138)	(0.135)	(0.147)	(0.215)	(0.245)	(0.245)	(0.189)	(0.235)	(0.239)	(0.236)	(0.152)
1	-0.231	-0.242*	-0.297	-0.235	-0.233*	-0.207	-0.024	-0.301	-0.292	-0.241	-0.296	-0.238	-0.283	-0.006
	(0.144)	(0.143)	(0.208)	(0.146)	(0.139)	(0.164)	(0.235)	(0.223)	(0.219)	(0.192)	(0.200)	(0.212)	(0.229)	(0.190)
2	-0.203	-0.221	-0.209	-0.224	-0.206	-0.096	0.257	-0.121	-0.110	-0.041	-0.115	-0.049	-0.064	0.300
	(0.149)	(0.147)	(0.214)	(0.168)	(0.141)	(0.175)	(0.279)	(0.240)	(0.234)	(0.221)	(0.216)	(0.227)	(0.249)	(0.236)
3	-0.177	-0.145	-0.081	-0.192	-0.180	0.039	0.526*	-0.258	-0.193	-0.134	-0.251	-0.192	-0.151	0.321
	(0.171)	(0.174)	(0.241)	(0.186)	(0.159)	(0.214)	(0.314)	(0.277)	(0.271)	(0.236)	(0.248)	(0.260)	(0.299)	(0.274)
4	-0.438***	-0.335*	-0.441*	-0.440**	-0.439***	-0.206	0.192	-0.519*	-0.362	-0.409*	-0.518*	-0.505*	-0.349	0.103
	(0.169)	(0.171)	(0.233)	(0.171)	(0.165)	(0.206)	(0.297)	(0.272)	(0.269)	(0.243)	(0.264)	(0.267)	(0.281)	(0.286)
5	-0.755***	-0.632***	-0.852***	-0.771***	-0.755***	-0.500**	0.131	-0.732***	-0.544**	-0.756***	-0.729***	-0.746***	-0.601**	-0.182
	(0.166)	(0.162)	(0.217)	(0.175)	(0.165)	(0.207)	(0.358)	(0.257)	(0.258)	(0.266)	(0.243)	(0.259)	(0.281)	(0.303)
6	-0.531***	-0.419***	-0.635***	-0.551***	-0.532***	-0.291	0.371	-0.450*	-0.292	-0.562*	-0.446*	-0.454*	-0.302	0.044
	(0.156)	(0.155)	(0.218)	(0.169)	(0.154)	(0.216)	(0.374)	(0.259)	(0.263)	(0.292)	(0.243)	(0.259)	(0.309)	(0.325)
7	-0.508***	-0.354**	-0.613***	-0.507***	-0.507***	-0.232	0.289	-0.071	0.107	-0.169	-0.068	-0.129	0.120	0.374
	(0.169)	(0.170)	(0.234)	(0.169)	(0.170)	(0.216)	(0.331)	(0.259)	(0.263)	(0.271)	(0.244)	(0.273)	(0.303)	(0.328)
Market price			0.019				0.160**			0.000				-0.000
			(0.051)				(0.079)			(0.002)				(0.002)
Market supply				0.000			-0.003**				0.001			0.001
				(0.001)			(0.001)				(0.009)			(0.007)
Competitors					0.000		-0.000					-0.009**		-0.010*
					(0.002)		(0.003)					(0.004)		(0.006)
7-day SD of BTC						0.019***	0.028***						0.003	0.014*
						(0.007)	(0.009)						(0.007)	(0.008)
7-day SD of BTC lag 1						0.009	0.021***						0.015**	0.021**
						(0.005)	(0.008)						(0.007)	(0.010)
7-day SD of BTC lag 2						0.002	0.004						0.004	0.003
						(0.004)	(0.006)						(0.006)	(0.007)
7-day SD of BTC lag 3						-0.003	0.013**						-0.005	0.004
						(0.005)	(0.006)						(0.007)	(0.009)
Constant	0.244**	0.162	-0.167	0.196	0.214	-0.201	-1.666	0.176	-0.557	-0.219	0.156	1.464**	-0.098	-1.040
	(0.099)	(0.278)	(0.386)	(0.159)	(0.484)	(0.271)	(1.081)	(0.170)	(0.954)	(0.299)	(0.189)	(0.741)	(0.315)	(1.740)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	49,862	49,862	30,986	49,862	49,862	49,862	30,986	25,749	25,749	14,448	25,749	25,749	25,749	14,448
Mean of dep. var.	97.38	97.38	97.38	97.38	97.38	97.38	97.38	97.27	97.27	97.27	97.27	97.27	97.27	97.27
R-squared	0.002	0.003	0.003	0.002	0.002	0.003	0.009	0.003	0.008	0.004	0.003	0.003	0.003	0.020

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 15: Dynamic effects of shocks to holding risk. Dep.var.: Expected probability of finalize early

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	-0.027***	-0.028***	-0.023***	-0.025***	-0.033***	-0.026***	-0.023***	-0.030***	-0.033***	-0.028***	-0.031***	-0.031***	-0.028***	-0.030***
	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.011)
-6	-0.012**	-0.013**	-0.005	-0.012**	-0.016***	-0.010**	-0.008	-0.018***	-0.020***	-0.022***	-0.018***	-0.018***	-0.015**	-0.022**
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)	(0.010)
-5	-0.003	-0.003	-0.001	-0.004	-0.006	-0.003	-0.004	-0.012***	-0.012***	-0.012**	-0.013**	-0.012***	-0.009**	-0.012*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)
-3	0.013***	0.012***	0.013**	0.012***	0.015***	0.013***	0.008*	0.013**	0.012**	0.012**	0.012**	0.013**	0.012**	0.005
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)
-2	0.029***	0.024***	0.030***	0.029***	0.035***	0.029***	0.021***	0.027***	0.021***	0.016*	0.027***	0.027***	0.027***	0.003
	(0.005)	(0.005)	(0.007)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.009)	(0.007)	(0.007)	(0.008)	(0.010)
-1	0.039***	0.032***	0.037***	0.038***	0.048***	0.039***	0.023***	0.034***	0.027***	0.019**	0.034***	0.035***	0.034***	0.010
	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.010)
Post-event weeks:														
0	0.052***	0.048***	0.049***	0.049***	0.061***	0.053***	0.031***	0.049***	0.047***	0.031***	0.050***	0.050***	0.050***	0.027**
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.010)	(0.010)	(0.012)	(0.009)	(0.010)	(0.009)	(0.012)
1	0.064***	0.058***	0.059***	0.059***	0.077***	0.064***	0.033***	0.059***	0.054***	0.044***	0.059***	0.060***	0.061***	0.036**
	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)	(0.008)	(0.010)	(0.011)	(0.011)	(0.014)	(0.011)	(0.012)	(0.011)	(0.014)
2	0.091***	0.077***	0.082***	0.084***	0.103***	0.092***	0.042***	0.080***	0.067***	0.059***	0.080***	0.081***	0.081***	0.039**
	(0.009)	(0.009)	(0.012)	(0.010)	(0.010)	(0.009)	(0.012)	(0.012)	(0.012)	(0.016)	(0.012)	(0.014)	(0.012)	(0.017)
3	0.110***	0.086***	0.102***	0.104***	0.121***	0.110***	0.051***	0.094***	0.076***	0.074***	0.095***	0.095***	0.095***	0.047***
	(0.010)	(0.010)	(0.013)	(0.011)	(0.011)	(0.010)	(0.013)	(0.013)	(0.012)	(0.016)	(0.012)	(0.015)	(0.014)	(0.017)
4	0.140***	0.103***	0.130***	0.136***	0.146***	0.140***	0.073***	0.123***	0.098***	0.103***	0.124***	0.123***	0.122***	0.074***
	(0.012)	(0.011)	(0.015)	(0.013)	(0.013)	(0.012)	(0.015)	(0.016)	(0.014)	(0.020)	(0.015)	(0.016)	(0.016)	(0.019)
5	0.156***	0.115***	0.147***	0.149***	0.165***	0.156***	0.075***	0.130***	0.100***	0.112***	0.130***	0.131***	0.129***	0.073***
	(0.012)	(0.011)	(0.016)	(0.014)	(0.014)	(0.012)	(0.017)	(0.016)	(0.015)	(0.021)	(0.016)	(0.018)	(0.017)	(0.022)
6	0.178***	0.141***	0.165***	0.169***	0.191***	0.178***	0.090***	0.149***	0.122***	0.129***	0.150***	0.150***	0.150***	0.091***
	(0.013)	(0.012)	(0.019)	(0.015)	(0.015)	(0.013)	(0.019)	(0.017)	(0.016)	(0.022)	(0.017)	(0.020)	(0.018)	(0.024)
7	0.180***	0.123***	0.174***	0.175***	0.189***	0.180***	0.092***	0.148***	0.103***	0.116***	0.148***	0.148***	0.147***	0.064**
	(0.016)	(0.014)	(0.021)	(0.017)	(0.017)	(0.016)	(0.021)	(0.020)	(0.018)	(0.026)	(0.020)	(0.022)	(0.022)	(0.028)
Market price			0.005				0.003			0.000				0.000
			(0.005)				(0.007)			(0.000)				(0.000)
Market supply				0.000			0.000**				-0.000			-0.001
				(0.000)			(0.000)				(0.000)			(0.001)
Competitors					-0.001**		0.000					-0.000		0.000
					(0.000)		(0.000)					(0.001)		(0.001)
7-day SD of BTC						-0.000	-0.000						-0.000	-0.001
						(0.000)	(0.000)						(0.001)	(0.001)
7-day SD of BTC lag 1						-0.000	-0.000						-0.000	-0.000
						(0.000)	(0.000)						(0.000)	(0.001)
7-day SD of BTC lag 2						0.000	0.000						-0.000	-0.001
						(0.000)	(0.000)						(0.000)	(0.001)
7-day SD of BTC lag 3						0.000	-0.001						0.000	0.000
						(0.000)	(0.000)						(0.000)	(0.001)
Constant	0.201***	0.125***	0.163***	0.188***	0.344***	0.201***	0.073	0.207***	0.070	0.244***	0.208***	0.224**	0.208***	0.049
	(0.006)	(0.038)	(0.040)	(0.013)	(0.062)	(0.012)	(0.089)	(0.008)	(0.052)	(0.036)	(0.012)	(0.112)	(0.017)	(0.130)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	35,668	35,668	22,350	35,668	35,668	35,668	22,350	19,753	19,753	11,488	19,753	19,753	19,753	11,488
Mean of dep. var.	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
R-squared	0.060	0.090	0.056	0.061	0.062	0.060	0.089	0.050	0.089	0.043	0.050	0.050	0.050	0.084

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 16: Dynamic effects of shocks to holding risk. Dep.var.: Expected probability of entry

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	0.016***	0.023***	0.027***	0.025***	0.015***	0.013***	0.019***	0.018***	0.026***	0.033***	0.031***	0.016***	0.019***	0.034***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)	(0.006)	(0.008)	(0.006)	(0.004)	(0.005)	(0.008)
-6	0.005*	0.011**	0.017***	0.014***	0.005	0.005	0.014**	0.007	0.013*	0.010	0.018***	0.006	0.009*	0.012
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)	(0.006)	(0.008)	(0.006)	(0.005)	(0.005)	(0.009)
-5	0.013***	0.022***	0.034***	0.023***	0.013***	0.013***	0.036***	0.010***	0.017***	0.023***	0.020***	0.010***	0.009**	0.021***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)	(0.008)	(0.005)	(0.004)	(0.004)	(0.008)
-3	-0.009***	-0.010***	-0.009**	-0.008**	-0.009***	-0.007***	-0.007	-0.011***	-0.013***	-0.017***	-0.010**	-0.011***	-0.010***	-0.016***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.006)
-2	-0.011***	-0.011***	-0.003	-0.010**	-0.010***	-0.010***	-0.001	-0.016***	-0.020***	-0.019**	-0.016***	-0.016***	-0.016***	-0.019**
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.006)	(0.008)	(0.005)	(0.004)	(0.004)	(0.007)
-1	-0.007**	-0.008**	-0.006	-0.009**	-0.006**	-0.008***	-0.004	-0.016***	-0.020***	-0.021***	-0.017***	-0.015***	-0.014***	-0.017**
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.007)
Post-event weeks:														
0	-0.005	-0.008**	-0.008*	-0.009**	-0.004	-0.006**	-0.006	-0.014***	-0.019***	-0.024***	-0.017***	-0.012***	-0.011***	-0.021***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.006)	(0.008)	(0.005)	(0.004)	(0.004)	(0.008)
1	-0.019***	-0.023***	-0.015***	-0.023***	-0.018***	-0.019***	-0.012**	-0.021***	-0.027***	-0.034***	-0.025***	-0.020***	-0.019***	-0.029***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.006)	(0.008)	(0.006)	(0.004)	(0.004)	(0.008)
2	-0.032***	-0.040***	-0.037***	-0.042***	-0.030***	-0.031***	-0.030***	-0.032***	-0.041***	-0.041***	-0.038***	-0.031***	-0.031***	-0.038***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)	(0.006)	(0.008)	(0.006)	(0.004)	(0.005)	(0.008)
3	-0.033***	-0.047***	-0.040***	-0.048***	-0.032***	-0.032***	-0.033***	-0.031***	-0.044***	-0.040***	-0.040***	-0.029***	-0.030***	-0.039***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)	(0.006)	(0.008)	(0.006)	(0.004)	(0.005)	(0.008)
4	-0.039***	-0.054***	-0.047***	-0.052***	-0.039***	-0.039***	-0.048***	-0.035***	-0.050***	-0.045***	-0.046***	-0.035***	-0.032***	-0.046***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)	(0.005)	(0.006)	(0.008)	(0.006)	(0.005)	(0.005)	(0.009)
5	-0.052***	-0.066***	-0.061***	-0.065***	-0.052***	-0.050***	-0.056***	-0.049***	-0.064***	-0.066***	-0.058***	-0.050***	-0.044***	-0.066***
	(0.003)	(0.005)	(0.006)	(0.005)	(0.003)	(0.004)	(0.006)	(0.005)	(0.006)	(0.009)	(0.006)	(0.005)	(0.005)	(0.010)
6	-0.066***	-0.085***	-0.080***	-0.085***	-0.065***	-0.065***	-0.076***	-0.062***	-0.078***	-0.070***	-0.073***	-0.062***	-0.059***	-0.076***
	(0.003)	(0.005)	(0.006)	(0.005)	(0.003)	(0.004)	(0.007)	(0.005)	(0.006)	(0.008)	(0.006)	(0.005)	(0.005)	(0.010)
7	-0.085***	-0.107***	-0.096***	-0.103***	-0.086***	-0.085***	-0.099***	-0.085***	-0.106***	-0.097***	-0.099***	-0.086***	-0.081***	-0.101***
	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.008)	(0.005)	(0.007)	(0.009)	(0.007)	(0.005)	(0.006)	(0.011)
Market price			0.002				0.006***			0.000				-0.000
			(0.001)				(0.002)			(0.000)				(0.000)
Market supply				0.000			-0.000*				0.000*			0.000
				(0.000)			(0.000)				(0.000)			(0.000)
Competitors					-0.000*		-0.000**					-0.000***		-0.000
					(0.000)		(0.000)					(0.000)		(0.000)
7-day SD of BTC						0.000**	0.000**						0.000	-0.000
						(0.000)	(0.000)						(0.000)	(0.000)
7-day SD of BTC lag 1						-0.000	-0.000						-0.000	-0.000
						(0.000)	(0.000)						(0.000)	(0.000)
7-day SD of BTC lag 2						-0.000	-0.000						0.000**	0.001**
						(0.000)	(0.000)						(0.000)	(0.000)
7-day SD of BTC lag 3						-0.000	0.000						-0.000	-0.000
						(0.000)	(0.000)						(0.000)	(0.000)
Constant	0.056***	0.099***	0.057***	0.068***	0.070***	0.055***	0.105***	0.053***	0.093***	0.069***	0.061***	0.078***	0.048***	0.118***
	(0.002)	(0.005)	(0.011)	(0.004)	(0.008)	(0.004)	(0.017)	(0.003)	(0.006)	(0.014)	(0.005)	(0.010)	(0.006)	(0.029)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	75,974	57,780	35,237	57,780	75,974	75,974	35,237	39,891	30,520	17,225	30,520	39,891	39,891	17,225
Mean of dep. var.	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
R-squared	0.027	0.036	0.031	0.034	0.027	0.027	0.034	0.026	0.033	0.030	0.032	0.026	0.027	0.034

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 17: Dynamic effects of shocks to holding risk. Dep.var.: Expected probability of exit

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	-0.017***	-0.018***	-0.012***	-0.015***	-0.015***	-0.019***	-0.021***	-0.018***	-0.019***	-0.017***	-0.013***	-0.018***	-0.018***	-0.026***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.002)	(0.006)
-6	-0.010***	-0.007***	0.002	-0.002	-0.008***	-0.013***	-0.012***	-0.008***	-0.005	0.003	0.001	-0.008***	-0.011***	-0.009
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.002)	(0.006)
-5	-0.005***	-0.004*	0.003	-0.001	-0.005***	-0.011***	-0.007**	-0.005**	-0.003	0.001	0.001	-0.005**	-0.010***	-0.006
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)	(0.005)
-3	0.002	0.006***	0.010***	0.009***	0.001	-0.004***	0.003	0.004*	0.009***	0.016***	0.012***	0.004*	-0.002	0.010**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)	(0.004)
-2	0.005**	0.015***	0.023***	0.015***	0.004*	-0.001	0.016***	0.007**	0.016***	0.024***	0.019***	0.007**	0.002	0.020***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.006)
-1	0.016***	0.026***	0.034***	0.018***	0.015***	0.017***	0.029***	0.014***	0.023***	0.035***	0.025***	0.014***	0.015***	0.034***
	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.006)
Post-event weeks:														
0	0.011***	0.018***	0.020***	0.012***	0.009***	0.007***	0.009**	0.012***	0.018***	0.027***	0.018***	0.012***	0.010***	0.021***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.002)	(0.005)
1	0.010***	0.018***	0.024***	0.014***	0.008***	0.005**	0.013***	0.009***	0.015***	0.020***	0.016***	0.009***	0.004	0.018***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.006)
2	0.049***	0.058***	0.057***	0.045***	0.047***	0.043***	0.048***	0.050***	0.057***	0.059***	0.059***	0.050***	0.045***	0.057***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.006)	(0.008)	(0.006)	(0.004)	(0.004)	(0.008)
3	0.063***	0.076***	0.079***	0.065***	0.060***	0.056***	0.068***	0.063***	0.074***	0.074***	0.075***	0.063***	0.057***	0.070***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)	(0.003)	(0.006)	(0.005)	(0.006)	(0.009)	(0.007)	(0.005)	(0.005)	(0.009)
4	0.034***	0.051***	0.057***	0.046***	0.032***	0.031***	0.052***	0.035***	0.048***	0.055***	0.045***	0.035***	0.033***	0.055***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)	(0.005)	(0.008)	(0.005)	(0.004)	(0.004)	(0.008)
5	0.037***	0.056***	0.066***	0.044***	0.036***	0.032***	0.056***	0.036***	0.052***	0.071***	0.049***	0.036***	0.032***	0.064***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)	(0.005)	(0.008)	(0.005)	(0.004)	(0.004)	(0.009)
6	0.086***	0.109***	0.112***	0.094***	0.085***	0.076***	0.094***	0.086***	0.107***	0.119***	0.104***	0.086***	0.077***	0.106***
	(0.005)	(0.006)	(0.008)	(0.005)	(0.005)	(0.004)	(0.007)	(0.006)	(0.008)	(0.012)	(0.008)	(0.006)	(0.006)	(0.011)
7	0.055***	0.081***	0.101***	0.076***	0.056***	0.050***	0.091***	0.051***	0.072***	0.091***	0.069***	0.051***	0.047***	0.084***
	(0.003)	(0.005)	(0.007)	(0.005)	(0.003)	(0.003)	(0.008)	(0.004)	(0.006)	(0.009)	(0.006)	(0.004)	(0.005)	(0.010)
Market price			0.011***				0.011***			0.000***				0.000***
			(0.002)				(0.002)			(0.000)				(0.000)
Market supply				0.000***			-0.000				0.000***			0.000
				(0.000)			(0.000)				(0.000)			(0.000)
Competitors					0.000***		0.000					-0.000		-0.000
					(0.000)		(0.000)					(0.000)		(0.000)
7-day SD of BTC						-0.001***	-0.001***						-0.001***	-0.001***
						(0.000)	(0.000)						(0.000)	(0.000)
7-day SD of BTC lag 1						0.000	0.000						0.000	0.000
						(0.000)	(0.000)						(0.000)	(0.000)
7-day SD of BTC lag 2						0.001***	0.000**						0.001***	0.000
						(0.000)	(0.000)						(0.000)	(0.000)
7-day SD of BTC lag 3						-0.001***	-0.002***						-0.001***	-0.001***
						(0.000)	(0.000)						(0.000)	(0.000)
Constant	0.005***	0.027***	-0.080***	-0.022***	-0.023***	0.022***	-0.016	0.003	0.022***	-0.079***	-0.007	0.005	0.017***	0.023
	(0.002)	(0.004)	(0.014)	(0.005)	(0.009)	(0.002)	(0.022)	(0.002)	(0.006)	(0.016)	(0.005)	(0.010)	(0.003)	(0.028)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	75,974	57,780	35,237	57,780	75,974	75,974	35,237	39,891	30,520	17,225	30,520	39,891	39,891	17,225
Mean of dep. var.	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
R-squared	0.035	0.042	0.046	0.042	0.036	0.040	0.055	0.037	0.041	0.046	0.039	0.037	0.041	0.054

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 18: Dynamic effects of shocks to transaction risk. Dep.var.: Price in USD/g

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	-0.122	-0.121	-0.143	-0.107	-0.200	-0.079	-0.207	-5.351	-6.642	-3.685	-2.850	-8.482	-12.162	-13.696
	(0.203)	(0.214)	(0.206)	(0.209)	(0.221)	(0.284)	(0.290)	(8.866)	(8.728)	(8.726)	(9.016)	(9.832)	(9.447)	(10.859)
-6	0.027	0.087	0.015	0.014	-0.035	0.034	-0.000	-14.846	-11.282	-15.518	-15.829	-17.701	17.477	4.577
	(0.706)	(0.706)	(0.707)	(0.691)	(0.703)	(0.669)	(0.708)	(17.468)	(16.903)	(17.652)	(17.360)	(18.073)	(11.413)	(11.348)
-5	0.761	0.710	0.738	0.733	0.667	-0.036	-0.175	-11.536	-5.625	-12.606	-11.167	-16.741	12.730	9.765
	(0.599)	(0.571)	(0.604)	(0.582)	(0.579)	(0.633)	(0.529)	(13.526)	(12.899)	(13.575)	(13.485)	(13.562)	(12.383)	(11.730)
-3	-0.186	-0.124	-0.206	-0.176	-0.113	0.595	0.593	19.644	22.610*	19.156	15.441	22.293*	33.482***	22.924**
	(0.425)	(0.432)	(0.426)	(0.429)	(0.426)	(0.573)	(0.598)	(13.422)	(13.193)	(13.563)	(13.147)	(13.400)	(10.578)	(9.710)
-2	1.233**	1.014*	1.178*	1.208**	1.233**	0.685	0.358	17.637	24.717*	13.956	12.506	16.198	57.722***	46.572***
	(0.584)	(0.568)	(0.606)	(0.549)	(0.583)	(0.537)	(0.468)	(15.863)	(14.856)	(15.493)	(15.788)	(15.614)	(13.387)	(12.247)
-1	0.387	0.405	0.359	0.367	0.452	-0.205	-0.177	3.939	4.393	0.696	0.835	6.199	48.566***	38.099***
	(0.435)	(0.436)	(0.440)	(0.416)	(0.458)	(0.413)	(0.381)	(10.857)	(11.182)	(10.947)	(11.079)	(11.082)	(9.070)	(10.883)
Post-event weeks:														
0	-0.147	-0.190	-0.148	-0.170	0.029	-0.317	-0.139	10.368	14.218	6.868	4.033	17.201	62.643***	42.369***
	(0.437)	(0.447)	(0.436)	(0.408)	(0.502)	(0.420)	(0.454)	(15.380)	(15.473)	(15.639)	(15.264)	(15.945)	(11.861)	(12.854)
1	0.748	0.560	0.639	0.730	0.964	0.424	0.030	45.899***	53.046***	44.048***	32.945**	53.580***	85.227***	74.232***
	(0.610)	(0.619)	(0.651)	(0.589)	(0.707)	(0.676)	(0.619)	(14.658)	(14.577)	(14.431)	(14.673)	(16.229)	(15.657)	(16.218)
2	1.519***	1.496***	1.397**	1.512***	1.786***	1.197*	1.024	42.932***	46.563***	42.140***	26.894*	52.902***	81.189***	65.795***
	(0.552)	(0.560)	(0.580)	(0.549)	(0.645)	(0.610)	(0.658)	(14.172)	(13.769)	(14.158)	(14.829)	(16.121)	(15.648)	(17.697)
3	0.425	0.395	0.441	0.385	0.799	0.325	0.498	33.239*	40.256**	28.921	26.382	48.233**	85.143***	76.503***
	(0.590)	(0.617)	(0.587)	(0.571)	(0.730)	(0.695)	(0.758)	(18.524)	(18.009)	(19.106)	(18.585)	(20.642)	(18.344)	(20.244)
4	0.220	0.023	0.113	0.212	0.549	-0.122	-0.246	35.916**	43.141**	33.932**	21.737	48.421**	84.642***	74.181***
	(0.569)	(0.602)	(0.602)	(0.559)	(0.718)	(0.644)	(0.703)	(17.267)	(17.024)	(17.248)	(17.363)	(19.872)	(16.827)	(19.058)
5	1.681**	1.635**	1.631**	1.669**	2.022**	1.365*	1.388	39.716**	45.344**	34.098*	24.991	52.634**	90.286***	78.706***
	(0.662)	(0.673)	(0.680)	(0.648)	(0.808)	(0.772)	(0.882)	(18.334)	(18.189)	(17.797)	(19.108)	(21.694)	(17.991)	(22.284)
6	1.612**	1.609**	1.615**	1.553**	2.133**	0.966	0.994	55.723***	66.442***	51.358**	50.639**	76.129***	98.621***	101.649***
	(0.710)	(0.735)	(0.709)	(0.685)	(0.930)	(0.956)	(1.039)	(20.631)	(20.456)	(20.095)	(20.706)	(26.330)	(22.087)	(27.060)
7	1.242*	1.024	1.115	1.233*	1.714*	0.698	0.592	57.306***	67.266***	56.037***	41.082*	77.253***	105.890***	100.735***
	(0.750)	(0.767)	(0.777)	(0.745)	(0.946)	(0.832)	(0.919)	(21.406)	(20.430)	(21.333)	(21.565)	(26.064)	(22.079)	(25.641)
Market price			0.093				0.348**			-0.108				-0.556***
			(0.093)				(0.155)			(0.106)				(0.146)
Market supply				-0.000			-0.003				0.750***			1.704***
				(0.002)			(0.003)				(0.266)			(0.395)
Competitors					-0.008		-0.006					-0.556		-0.069
					(0.007)		(0.007)					(0.391)		(0.407)
Number of arrests						-0.010	0.047						-0.118	-4.672**
						(0.090)	(0.099)						(2.158)	(1.942)
Number of arrests lag 1						0.091	0.070						2.512	9.456***
						(0.091)	(0.083)						(2.173)	(2.240)
Number of arrests lag 2						-0.112	-0.060						2.624	11.391***
						(0.127)	(0.135)						(4.303)	(3.494)
Number of arrests lag 3						-0.307*	-0.264						0.994	12.876***
						(0.185)	(0.188)						(5.431)	(4.387)
Constant	-0.761*	0.054	-1.426**	-0.618	0.162	-0.024	-0.468	-29.001**	-14.039	-2.346	-33.019**	7.551	-81.257***	-10.538
	(0.420)	(0.958)	(0.689)	(0.567)	(0.790)	(0.668)	(1.429)	(12.921)	(36.102)	(28.167)	(13.124)	(27.969)	(19.719)	(44.622)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	12,451	12,451	12,451	12,451	12,451	11,450	11,450	6,826	6,826	6,826	6,826	6,826	6,277	6,277
Mean of dep. var.	17.25	17.25	17.25	17.25	17.25	17.25	17.25	587.87	587.87	587.87	587.87	587.87	587.87	587.87
R-squared	0.004	0.008	0.004	0.004	0.004	0.006	0.010	0.011	0.017	0.012	0.014	0.014	0.022	0.042

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 19: Dynamic effects of shocks to transaction risk. Dep.var.: Quantity in grams

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	0.882	3.027	-3.833	-15.980	5.809	-40.220**	-45.277	0.995	-0.237	-2.858	-0.917	3.226*	-1.245	1.341
	(17.692)	(17.193)	(40.756)	(24.283)	(17.178)	(17.985)	(35.569)	(1.957)	(2.564)	(5.526)	(2.738)	(1.889)	(1.678)	(4.822)
-6	-77.691	-77.815	-196.558	-72.922	-73.237	-110.403***	-78.500	6.028	5.135	4.995	6.314	7.954**	-0.024	6.594
	(52.721)	(53.433)	(133.783)	(73.479)	(54.568)	(34.885)	(74.776)	(3.702)	(4.760)	(7.303)	(4.277)	(3.762)	(1.209)	(9.327)
-5	-80.603*	-86.449**	-255.823**	-73.221	-74.064*	-119.996***	-158.123*	-8.323	-7.582	-17.486	-9.882	-5.150	-13.914	-30.334
	(43.197)	(44.007)	(102.928)	(61.115)	(44.966)	(41.157)	(82.665)	(7.221)	(8.835)	(15.716)	(8.463)	(5.281)	(8.923)	(23.225)
-3	-27.511	-29.024	-84.710	-32.330	-31.149	-70.066***	-54.105	6.651*	6.291*	9.219	9.613**	5.063	0.382	3.529
	(29.215)	(29.951)	(74.211)	(36.306)	(30.260)	(25.905)	(52.075)	(3.528)	(3.595)	(7.235)	(4.455)	(3.221)	(1.715)	(4.824)
-2	-58.498	-66.091	-228.454*	-48.503	-58.804	-30.074	-86.636	-6.212**	-4.945	1.649	-3.141	-5.626**	-7.870***	-10.045
	(44.581)	(45.774)	(128.390)	(63.805)	(44.483)	(32.582)	(74.332)	(2.683)	(3.853)	(9.677)	(2.919)	(2.669)	(2.774)	(7.827)
-1	-3.293	-2.008	-44.665	17.076	-8.006	43.652**	45.798	-3.430	-2.463	6.928	-1.182	-5.125*	-1.428	4.786
	(49.101)	(49.617)	(137.788)	(69.144)	(46.847)	(21.321)	(45.612)	(2.682)	(2.519)	(7.018)	(3.007)	(2.871)	(2.628)	(4.331)
Post-event weeks:														
0	-60.636	-64.773	-209.633	-44.281	-71.212	10.211	35.820	1.108	2.071	9.775	4.815	-3.074	-1.135	5.752
	(79.963)	(80.536)	(223.310)	(112.778)	(74.980)	(22.422)	(36.000)	(2.999)	(3.320)	(8.596)	(3.965)	(3.222)	(2.706)	(5.024)
1	-75.282	-86.775	-319.103**	-71.135	-88.025*	-2.010	-109.784	4.768	6.282	24.210	13.884	-0.205	4.042	18.077
	(54.221)	(55.815)	(154.462)	(73.462)	(52.148)	(36.920)	(95.962)	(10.222)	(10.716)	(28.140)	(14.060)	(7.517)	(9.298)	(17.152)
2	-37.749	-47.798	-191.707	-37.434	-54.286	45.682	-4.404	9.371	10.165	33.248	20.714	2.678	10.652	34.509
	(53.309)	(54.281)	(144.677)	(69.980)	(46.575)	(35.358)	(67.021)	(13.357)	(14.075)	(35.079)	(18.142)	(9.464)	(13.123)	(28.818)
3	-122.540	-136.303*	-233.209	-104.498	-145.364**	-22.110	39.165	0.887	2.561	22.919	5.870	-8.808***	1.138	2.569
	(79.375)	(81.492)	(216.237)	(113.134)	(70.936)	(28.816)	(56.726)	(6.358)	(7.204)	(21.456)	(8.230)	(3.072)	(6.022)	(6.430)
4	-24.074	-40.651	-240.208	-17.166	-44.485	67.442	-17.062	10.436	11.848	41.057	21.419	2.295	10.477	29.838
	(75.897)	(75.037)	(195.547)	(98.620)	(70.277)	(43.916)	(80.921)	(13.590)	(13.813)	(37.056)	(18.075)	(9.086)	(13.202)	(22.127)
5	-2.235	-12.616	-133.345	21.803	-22.966	107.777**	39.328	10.016	11.557	48.804	21.295	1.679	10.858	34.460
	(67.814)	(67.249)	(176.595)	(88.347)	(68.445)	(43.530)	(110.569)	(16.135)	(17.385)	(46.946)	(21.162)	(11.385)	(14.264)	(25.065)
6	-86.570	-107.646	-280.829*	-54.149	-117.587	-39.749	-40.817	7.378	10.259	31.791	12.760	-5.491	2.780	-3.337
	(65.780)	(68.093)	(157.848)	(90.423)	(72.642)	(41.120)	(99.460)	(8.833)	(11.193)	(28.134)	(11.136)	(3.510)	(6.555)	(12.785)
7	30.740	5.307	-164.785	45.511	1.044	96.929*	-11.606	12.985	15.160	50.103	26.019	0.692	14.493	35.306
	(67.970)	(62.820)	(168.866)	(87.517)	(63.248)	(57.768)	(112.965)	(17.861)	(19.050)	(47.704)	(23.335)	(11.297)	(17.148)	(24.442)
Market price			75.385**				64.885*			0.157*				0.348*
			(30.163)				(37.933)			(0.091)				(0.205)
Market supply				0.351*			0.646*				-0.395**			-1.824
				(0.187)			(0.343)				(0.168)			(1.149)
Competitors					0.584		-0.556					0.395		0.461
					(0.614)		(0.922)					(0.259)		(0.708)
Number of arrests						-9.185	-8.940						0.198	3.174
						(7.054)	(13.002)						(0.531)	(3.391)
Number of arrests lag 1						21.374***	13.771						1.165***	-4.942
						(5.301)	(12.319)						(0.338)	(4.640)
Number of arrests lag 2						18.393*	25.703						0.179	-11.788
						(10.704)	(29.473)						(1.274)	(10.865)
Number of arrests lag 3						34.396**	6.823						2.752	-10.146
						(14.854)	(33.246)						(2.057)	(12.083)
Constant	39.449	-72.001	-12.545	-2.086	-15.023	-107.912**	-121.849	-4.830	-11.845	-37.398	-1.972	-27.575	-9.438*	-46.996
	(48.270)	(96.728)	(248.978)	(106.745)	(87.463)	(46.797)	(309.212)	(7.195)	(9.195)	(42.182)	(7.587)	(21.766)	(5.450)	(63.410)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	29,072	29,072	12,451	23,245	29,072	26,314	11,450	15,256	15,256	6,826	13,135	15,256	13,897	6,277
Mean of dep. var.	337.20	337.20	337.20	337.20	337.20	337.20	337.20	7.70	7.70	7.70	7.70	7.70	7.70	7.70
R-squared	0.001	0.002	0.008	0.003	0.001	0.004	0.022	0.001	0.002	0.004	0.001	0.002	0.001	0.008

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 20: Dynamic effects of shocks to transaction risk. Dep.var.: Rating in percentage points

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	0.514	0.536*	1.143**	0.549	0.518	0.490	0.831	0.996**	0.924**	0.858*	0.979**	0.981**	0.771*	0.543
	(0.331)	(0.317)	(0.567)	(0.345)	(0.333)	(0.306)	(0.557)	(0.441)	(0.389)	(0.497)	(0.447)	(0.448)	(0.431)	(0.566)
-6	0.331	0.344	0.731	0.314	0.337	0.395	0.593	0.136	0.023	0.019	0.160	0.104	0.968*	1.449*
	(0.369)	(0.363)	(0.597)	(0.370)	(0.379)	(0.460)	(0.731)	(0.607)	(0.592)	(0.702)	(0.596)	(0.636)	(0.556)	(0.787)
-5	0.168	0.226	-0.042	0.080	0.179	-0.318	-0.542	0.402	0.268	0.139	0.404	0.341	0.550	0.988
	(0.255)	(0.265)	(0.308)	(0.280)	(0.271)	(0.234)	(0.398)	(0.429)	(0.525)	(0.777)	(0.429)	(0.472)	(0.544)	(0.859)
-3	-0.453	-0.489	-0.210	-0.436	-0.458	-0.170	-0.290	-0.445	-0.536	-0.298	-0.398	-0.423	0.494	1.374
	(0.428)	(0.426)	(0.604)	(0.423)	(0.427)	(0.339)	(0.402)	(0.637)	(0.626)	(0.755)	(0.622)	(0.624)	(0.505)	(0.862)
-2	-0.270	-0.175	-0.046	-0.330	-0.267	-0.602*	-0.797*	0.480	0.360	-0.225	0.542	0.453	0.437	0.950
	(0.318)	(0.321)	(0.367)	(0.343)	(0.321)	(0.320)	(0.411)	(0.532)	(0.599)	(0.798)	(0.531)	(0.530)	(0.615)	(0.953)
-1	0.157	0.135	0.300	0.132	0.150	-0.315	-0.484	0.287	0.301	-0.212	0.333	0.311	-0.112	0.417
	(0.249)	(0.250)	(0.347)	(0.254)	(0.255)	(0.200)	(0.297)	(0.329)	(0.305)	(0.322)	(0.340)	(0.334)	(0.297)	(0.551)
Post-event weeks:														
0	-0.420	-0.447	-0.726	-0.461	-0.431	-0.549*	-0.586	-0.487	-0.486	-0.570	-0.429	-0.442	-0.179	1.309
	(0.383)	(0.381)	(0.586)	(0.402)	(0.397)	(0.331)	(0.543)	(0.526)	(0.525)	(0.791)	(0.523)	(0.526)	(0.569)	(1.214)
1	-0.626	-0.625	-0.932**	-0.664	-0.639	-0.971*	-1.577**	-0.036	-0.113	-0.420	0.103	0.016	-0.237	0.972
	(0.388)	(0.390)	(0.468)	(0.413)	(0.389)	(0.502)	(0.664)	(0.539)	(0.585)	(0.753)	(0.494)	(0.537)	(0.677)	(1.140)
2	-0.394	-0.444	-0.337	-0.399	-0.414	-0.732	-1.283	-0.173	-0.204	-0.424	0.012	-0.086	-0.491	1.207
	(0.465)	(0.467)	(0.468)	(0.468)	(0.462)	(0.552)	(0.794)	(0.559)	(0.547)	(0.695)	(0.540)	(0.521)	(0.598)	(0.927)
3	-0.842	-0.907*	-1.120	-0.917	-0.867*	-0.989*	-1.744*	-0.111	-0.212	-0.619	-0.041	-0.002	-0.167	1.224
	(0.514)	(0.513)	(0.748)	(0.569)	(0.526)	(0.513)	(1.037)	(0.626)	(0.622)	(0.872)	(0.638)	(0.665)	(0.664)	(1.405)
4	-1.010**	-1.034**	-1.618**	-1.024**	-1.031**	-1.275**	-2.145**	-0.225	-0.327	-0.949	-0.076	-0.138	-0.442	0.705
	(0.484)	(0.481)	(0.655)	(0.492)	(0.509)	(0.510)	(0.868)	(0.605)	(0.604)	(0.949)	(0.632)	(0.666)	(0.658)	(1.397)
5	-0.311	-0.383	-0.685	-0.329	-0.335	-0.940	-1.669	-0.441	-0.477	-0.812	-0.288	-0.339	-0.831	0.945
	(0.472)	(0.477)	(0.617)	(0.479)	(0.527)	(0.619)	(1.073)	(0.620)	(0.622)	(0.962)	(0.670)	(0.649)	(0.732)	(1.537)
6	-0.358	-0.543	-0.543	-0.468	-0.391	-1.524*	-2.854	-0.398	-0.496	-0.828	-0.350	-0.252	-0.856	1.134
	(0.520)	(0.524)	(0.777)	(0.608)	(0.577)	(0.915)	(1.918)	(0.714)	(0.727)	(0.967)	(0.727)	(0.715)	(0.933)	(1.953)
7	-1.364**	-1.421**	-2.311**	-1.373**	-1.393**	-1.922**	-3.262**	-0.721	-0.792	-1.159	-0.562	-0.591	-1.297	0.521
	(0.640)	(0.641)	(0.895)	(0.647)	(0.656)	(0.807)	(1.356)	(0.697)	(0.709)	(1.067)	(0.737)	(0.718)	(0.811)	(1.700)
Market price			-0.144				0.030			0.001				0.013**
			(0.165)				(0.208)			(0.004)				(0.005)
Market supply				-0.001			-0.003				-0.007			-0.025*
				(0.001)			(0.004)				(0.014)			(0.015)
Competitors					0.001		-0.007					-0.004		-0.021
					(0.005)		(0.013)					(0.009)		(0.020)
Number of arrests						0.106	0.161						0.041	0.083
						(0.065)	(0.121)						(0.070)	(0.073)
Number of arrests lag 1						0.075	0.108						0.018	-0.115
						(0.051)	(0.084)						(0.068)	(0.164)
Number of arrests lag 2						-0.052	-0.001						-0.032	0.132
						(0.064)	(0.111)						(0.084)	(0.181)
Number of arrests lag 3						-0.194	-0.179						-0.356**	-0.297
						(0.134)	(0.189)						(0.143)	(0.199)
Constant	0.502	-0.838	1.536	0.760	0.443	0.958*	0.759	0.151	-2.069*	-0.133	0.184	0.417	0.675	-3.334*
	(0.351)	(0.829)	(1.559)	(0.616)	(0.720)	(0.512)	(1.799)	(0.464)	(1.250)	(1.216)	(0.479)	(0.788)	(0.638)	(2.010)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	15,178	15,178	8,925	15,178	15,178	14,266	8,400	8,228	8,228	4,516	8,228	8,228	7,766	4,262
Mean of dep. var.	96.99	96.99	96.99	96.99	96.99	96.99	96.99	97.80	97.80	97.80	97.80	97.80	97.80	97.80
R-squared	0.004	0.007	0.011	0.004	0.004	0.006	0.022	0.002	0.010	0.003	0.002	0.002	0.006	0.027

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 21: Dynamic effects of shocks to transaction risk. Dep.var.: Expected probability of finalize early

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	-0.057***	-0.056***	-0.058***	-0.057***	-0.055***	-0.036***	-0.032*	-0.052***	-0.053***	-0.051**	-0.052***	-0.049***	-0.029**	-0.039*
	(0.012)	(0.012)	(0.019)	(0.012)	(0.012)	(0.011)	(0.016)	(0.014)	(0.014)	(0.025)	(0.014)	(0.014)	(0.013)	(0.021)
-6	-0.054***	-0.052***	-0.057***	-0.054***	-0.053***	-0.057***	-0.055***	-0.038***	-0.038***	-0.021	-0.038***	-0.036***	-0.037***	-0.026
	(0.010)	(0.010)	(0.018)	(0.010)	(0.010)	(0.011)	(0.018)	(0.012)	(0.012)	(0.019)	(0.012)	(0.012)	(0.012)	(0.018)
-5	-0.012**	-0.013**	-0.025***	-0.017***	-0.012**	-0.014**	-0.026***	-0.017**	-0.020***	-0.014	-0.017**	-0.016**	-0.018**	-0.012
	(0.005)	(0.006)	(0.010)	(0.006)	(0.005)	(0.005)	(0.009)	(0.007)	(0.007)	(0.011)	(0.008)	(0.007)	(0.007)	(0.011)
-3	0.000	-0.003	-0.011	-0.000	-0.000	0.001	-0.006	0.004	-0.006	-0.004	0.004	0.004	0.006	-0.010
	(0.006)	(0.006)	(0.010)	(0.006)	(0.006)	(0.006)	(0.010)	(0.008)	(0.007)	(0.012)	(0.008)	(0.008)	(0.007)	(0.010)
-2	0.006	0.002	-0.002	0.005	0.005	0.010	0.007	-0.003	-0.014	0.006	-0.003	-0.004	0.001	0.003
	(0.009)	(0.009)	(0.013)	(0.009)	(0.009)	(0.008)	(0.014)	(0.011)	(0.011)	(0.016)	(0.012)	(0.011)	(0.011)	(0.017)
-1	0.010	0.008	-0.001	0.008	0.009	0.009	0.009	0.014	0.005	0.030**	0.014	0.014	0.007	0.021
	(0.008)	(0.008)	(0.011)	(0.008)	(0.008)	(0.009)	(0.012)	(0.010)	(0.010)	(0.015)	(0.012)	(0.010)	(0.012)	(0.015)
Post-event weeks:														
0	0.045***	0.041***	0.029**	0.038***	0.042***	0.047***	0.037**	0.051***	0.039***	0.052***	0.051***	0.048***	0.047***	0.046**
	(0.008)	(0.008)	(0.013)	(0.009)	(0.009)	(0.009)	(0.015)	(0.011)	(0.011)	(0.016)	(0.011)	(0.011)	(0.012)	(0.019)
1	0.047***	0.044***	0.043***	0.038***	0.045***	0.056***	0.053***	0.056***	0.046***	0.052***	0.056***	0.053***	0.062***	0.054***
	(0.009)	(0.009)	(0.014)	(0.010)	(0.010)	(0.009)	(0.018)	(0.011)	(0.011)	(0.017)	(0.011)	(0.011)	(0.012)	(0.020)
2	0.055***	0.055***	0.046***	0.047***	0.053***	0.065***	0.066***	0.069***	0.064***	0.076***	0.069***	0.067***	0.075***	0.077***
	(0.009)	(0.010)	(0.016)	(0.011)	(0.010)	(0.010)	(0.018)	(0.012)	(0.012)	(0.018)	(0.012)	(0.012)	(0.013)	(0.019)
3	0.046***	0.042***	0.045***	0.045***	0.042***	0.046***	0.047**	0.064***	0.052***	0.075***	0.064***	0.060***	0.059***	0.070***
	(0.010)	(0.010)	(0.016)	(0.010)	(0.012)	(0.011)	(0.021)	(0.012)	(0.012)	(0.018)	(0.013)	(0.013)	(0.013)	(0.022)
4	0.070***	0.067***	0.063***	0.064***	0.066***	0.072***	0.072***	0.080***	0.070***	0.091***	0.080***	0.076***	0.078***	0.087***
	(0.009)	(0.009)	(0.016)	(0.010)	(0.011)	(0.010)	(0.020)	(0.012)	(0.012)	(0.019)	(0.012)	(0.013)	(0.013)	(0.022)
5	0.089***	0.087***	0.089***	0.084***	0.084***	0.100***	0.111***	0.103***	0.093***	0.103***	0.103***	0.097***	0.108***	0.106***
	(0.010)	(0.010)	(0.017)	(0.010)	(0.013)	(0.011)	(0.024)	(0.013)	(0.013)	(0.021)	(0.013)	(0.014)	(0.014)	(0.026)
6	0.096***	0.091***	0.095***	0.090***	0.090***	0.098***	0.108***	0.100***	0.086***	0.093***	0.100***	0.094***	0.095***	0.092***
	(0.012)	(0.012)	(0.020)	(0.013)	(0.015)	(0.013)	(0.028)	(0.015)	(0.015)	(0.023)	(0.017)	(0.016)	(0.017)	(0.030)
7	0.106***	0.102***	0.106***	0.095***	0.100***	0.111***	0.124***	0.113***	0.100***	0.120***	0.113***	0.106***	0.104***	0.115***
	(0.013)	(0.013)	(0.020)	(0.015)	(0.016)	(0.015)	(0.031)	(0.016)	(0.016)	(0.025)	(0.017)	(0.018)	(0.019)	(0.032)
Market price			0.010				0.005			-0.000				-0.000
			(0.007)				(0.009)			(0.000)				(0.000)
Market supply				0.000**			0.000				0.000			-0.001
				(0.000)			(0.000)				(0.000)			(0.001)
Competitors					0.000		0.000					0.000		-0.000
					(0.000)		(0.000)					(0.000)		(0.001)
Number of arrests						0.000	-0.001						0.001	0.001
						(0.001)	(0.001)						(0.001)	(0.001)
Number of arrests lag 1						-0.000	-0.001						0.001	0.000
						(0.001)	(0.001)						(0.001)	(0.001)
Number of arrests lag 2						-0.000	-0.001						0.000	-0.001
						(0.001)	(0.001)						(0.001)	(0.001)
Number of arrests lag 3						-0.003***	-0.003***						-0.002***	-0.002**
						(0.001)	(0.001)						(0.001)	(0.001)
Constant	0.185***	0.072	0.143***	0.166***	0.143**	0.187***	0.002	0.197***	0.068	0.265***	0.197***	0.145**	0.196***	0.112
	(0.007)	(0.057)	(0.038)	(0.010)	(0.059)	(0.007)	(0.126)	(0.009)	(0.063)	(0.033)	(0.009)	(0.073)	(0.009)	(0.137)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	20,069	20,069	9,859	20,069	20,069	20,069	9,859	13,028	13,028	5,311	13,028	13,028	13,028	5,311
Mean of dep. var.	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.25	0.25	0.25	0.25	0.25	0.25	0.25
R-squared	0.039	0.044	0.038	0.039	0.039	0.040	0.046	0.040	0.053	0.044	0.040	0.040	0.042	0.066

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 22: Dynamic effects of shocks to transaction risk. Dep.var.: Expected probability of entry

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	0.036***	0.031***	0.033***	0.030***	0.036***	0.040***	0.046***	0.040***	0.038***	0.042***	0.038***	0.040***	0.040***	0.035***
	(0.004)	(0.005)	(0.008)	(0.005)	(0.004)	(0.004)	(0.009)	(0.006)	(0.007)	(0.012)	(0.008)	(0.006)	(0.006)	(0.014)
-6	-0.048***	-0.061***	-0.086***	-0.060***	-0.047***	-0.028***	-0.003	-0.044***	-0.047**	-0.075***	-0.053***	-0.044***	-0.021*	-0.031
	(0.010)	(0.014)	(0.019)	(0.014)	(0.010)	(0.008)	(0.016)	(0.014)	(0.019)	(0.026)	(0.018)	(0.014)	(0.011)	(0.021)
-5	-0.000	0.020	0.014	0.019	0.001	-0.037***	-0.033*	-0.016	-0.011	-0.033	-0.017	-0.016	-0.038***	-0.059**
	(0.012)	(0.018)	(0.025)	(0.018)	(0.012)	(0.008)	(0.018)	(0.017)	(0.023)	(0.034)	(0.023)	(0.017)	(0.012)	(0.024)
-3	-0.074***	-0.101***	-0.134***	-0.100***	-0.076***	-0.058***	-0.059***	-0.071***	-0.085***	-0.117***	-0.091***	-0.071***	-0.050***	-0.065***
	(0.010)	(0.014)	(0.020)	(0.014)	(0.010)	(0.008)	(0.015)	(0.015)	(0.019)	(0.028)	(0.019)	(0.015)	(0.011)	(0.019)
-2	-0.018*	-0.007	-0.019	-0.009	-0.018*	-0.045***	-0.067***	-0.028*	-0.027	-0.052*	-0.035*	-0.028*	-0.042***	-0.069***
	(0.011)	(0.015)	(0.021)	(0.015)	(0.011)	(0.009)	(0.018)	(0.015)	(0.021)	(0.030)	(0.020)	(0.015)	(0.013)	(0.025)
-1	-0.023***	-0.029***	-0.032***	-0.027***	-0.024***	-0.028***	-0.046***	-0.024***	-0.028***	-0.027*	-0.031***	-0.024***	-0.024***	-0.025
	(0.005)	(0.007)	(0.010)	(0.007)	(0.005)	(0.004)	(0.010)	(0.007)	(0.009)	(0.014)	(0.009)	(0.007)	(0.007)	(0.017)
Post-event weeks:														
0	-0.068***	-0.100***	-0.118***	-0.094***	-0.073***	-0.060***	-0.085***	-0.066***	-0.085***	-0.101***	-0.087***	-0.066***	-0.052***	-0.063***
	(0.008)	(0.011)	(0.016)	(0.011)	(0.008)	(0.006)	(0.014)	(0.012)	(0.015)	(0.023)	(0.015)	(0.012)	(0.009)	(0.019)
1	-0.059***	-0.082***	-0.098***	-0.077***	-0.064***	-0.073***	-0.128***	-0.064***	-0.091***	-0.114***	-0.099***	-0.064***	-0.067***	-0.112***
	(0.011)	(0.015)	(0.021)	(0.015)	(0.011)	(0.009)	(0.019)	(0.015)	(0.020)	(0.030)	(0.019)	(0.016)	(0.013)	(0.028)
2	-0.058***	-0.083***	-0.106***	-0.082***	-0.063***	-0.073***	-0.141***	-0.065***	-0.090***	-0.084***	-0.099***	-0.065***	-0.071***	-0.088***
	(0.009)	(0.012)	(0.018)	(0.013)	(0.009)	(0.008)	(0.018)	(0.013)	(0.017)	(0.026)	(0.017)	(0.013)	(0.012)	(0.028)
3	-0.117***	-0.159***	-0.177***	-0.154***	-0.124***	-0.120***	-0.158***	-0.124***	-0.160***	-0.171***	-0.165***	-0.124***	-0.120***	-0.137***
	(0.009)	(0.013)	(0.020)	(0.013)	(0.010)	(0.009)	(0.020)	(0.013)	(0.017)	(0.026)	(0.017)	(0.014)	(0.012)	(0.029)
4	-0.112***	-0.161***	-0.176***	-0.163***	-0.120***	-0.122***	-0.192***	-0.123***	-0.171***	-0.186***	-0.179***	-0.122***	-0.123***	-0.169***
	(0.009)	(0.013)	(0.019)	(0.013)	(0.011)	(0.008)	(0.020)	(0.014)	(0.018)	(0.027)	(0.018)	(0.015)	(0.012)	(0.029)
5	-0.124***	-0.162***	-0.168***	-0.158***	-0.131***	-0.125***	-0.204***	-0.132***	-0.173***	-0.158***	-0.179***	-0.131***	-0.124***	-0.132***
	(0.010)	(0.013)	(0.019)	(0.013)	(0.011)	(0.009)	(0.021)	(0.014)	(0.018)	(0.028)	(0.019)	(0.015)	(0.012)	(0.033)
6	-0.151***	-0.202***	-0.199***	-0.189***	-0.161***	-0.191***	-0.280***	-0.171***	-0.223***	-0.227***	-0.224***	-0.170***	-0.194***	-0.234***
	(0.011)	(0.016)	(0.024)	(0.017)	(0.012)	(0.012)	(0.030)	(0.017)	(0.022)	(0.033)	(0.022)	(0.018)	(0.017)	(0.041)
7	-0.209***	-0.282***	-0.289***	-0.283***	-0.219***	-0.239***	-0.335***	-0.224***	-0.296***	-0.290***	-0.302***	-0.224***	-0.246***	-0.287***
	(0.012)	(0.016)	(0.024)	(0.017)	(0.013)	(0.013)	(0.029)	(0.017)	(0.023)	(0.034)	(0.023)	(0.018)	(0.019)	(0.042)
Market price			0.003				-0.010*			0.000				0.000
			(0.003)				(0.005)			(0.000)				(0.000)
Market supply				0.000***			0.000***				0.000			0.001
				(0.000)			(0.000)				(0.000)			(0.001)
Competitors					0.000**		-0.000					-0.000		-0.001
					(0.000)		(0.000)					(0.000)		(0.001)
Number of arrests						-0.001	0.003						-0.001	-0.003
						(0.001)	(0.002)						(0.001)	(0.002)
Number of arrests lag 1						0.013***	0.015***						0.011***	0.016***
						(0.001)	(0.003)						(0.002)	(0.004)
Number of arrests lag 2						-0.005***	-0.020***						-0.002	0.003
						(0.002)	(0.004)						(0.002)	(0.006)
Number of arrests lag 3						-0.008***	-0.037***						-0.007***	-0.008
						(0.002)	(0.005)						(0.003)	(0.006)
Constant	0.157***	0.230***	0.214***	0.194***	0.135***	0.169***	0.351***	0.170***	0.236***	0.203***	0.224***	0.171***	0.170***	0.269***
	(0.008)	(0.015)	(0.025)	(0.014)	(0.011)	(0.008)	(0.037)	(0.012)	(0.021)	(0.036)	(0.016)	(0.016)	(0.011)	(0.046)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	30,864	21,141	11,450	21,141	30,864	30,864	11,450	16,294	11,979	6,277	11,979	16,294	16,294	6,277
Mean of dep. var.	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
R-squared	0.066	0.091	0.092	0.091	0.067	0.080	0.123	0.069	0.089	0.087	0.088	0.069	0.077	0.103

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 23: Dynamic effects of shocks to transaction risk. Dep.var.: Expected probability of exit

	Cannabis							Opioids						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Pre-event weeks:														
-7	-0.017***	-0.018***	-0.022***	-0.018***	-0.017***	-0.021***	-0.030***	-0.027***	-0.031***	-0.027***	-0.033***	-0.028***	-0.032***	-0.037***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.006)	(0.004)	(0.005)	(0.008)	(0.005)	(0.004)	(0.006)	(0.011)
-6	0.010***	0.016***	0.021**	0.018***	0.011***	-0.007***	-0.021***	0.000	0.006	0.007	0.007	0.000	-0.013***	-0.016*
	(0.003)	(0.005)	(0.009)	(0.005)	(0.003)	(0.002)	(0.007)	(0.005)	(0.007)	(0.013)	(0.007)	(0.005)	(0.004)	(0.008)
-5	0.004	0.007*	-0.002	0.009**	0.004	-0.002	-0.008	0.008	0.012*	0.012	0.012*	0.007	0.003	-0.006
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.002)	(0.006)	(0.005)	(0.007)	(0.013)	(0.007)	(0.005)	(0.004)	(0.011)
-3	0.019***	0.027***	0.041***	0.027***	0.019***	0.007***	0.015***	0.016***	0.025***	0.025*	0.027***	0.016***	0.007**	0.015**
	(0.004)	(0.005)	(0.010)	(0.006)	(0.004)	(0.002)	(0.004)	(0.006)	(0.008)	(0.013)	(0.008)	(0.006)	(0.003)	(0.007)
-2	0.011***	0.017***	0.007	0.019***	0.011***	0.008***	0.009*	0.017***	0.024***	0.024*	0.027***	0.017***	0.012***	0.015
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.002)	(0.005)	(0.005)	(0.007)	(0.012)	(0.007)	(0.005)	(0.003)	(0.009)
-1	0.006***	0.009***	0.005	0.010***	0.006***	0.003**	0.005	0.014***	0.018***	0.018**	0.020***	0.015***	0.012***	0.018*
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.005)	(0.008)	(0.005)	(0.004)	(0.004)	(0.009)
Post-event weeks:														
0	0.019***	0.032***	0.042***	0.034***	0.019***	0.008***	0.024***	0.019***	0.030***	0.032**	0.033***	0.020***	0.009***	0.031***
	(0.004)	(0.006)	(0.009)	(0.006)	(0.004)	(0.002)	(0.006)	(0.005)	(0.007)	(0.013)	(0.007)	(0.005)	(0.003)	(0.011)
1	0.014***	0.023***	0.019***	0.024***	0.014***	0.010***	0.024***	0.019***	0.028***	0.031***	0.035***	0.020***	0.012***	0.035***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.002)	(0.007)	(0.004)	(0.006)	(0.010)	(0.007)	(0.005)	(0.003)	(0.012)
2	0.014***	0.022***	0.015***	0.022***	0.014***	0.013***	0.024***	0.023***	0.032***	0.033***	0.041***	0.025***	0.019***	0.042***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.007)	(0.005)	(0.007)	(0.011)	(0.008)	(0.005)	(0.005)	(0.015)
3	0.024***	0.039***	0.047***	0.041***	0.023***	0.019***	0.046***	0.030***	0.046***	0.042***	0.048***	0.033***	0.023***	0.048***
	(0.004)	(0.006)	(0.009)	(0.007)	(0.004)	(0.003)	(0.010)	(0.006)	(0.009)	(0.014)	(0.009)	(0.006)	(0.005)	(0.016)
4	0.028***	0.042***	0.046***	0.042***	0.027***	0.023***	0.050***	0.036***	0.051***	0.056***	0.058***	0.038***	0.029***	0.064***
	(0.004)	(0.006)	(0.008)	(0.006)	(0.004)	(0.003)	(0.009)	(0.006)	(0.009)	(0.014)	(0.009)	(0.007)	(0.005)	(0.017)
5	0.022***	0.034***	0.032***	0.034***	0.021***	0.020***	0.041***	0.033***	0.049***	0.054***	0.057***	0.035***	0.032***	0.073***
	(0.003)	(0.005)	(0.007)	(0.005)	(0.003)	(0.003)	(0.009)	(0.006)	(0.008)	(0.013)	(0.009)	(0.007)	(0.006)	(0.021)
6	0.022***	0.037***	0.038***	0.039***	0.020***	0.023***	0.066***	0.029***	0.046***	0.052***	0.046***	0.032***	0.031***	0.080***
	(0.003)	(0.005)	(0.008)	(0.006)	(0.003)	(0.003)	(0.014)	(0.005)	(0.008)	(0.013)	(0.008)	(0.006)	(0.005)	(0.023)
7	0.027***	0.041***	0.044***	0.040***	0.026***	0.031***	0.068***	0.034***	0.050***	0.059***	0.057***	0.037***	0.037***	0.089***
	(0.003)	(0.005)	(0.007)	(0.005)	(0.003)	(0.004)	(0.012)	(0.005)	(0.008)	(0.012)	(0.008)	(0.006)	(0.006)	(0.022)
Market price			0.003**				0.003			-0.000				0.000*
			(0.001)				(0.003)			(0.000)				(0.000)
Market supply				0.000*			-0.000				-0.000***			-0.001***
				(0.000)			(0.000)				(0.000)			(0.000)
Competitors					0.000		-0.000*					-0.000		-0.001**
					(0.000)		(0.000)					(0.000)		(0.000)
Number of arrests						-0.001**	-0.000						-0.002**	-0.000
						(0.000)	(0.001)						(0.001)	(0.001)
Number of arrests lag 1						-0.001***	-0.004***						-0.002**	-0.006**
						(0.000)	(0.001)						(0.001)	(0.002)
Number of arrests lag 2						-0.001**	0.001						-0.002**	-0.009**
						(0.001)	(0.001)						(0.001)	(0.004)
Number of arrests lag 3						0.006***	0.011***						0.004	-0.003
						(0.001)	(0.003)						(0.002)	(0.005)
Constant	-0.002	-0.003	-0.020	-0.012*	-0.004	-0.001	0.004	-0.002	0.003	0.013	-0.002	0.003	0.003	0.043**
	(0.002)	(0.006)	(0.013)	(0.006)	(0.004)	(0.003)	(0.012)	(0.004)	(0.006)	(0.022)	(0.005)	(0.006)	(0.004)	(0.021)
Market controls	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Observations	33,180	23,245	12,451	23,245	33,180	30,864	11,450	17,554	13,135	6,826	13,135	17,554	16,294	6,277
Mean of dep. var.	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
R-squared	0.011	0.016	0.024	0.017	0.011	0.018	0.038	0.014	0.020	0.018	0.021	0.014	0.020	0.032

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 24: Different event definitions: Effects of shocks to holding risk. Dep.var.: Price in USD/g

	Cannabis			Opioids		
	(1) Arrests > 5	(2) Arrests > 7	(3) Arrests > 10	(4) Arrests > 5	(5) Arrests > 7	(6) Arrests > 10
Pre-event weeks:						
-7	0.178	0.283	0.833**	12.386**	15.441**	34.854***
	(0.201)	(0.282)	(0.396)	(5.039)	(7.045)	(10.834)
-6	0.162	0.229	0.151	0.025	1.066	3.187
	(0.185)	(0.232)	(0.374)	(4.903)	(6.911)	(9.819)
-5	0.043	0.085	0.982**	-0.489	0.937	24.040**
	(0.150)	(0.182)	(0.468)	(3.740)	(4.907)	(9.469)
-3	-0.082	-0.170	0.313	-1.037	0.793	19.038**
	(0.178)	(0.183)	(0.327)	(4.257)	(5.004)	(8.238)
-2	-0.097	-0.199	0.570	-0.958	1.376	10.904
	(0.178)	(0.252)	(0.410)	(4.445)	(6.056)	(8.209)
-1	0.043	0.001	0.128	0.995	-3.665	3.322
	(0.191)	(0.252)	(0.361)	(4.496)	(6.037)	(8.531)
Post-event weeks:						
0	-0.040	-0.159	0.731*	8.544	-0.346	28.497***
	(0.189)	(0.221)	(0.400)	(5.237)	(6.398)	(8.819)
1	0.286	0.203	0.758*	19.803***	19.867***	41.348***
	(0.184)	(0.230)	(0.401)	(6.058)	(7.085)	(9.381)
2	0.116	0.326	0.543	13.619**	19.424**	24.516**
	(0.226)	(0.286)	(0.427)	(6.682)	(7.989)	(10.122)
3	0.502**	0.314	1.131***	6.198	7.267	12.939
	(0.222)	(0.242)	(0.391)	(6.941)	(8.602)	(9.616)
4	0.391	0.812***	1.690***	-3.595	11.058	7.342
	(0.249)	(0.285)	(0.467)	(7.447)	(8.961)	(11.426)
5	0.231	0.575*	0.590	1.613	1.612	-20.343*
	(0.284)	(0.327)	(0.449)	(7.753)	(9.933)	(11.583)
6	-0.076	-0.170	0.341	-7.109	-13.178	-14.707
	(0.295)	(0.344)	(0.433)	(8.648)	(10.248)	(12.825)
7	-0.196	-0.567	-0.145	-10.800	-9.241	-6.419
	(0.330)	(0.366)	(0.503)	(9.408)	(11.015)	(13.175)
Constant	1.353***	1.422***	1.007*	6.304	5.938	-0.295
	(0.483)	(0.483)	(0.586)	(10.793)	(11.700)	(12.587)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,249	35,237	16,783	26,112	17,225	8,221
Number events	9	6	3	9	6	3
Mean of dep. var.	16.72	16.79	16.84	467.94	468.20	475.46
R-squared	0.002	0.004	0.006	0.005	0.006	0.015

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * p < 0.10 ** p < 0.05 *** p < 0.01.

Table 25: Different event definitions: Effects of shocks to holding risk. Dep.var.: Quantity in grams

	Cannabis			Opioids		
	(1) Arrests > 5	(2) Arrests > 7	(3) Arrests > 10	(4) Arrests > 5	(5) Arrests > 7	(6) Arrests > 10
Pre-event weeks:						
-7	17.627	25.928	22.621	-10.721	-14.390	-27.222
	(18.505)	(21.870)	(31.419)	(8.128)	(11.810)	(21.160)
-6	14.918	9.031	-6.720	-9.342	-13.966	-23.410
	(16.825)	(22.223)	(42.888)	(7.758)	(13.057)	(20.872)
-5	7.488	10.528	17.679	-9.367	-12.018	-17.563
	(15.364)	(18.836)	(31.005)	(6.128)	(9.378)	(15.985)
-3	5.873	-27.575*	-59.167	-4.652	-9.238	-25.564
	(11.576)	(14.379)	(39.703)	(5.283)	(7.794)	(18.288)
-2	-12.367	-18.623	23.353	-4.452	-8.013	-11.334
	(17.052)	(26.573)	(42.790)	(5.134)	(7.875)	(14.706)
-1	5.322	22.493	22.129	-0.870	-4.128	-12.681
	(16.467)	(25.035)	(42.205)	(4.998)	(6.500)	(11.036)
Post-event weeks:						
0	9.437	2.817	-44.496	-2.159	-2.840	-7.681
	(20.389)	(20.986)	(42.588)	(4.970)	(7.113)	(11.523)
1	2.301	-17.168	26.163	-6.582	-10.246	-25.349
	(20.946)	(27.457)	(46.631)	(7.065)	(10.352)	(19.474)
2	34.436	36.614	53.043	-7.901	-10.584	-20.473
	(23.388)	(29.206)	(44.748)	(7.192)	(9.670)	(18.379)
3	29.824	24.217	15.016	-7.740	-10.340	-20.686
	(21.185)	(26.257)	(35.611)	(7.460)	(9.988)	(20.071)
4	35.278	-1.482	26.055	-8.973	-9.848	-21.100
	(22.194)	(22.261)	(37.127)	(8.238)	(11.444)	(22.693)
5	72.501***	78.124***	88.904**	-10.538	-17.468	-29.355
	(23.039)	(30.078)	(44.500)	(7.742)	(11.791)	(21.358)
6	63.103***	71.672***	58.727	-12.431*	-16.714	-19.048
	(23.620)	(26.789)	(43.433)	(7.537)	(11.657)	(23.587)
7	47.684*	37.718	38.734	-6.854	-12.349	-14.314
	(25.286)	(24.628)	(35.613)	(8.321)	(11.095)	(18.262)
Constant	-248.703*	-228.897**	-211.762**	-21.572*	-18.971	-9.828
	(128.316)	(116.506)	(87.845)	(11.516)	(13.500)	(18.026)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,719	67,754	32,687	53,022	34,941	16,851
Number events	9	6	3	9	6	3
Mean of dep. var.	274.13	267.12	272.98	27.79	32.98	44.85
R-squared	0.005	0.005	0.005	0.012	0.011	0.006

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 26: Different event definitions: Effects of shocks to holding risk. Dep.var.: Vendor rating in percentage points

	Cannabis			Opioids		
	(1) Arrests > 5	(2) Arrests > 7	(3) Arrests > 10	(4) Arrests > 5	(5) Arrests > 7	(6) Arrests > 10
Pre-event weeks:						
-7	0.091	-0.059	0.147	0.327**	0.326	0.406*
	(0.085)	(0.094)	(0.182)	(0.136)	(0.200)	(0.240)
-6	0.194**	-0.050	0.130	0.386***	0.218	0.337
	(0.079)	(0.105)	(0.164)	(0.111)	(0.195)	(0.212)
-5	0.067	-0.007	0.051	0.060	0.045	-0.001
	(0.068)	(0.078)	(0.148)	(0.081)	(0.102)	(0.153)
-3	0.048	-0.068	-0.042	-0.110	-0.074	-0.211
	(0.080)	(0.086)	(0.131)	(0.110)	(0.119)	(0.209)
-2	0.072	-0.126	-0.265	0.109	0.017	-0.021
	(0.082)	(0.125)	(0.185)	(0.143)	(0.202)	(0.221)
-1	-0.115	-0.306**	-0.431**	-0.073	-0.241	-0.523*
	(0.088)	(0.144)	(0.177)	(0.167)	(0.239)	(0.288)
Post-event weeks:						
0	-0.089	-0.216	-0.382**	-0.141	-0.374	-0.315
	(0.119)	(0.138)	(0.179)	(0.192)	(0.245)	(0.229)
1	-0.032	-0.242*	-0.517***	-0.041	-0.292	-0.359
	(0.124)	(0.143)	(0.158)	(0.186)	(0.219)	(0.230)
2	0.009	-0.221	-0.343*	0.066	-0.110	-0.061
	(0.122)	(0.147)	(0.184)	(0.184)	(0.234)	(0.249)
3	-0.020	-0.145	-0.372*	-0.043	-0.193	-0.495
	(0.144)	(0.174)	(0.215)	(0.204)	(0.271)	(0.306)
4	-0.188	-0.335*	-0.835***	-0.246	-0.362	-0.654**
	(0.140)	(0.171)	(0.182)	(0.204)	(0.269)	(0.258)
5	-0.414***	-0.632***	-0.906***	-0.392*	-0.544**	-0.812***
	(0.138)	(0.162)	(0.194)	(0.201)	(0.258)	(0.290)
6	-0.218	-0.419***	-0.832***	-0.042	-0.292	-0.626**
	(0.136)	(0.155)	(0.174)	(0.194)	(0.263)	(0.268)
7	-0.152	-0.354**	-0.787***	0.100	0.107	-0.045
	(0.151)	(0.170)	(0.219)	(0.207)	(0.263)	(0.292)
Constant	-0.090	0.162	0.192	-0.718	-0.557	-0.226
	(0.312)	(0.278)	(0.315)	(1.008)	(0.954)	(0.729)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,600	49,862	24,351	39,074	25,749	12,589
Number events	9	6	3	9	6	3
Mean of dep. var.	97.30	97.38	97.22	97.25	97.27	97.58
R-squared	0.004	0.003	0.007	0.008	0.008	0.010

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 27: Different event definitions: Effects of shocks to transaction risk. Dep.var.: Price in USD/g

	Cannabis						Opioids					
	(1) SD ≥ 25	(2) SD ≥ 30	(3) SD ≥ 35	(4) SD ≥ 40	(5) Peak ≥ 25	(6) Exogenous	(7) SD ≥ 25	(8) SD ≥ 30	(9) SD ≥ 35	(10) SD ≥ 40	(11) Peak ≥ 25	(12) Exogenous
Pre-event weeks:												
-7	0.288	0.266	-0.121	-0.058	-0.847***	0.475	15.118**	5.596	-6.642	37.583	-22.929***	13.919
	(0.267)	(0.531)	(0.214)	(0.762)	(0.279)	(0.617)	(7.101)	(9.352)	(8.728)	(23.855)	(7.518)	(19.801)
-6	0.612**	0.405	0.087	-0.087	0.659	-1.323	12.505*	-11.408	-11.282	-1.465	-6.649	23.953
	(0.260)	(0.607)	(0.706)	(0.844)	(0.456)	(0.952)	(7.470)	(14.959)	(16.903)	(26.280)	(7.695)	(19.576)
-5	0.204	0.794	0.710	1.114	-0.037	0.873	3.696	-5.434	-5.625	-5.830	-13.060*	50.038***
	(0.255)	(0.502)	(0.571)	(1.191)	(0.297)	(0.725)	(6.059)	(11.724)	(12.899)	(19.071)	(7.387)	(18.637)
-3	0.413**	0.972	-0.124	-1.216	0.043	-0.758	7.101	16.957	22.610*	93.161***	3.317	42.802***
	(0.187)	(0.645)	(0.432)	(0.864)	(0.318)	(0.527)	(4.784)	(11.473)	(13.193)	(20.781)	(6.829)	(15.206)
-2	0.457**	1.288**	1.014*	1.379*	-0.240	0.036	8.233	22.117*	24.717*	73.840***	9.063	11.291
	(0.205)	(0.609)	(0.568)	(0.769)	(0.302)	(0.497)	(5.192)	(13.035)	(14.856)	(16.773)	(7.414)	(15.770)
-1	0.410*	-0.065	0.405	0.650	0.047	0.028	5.963	5.392	4.393	46.767***	16.313**	12.771
	(0.231)	(0.414)	(0.436)	(0.671)	(0.353)	(0.525)	(5.531)	(9.508)	(11.182)	(17.306)	(7.864)	(16.358)
Post-event weeks:												
0	-0.381	0.208	-0.190	-0.004	-0.280	0.416	-6.150	8.304	14.218	36.716**	0.231	21.521
	(0.241)	(0.428)	(0.447)	(0.510)	(0.294)	(0.590)	(5.721)	(12.043)	(15.473)	(15.307)	(6.685)	(20.187)
1	0.625**	1.367***	0.560	-0.157	0.411	-0.648	6.681	42.705***	53.046***	70.765***	18.495**	15.646
	(0.276)	(0.390)	(0.619)	(0.903)	(0.360)	(0.438)	(6.190)	(11.549)	(14.577)	(16.763)	(8.672)	(14.265)
2	0.709***	2.065***	1.496***	1.946**	0.641*	0.413	-3.176	43.746***	46.563***	89.188***	17.668**	41.849**
	(0.258)	(0.702)	(0.560)	(0.815)	(0.362)	(0.585)	(6.290)	(12.270)	(13.769)	(15.590)	(8.514)	(18.122)
3	0.785***	1.284**	0.395	1.039	0.610	0.295	2.440	34.478**	40.256**	78.605***	7.556	56.293***
	(0.304)	(0.583)	(0.617)	(0.866)	(0.448)	(0.513)	(7.557)	(14.075)	(18.009)	(18.405)	(8.407)	(15.462)
4	0.318	0.790*	0.023	-0.022	0.449	-0.235	1.503	42.526***	43.141**	74.563***	15.603*	44.262**
	(0.313)	(0.468)	(0.602)	(0.684)	(0.377)	(0.670)	(8.148)	(14.111)	(17.024)	(16.162)	(9.371)	(17.429)
5	0.240	1.958**	1.635**	1.046	0.383	1.087	0.025	42.592**	45.344**	66.503***	17.931*	43.249**
	(0.329)	(0.794)	(0.673)	(0.769)	(0.448)	(0.680)	(8.881)	(17.175)	(18.189)	(18.496)	(9.547)	(17.806)
6	0.475	1.984***	1.609**	1.631*	0.345	-1.010	1.838	59.939***	66.442***	86.092***	18.237*	71.531***
	(0.381)	(0.755)	(0.735)	(0.839)	(0.481)	(0.641)	(10.011)	(19.450)	(20.456)	(19.774)	(10.404)	(20.027)
7	0.563	1.876**	1.024	1.668	1.002**	-0.330	-4.450	59.572***	67.266***	85.185***	21.300*	51.466***
	(0.379)	(0.728)	(0.767)	(1.100)	(0.506)	(0.637)	(9.888)	(17.838)	(20.430)	(22.888)	(11.080)	(19.637)
Constant	0.672	-0.310	0.054	0.142	1.063*	1.797**	12.902	-9.677	-14.039	-39.265	-2.320	-23.799
	(0.608)	(0.928)	(0.958)	(0.813)	(0.634)	(0.800)	(23.475)	(29.615)	(36.102)	(36.152)	(17.459)	(28.047)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,411	15,536	12,451	8,272	36,177	10,009	24,316	8,364	6,826	4,526	18,429	5,345
Number events	18	8	7	5	12	4	18	8	7	5	12	4
Mean of dep. var.	17.79	17.76	17.25	15.80	18.09	17.43	501.32	567.72	587.87	529.76	503.50	539.28
R-squared	0.005	0.007	0.008	0.010	0.005	0.010	0.005	0.013	0.017	0.023	0.005	0.015

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 28: Different event definitions: Effects of shocks to transaction risk. Dep.var.: Quantity in grams

	Cannabis						Opioids					
	(1) SD $\geq$ 25	(2) SD $\geq$ 30	(3) SD $\geq$ 35	(4) SD $\geq$ 40	(5) Peak $\geq$ 25	(6) Exogenous	(7) SD $\geq$ 25	(8) SD $\geq$ 30	(9) SD $\geq$ 35	(10) SD $\geq$ 40	(11) Peak $\geq$ 25	(12) Exogenous
Pre-event weeks:												
-7	32.509*	34.229*	3.027	-38.819	31.649	51.497	-9.182	-9.136	-0.237	-7.815	-7.899	2.064
	(16.864)	(17.462)	(17.193)	(84.973)	(21.047)	(47.777)	(9.429)	(9.721)	(2.564)	(9.361)	(5.912)	(8.673)
-6	-5.484	-13.623	-77.815	-91.241	-25.506	-71.790	-12.639	-5.436	5.135	0.647	-9.472	5.913
	(14.507)	(35.444)	(53.433)	(64.446)	(23.581)	(59.889)	(10.604)	(14.835)	(4.760)	(13.759)	(6.933)	(7.347)
-5	-8.720	-71.167*	-86.449**	-224.989***	-6.936	57.581	1.451	-18.166	-7.582	-20.416	-5.070	-6.476
	(14.133)	(36.433)	(44.007)	(68.346)	(20.337)	(48.554)	(10.517)	(19.456)	(8.835)	(17.803)	(6.468)	(4.975)
-3	-17.779**	-32.423	-29.024	-46.424	58.582***	82.542**	-0.090	7.903	6.291*	2.438	2.068	8.341
	(7.619)	(20.445)	(29.951)	(102.758)	(15.843)	(35.803)	(2.872)	(5.158)	(3.595)	(4.242)	(5.689)	(6.901)
-2	-23.616*	-100.167**	-66.091	-23.395	-33.523	42.971	-2.971	-8.207	-4.945	-5.453	-3.919	-0.795
	(12.969)	(42.755)	(45.774)	(39.436)	(23.121)	(48.364)	(4.997)	(7.187)	(3.853)	(5.703)	(3.745)	(4.681)
-1	19.328	47.030	-2.008	-29.702	28.102	-1.218	0.164	-2.295	-2.463	-9.934	0.031	3.666
	(18.168)	(38.216)	(49.617)	(38.564)	(18.237)	(38.175)	(6.689)	(5.702)	(2.519)	(7.738)	(3.053)	(8.863)
Post-event weeks:												
0	7.354	-1.573	-64.773	-75.014	42.738***	84.531***	-2.063	-1.968	2.071	-2.931	1.340	3.308
	(18.861)	(59.673)	(80.536)	(53.270)	(13.319)	(31.784)	(4.198)	(5.173)	(3.320)	(4.981)	(5.244)	(6.602)
1	-28.002	-53.522	-86.775	-160.204***	-19.155	41.510	0.008	5.601	6.282	5.566	9.483	5.591
	(25.708)	(44.370)	(55.815)	(49.255)	(20.192)	(27.521)	(2.288)	(4.586)	(10.716)	(9.839)	(9.244)	(8.805)
2	-1.471	-17.291	-47.798	-100.519**	14.473	51.402	6.623*	7.444	10.165	15.476	1.323	7.729
	(26.734)	(40.080)	(54.281)	(40.131)	(22.454)	(46.096)	(3.396)	(9.035)	(14.075)	(18.244)	(6.137)	(7.547)
3	-35.442	-85.378	-136.303*	-184.283***	4.048	-26.110	3.095	4.858	2.561	-0.042	10.673	-0.160
	(27.195)	(59.226)	(81.492)	(49.696)	(18.515)	(46.441)	(2.770)	(4.530)	(7.204)	(7.643)	(10.242)	(6.067)
4	-5.054	-13.595	-40.651	-24.223	16.445	13.322	5.270*	10.314	11.848	7.584	5.680	15.224
	(30.019)	(57.491)	(75.037)	(51.525)	(21.879)	(52.232)	(2.963)	(6.906)	(13.813)	(9.155)	(7.705)	(16.584)
5	16.116	16.136	-12.616	-16.508	41.441*	-14.707	4.190	9.261	11.557	1.479	11.711	21.576
	(31.725)	(59.085)	(67.249)	(48.236)	(24.137)	(57.529)	(4.068)	(12.196)	(17.385)	(6.989)	(10.908)	(24.375)
6	-31.442	-70.134	-107.646	-83.354	23.571	2.180	4.743	6.319	10.259	9.845	1.506	6.094
	(34.427)	(58.746)	(68.093)	(53.033)	(26.225)	(54.042)	(3.999)	(5.788)	(11.193)	(8.438)	(7.243)	(14.360)
7	17.641	13.080	5.307	-63.129	38.158	118.960**	7.107*	11.110	15.160	14.452	4.365	6.794
	(34.695)	(50.591)	(62.820)	(47.902)	(27.762)	(59.012)	(4.156)	(13.393)	(19.050)	(17.592)	(7.571)	(11.403)
Constant	-141.396*	-101.640	-72.001	-60.180	-132.604*	-155.886**	-11.876**	-11.953**	-11.845	-6.731	-21.712**	-16.851
	(76.672)	(89.548)	(96.728)	(82.384)	(69.699)	(76.593)	(4.624)	(5.803)	(9.195)	(5.788)	(9.851)	(11.705)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,097	35,607	29,072	19,432	75,616	21,851	52,653	18,573	15,256	10,177	39,099	11,387
Number events	18	8	7	5	12	4	18	8	7	5	12	4
Mean of dep. var.	236.87	313.75	337.20	227.47	270.20	257.74	22.52	18.85	7.70	6.76	24.37	8.02
R-squared	0.001	0.002	0.002	0.003	0.002	0.002	0.004	0.002	0.002	0.002	0.001	0.002

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 29: Different event definitions: Effects of shocks to transaction risk. Dep.var.: Vendor rating in percentage points

	Cannabis						Opioids					
	(1) SD ≥ 25	(2) SD ≥ 30	(3) SD ≥ 35	(4) SD ≥ 40	(5) Peak ≥ 25	(6) Exogenous	(7) SD ≥ 25	(8) SD ≥ 30	(9) SD ≥ 35	(10) SD ≥ 40	(11) Peak ≥ 25	(12) Exogenous
Pre-event weeks:												
-7	0.298**	0.461*	0.536*	-0.269	0.404**	0.572	0.739***	1.104**	0.924**	1.307	0.171	0.955
	(0.134)	(0.269)	(0.317)	(0.822)	(0.160)	(0.491)	(0.239)	(0.529)	(0.389)	(0.901)	(0.257)	(0.716)
-6	-0.052	0.433	0.344	-0.569	0.422**	-0.049	-0.038	0.150	0.023	0.335	0.482**	-0.255
	(0.139)	(0.338)	(0.363)	(0.809)	(0.177)	(0.936)	(0.216)	(0.526)	(0.592)	(1.025)	(0.199)	(1.128)
-5	-0.178*	0.234	0.226	0.210	0.204	0.236	-0.057	0.245	0.268	1.189	-0.163	-0.100
	(0.101)	(0.272)	(0.265)	(0.527)	(0.152)	(0.391)	(0.139)	(0.499)	(0.525)	(0.890)	(0.227)	(0.641)
-3	0.021	-0.035	-0.489	-0.587	0.110	-0.453	0.557***	-0.278	-0.536	0.316	0.009	-0.437
	(0.100)	(0.321)	(0.426)	(0.949)	(0.169)	(0.445)	(0.151)	(0.408)	(0.626)	(1.233)	(0.216)	(0.579)
-2	-0.200*	0.108	-0.175	-0.694	0.334**	-0.226	0.196	0.637	0.360	0.783	0.143	0.705
	(0.110)	(0.267)	(0.321)	(0.766)	(0.152)	(0.459)	(0.207)	(0.516)	(0.599)	(1.110)	(0.196)	(0.499)
-1	-0.261*	-0.034	0.135	-0.476	-0.015	-0.212	0.086	0.487	0.301	0.765	0.322	-0.343
	(0.141)	(0.351)	(0.250)	(0.677)	(0.133)	(0.491)	(0.230)	(0.429)	(0.305)	(0.885)	(0.218)	(0.553)
Post-event weeks:												
0	-0.115	-0.122	-0.447	-0.996	0.036	-0.010	-0.158	-0.300	-0.486	-0.030	-0.255	-0.059
	(0.146)	(0.343)	(0.381)	(0.651)	(0.153)	(0.530)	(0.220)	(0.559)	(0.525)	(0.885)	(0.184)	(0.590)
1	-0.314**	-0.287	-0.625	-1.150	-0.101	-0.309	0.017	-0.088	-0.113	0.085	-0.114	0.151
	(0.148)	(0.282)	(0.390)	(0.724)	(0.181)	(0.422)	(0.172)	(0.417)	(0.585)	(0.957)	(0.217)	(0.510)
2	-0.495***	-0.179	-0.444	-0.818	-0.186	-0.842*	-0.554***	-0.050	-0.204	0.087	-0.411**	-0.552
	(0.165)	(0.373)	(0.467)	(0.866)	(0.183)	(0.510)	(0.158)	(0.414)	(0.547)	(1.013)	(0.193)	(0.578)
3	-0.407**	-0.657*	-0.907*	-0.957	-0.314*	-0.558	-0.519**	-0.123	-0.212	0.791	-0.294	-0.120
	(0.186)	(0.391)	(0.513)	(0.880)	(0.172)	(0.459)	(0.218)	(0.567)	(0.622)	(1.014)	(0.203)	(0.558)
4	-0.506**	-0.604	-1.034**	-1.577*	-0.406**	-0.723	-0.472**	-0.210	-0.327	0.242	-0.709***	-1.150*
	(0.203)	(0.381)	(0.481)	(0.852)	(0.195)	(0.521)	(0.228)	(0.539)	(0.604)	(0.993)	(0.233)	(0.662)
5	-0.526**	-0.129	-0.383	-0.989	-0.457**	-0.122	-0.544**	-0.340	-0.477	0.034	-0.371*	-0.321
	(0.232)	(0.423)	(0.477)	(0.835)	(0.181)	(0.471)	(0.262)	(0.598)	(0.622)	(1.051)	(0.208)	(0.601)
6	-0.473*	-0.296	-0.543	-1.285	-0.619***	-0.405	-0.433	-0.359	-0.496	-0.452	-0.450*	-0.050
	(0.247)	(0.453)	(0.524)	(0.947)	(0.216)	(0.485)	(0.314)	(0.739)	(0.727)	(1.152)	(0.266)	(0.612)
7	-0.720***	-1.049*	-1.421**	-2.144**	-0.677***	-0.642	-0.603**	-0.431	-0.792	-0.700	-0.571**	0.119
	(0.267)	(0.575)	(0.641)	(1.072)	(0.226)	(0.503)	(0.298)	(0.666)	(0.709)	(1.155)	(0.272)	(0.554)
Constant	-0.317	-0.682	-0.838	-0.266	-0.335	-0.160	-0.917	-1.907	-2.069*	-2.192	-0.711	-1.129
	(0.434)	(0.639)	(0.829)	(1.014)	(0.298)	(0.593)	(0.743)	(1.204)	(1.250)	(1.420)	(0.638)	(0.931)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,871	19,376	15,178	10,008	50,398	13,129	33,309	10,426	8,228	5,406	26,591	7,023
Number events	18	8	7	5	12	4	18	8	7	5	12	4
Mean of dep. var.	97.01	96.81	96.99	97.14	96.28	96.84	96.90	96.82	97.80	97.59	96.42	97.39
R-squared	0.004	0.004	0.007	0.008	0.004	0.006	0.007	0.008	0.010	0.012	0.005	0.011

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 30: Linear Probability Model vs. Conditional Logit Model: Effects of shocks to holding risk.

	Cannabis						Opioids					
	(1) Entry LPM	(2) Entry LOGIT	(3) Exit LPM	(4) Exit LOGIT	(5) Fin. early LPM	(6) Fin. early LOGIT	(7) Entry LPM	(8) Entry LOGIT	(9) Exit LPM	(10) Exit LOGIT	(11) Fin. early LPM	(12) Fin. early LOGIT
Pre-event weeks:												
-7	0.019***	0.559***	-0.021***	-0.708***	-0.021***	-0.335**	0.034***	0.328	-0.026***	-0.491	-0.034***	-0.267
	(0.006)	(0.183)	(0.004)	(0.271)	(0.007)	(0.161)	(0.008)	(0.232)	(0.006)	(0.432)	(0.011)	(0.191)
-6	0.014**	0.606***	-0.012***	-0.253	-0.003	0.180	0.012	-0.039	-0.009	0.250	-0.031***	-0.245
	(0.006)	(0.175)	(0.004)	(0.293)	(0.006)	(0.149)	(0.009)	(0.243)	(0.006)	(0.479)	(0.011)	(0.225)
-5	0.036***	1.163***	-0.007**	-0.286	0.001	0.099	0.021***	0.392**	-0.006	0.264	-0.013*	0.026
	(0.005)	(0.119)	(0.003)	(0.238)	(0.004)	(0.108)	(0.008)	(0.172)	(0.005)	(0.410)	(0.008)	(0.199)
-3	-0.007	-0.062	0.003	-0.426*	0.012**	0.060	-0.016***	-0.405**	0.010**	0.319	0.010	0.056
	(0.004)	(0.156)	(0.003)	(0.246)	(0.005)	(0.114)	(0.006)	(0.200)	(0.004)	(0.340)	(0.008)	(0.184)
-2	-0.001	0.474***	0.016***	-0.365	0.023***	0.244*	-0.019**	-0.365	0.020***	0.499	0.010	-0.268
	(0.005)	(0.163)	(0.004)	(0.280)	(0.006)	(0.141)	(0.007)	(0.230)	(0.006)	(0.406)	(0.010)	(0.228)
-1	-0.004	0.521***	0.029***	0.208	0.030***	0.183	-0.017**	-0.346*	0.034***	0.800**	0.029**	-0.110
	(0.005)	(0.136)	(0.005)	(0.228)	(0.007)	(0.122)	(0.007)	(0.194)	(0.006)	(0.379)	(0.012)	(0.195)
Post-event weeks:												
0	-0.006	0.307*	0.009**	-0.207	0.036***	0.107	-0.021***	-0.328	0.021***	0.729**	0.039***	0.024
	(0.005)	(0.157)	(0.004)	(0.249)	(0.007)	(0.105)	(0.008)	(0.231)	(0.005)	(0.361)	(0.012)	(0.142)
1	-0.012**	0.105	0.013***	-0.113	0.042***	0.056	-0.029***	-0.631**	0.018***	0.356	0.047***	0.199
	(0.005)	(0.188)	(0.005)	(0.278)	(0.009)	(0.151)	(0.008)	(0.253)	(0.006)	(0.441)	(0.013)	(0.209)
2	-0.030***	-0.299	0.048***	0.807***	0.048***	0.012	-0.038***	-1.178***	0.057***	1.544***	0.052***	0.042
	(0.006)	(0.204)	(0.005)	(0.258)	(0.011)	(0.167)	(0.008)	(0.291)	(0.008)	(0.425)	(0.015)	(0.227)
3	-0.033***	-0.643***	0.068***	1.137***	0.062***	0.168	-0.039***	-1.260***	0.070***	1.739***	0.060***	0.086
	(0.006)	(0.198)	(0.006)	(0.263)	(0.012)	(0.150)	(0.008)	(0.275)	(0.009)	(0.423)	(0.017)	(0.245)
4	-0.048***	-1.145***	0.052***	1.441***	0.072***	0.302**	-0.046***	-1.408***	0.055***	1.751***	0.075***	0.058
	(0.006)	(0.214)	(0.006)	(0.266)	(0.013)	(0.149)	(0.009)	(0.330)	(0.008)	(0.441)	(0.019)	(0.194)
5	-0.056***	-0.904***	0.056***	0.555**	0.080***	-0.024	-0.066***	-2.041***	0.064***	1.524***	0.082***	-0.052
	(0.006)	(0.246)	(0.006)	(0.282)	(0.015)	(0.136)	(0.010)	(0.378)	(0.009)	(0.460)	(0.021)	(0.172)
6	-0.076***	-1.562***	0.094***	1.320***	0.095***	0.174	-0.076***	-2.229***	0.106***	1.939***	0.086***	-0.056
	(0.007)	(0.265)	(0.007)	(0.265)	(0.017)	(0.152)	(0.010)	(0.373)	(0.011)	(0.463)	(0.023)	(0.251)
7	-0.099***	-0.856***	0.091***	1.923***	0.105***	0.430**	-0.101***	-1.612***	0.084***	1.600***	0.111***	0.131
	(0.008)	(0.272)	(0.008)	(0.292)	(0.019)	(0.195)	(0.011)	(0.416)	(0.010)	(0.468)	(0.029)	(0.343)
Market price	0.006***	0.633***	0.011***	-0.257**	-0.008	-0.441***	-0.000	0.006***	0.000***	0.027***	-0.000	0.002
	(0.002)	(0.083)	(0.002)	(0.109)	(0.006)	(0.141)	(0.000)	(0.002)	(0.000)	(0.007)	(0.000)	(0.004)
Market supply	-0.000*	-0.006***	-0.000	0.006***	-0.000	0.005***	0.000	-0.012	0.000	0.033***	-0.001**	0.003
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.010)	(0.000)	(0.010)	(0.001)	(0.013)
Competitors	-0.000**	-0.030***	0.000	0.022***	0.001**	0.026***	-0.000	-0.053***	-0.000	0.041***	0.000	0.075***
	(0.000)	(0.003)	(0.000)	(0.004)	(0.000)	(0.005)	(0.000)	(0.008)	(0.000)	(0.013)	(0.001)	(0.020)
7-day SD of BTC	0.000**	0.059***	-0.001***	-0.093***	0.001	0.004	-0.000	0.038***	-0.001***	-0.109***	0.001	0.005
	(0.000)	(0.009)	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)	(0.025)	(0.001)	(0.019)
7-day SD of BTC lag 1	-0.000	0.021***	0.000	-0.045***	0.001*	-0.002	-0.000	0.013	0.000	-0.037**	-0.000	-0.002
	(0.000)	(0.008)	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)	(0.016)	(0.000)	(0.014)
7-day SD of BTC lag 2	-0.000	-0.005	0.000**	-0.011	0.000	0.003	0.001**	0.036***	0.000	-0.055***	0.000	-0.016
	(0.000)	(0.008)	(0.000)	(0.010)	(0.000)	(0.010)	(0.000)	(0.010)	(0.000)	(0.020)	(0.000)	(0.016)
7-day SD of BTC lag 3	0.000	0.047***	-0.002***	-0.073***	0.000	-0.013	-0.000	0.018*	-0.001***	-0.064***	0.001	0.018
	(0.000)	(0.007)	(0.000)	(0.011)	(0.000)	(0.013)	(0.000)	(0.009)	(0.000)	(0.019)	(0.001)	(0.016)
Constant	0.105***		-0.016		0.074		0.118***		0.023		0.198	
	(0.017)		(0.022)		(0.077)		(0.029)		(0.028)		(0.121)	
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,237	13,253	35,237	9,723	22,350	5,203	17,225	6,582	17,225	4,793	11,488	2,683
Mean of dep. var.	0.03	0.03	0.01	0.01	0.17	0.17	0.03	0.03	0.01	0.01	0.17	0.17
R-squared	0.034		0.055		0.026		0.034		0.054		0.026	
Pseudo-R-squared		0.246		0.378		0.136		0.213		0.408		0.147

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 31: Linear Probability Model vs. Conditional Logit Model: Effects of shocks to transaction risk.

	Cannabis						Opioids					
	(1) Entry LPM	(2) Entry LOGIT	(3) Exit LPM	(4) Exit LOGIT	(5) Fin. early LPM	(6) Fin. early LOGIT	(7) Entry LPM	(8) Entry LOGIT	(9) Exit LPM	(10) Exit LOGIT	(11) Fin. early LPM	(12) Fin. early LOGIT
Pre-event weeks:												
-7	0.046***	-0.024	-0.030***	0.000	-0.019	0.451	0.035***	-0.075	-0.037***	0.114	-0.044**	-0.152
	(0.009)	(0.062)	(0.006)	(0.000)	(0.012)	(0.377)	(0.014)	(0.072)	(0.011)	(0.148)	(0.021)	(0.589)
-6	-0.003	-1.861***	-0.021***	0.644**	-0.035**	-0.045	-0.031	-0.466	-0.016*	-0.223	-0.037*	0.483
	(0.016)	(0.510)	(0.007)	(0.299)	(0.016)	(0.400)	(0.021)	(0.555)	(0.008)	(0.696)	(0.020)	(0.399)
-5	-0.033*	-1.007***	-0.008	-1.621***	-0.020**	-0.836**	-0.059**	-0.776**	-0.006	-1.247**	0.006	0.384
	(0.018)	(0.227)	(0.006)	(0.599)	(0.008)	(0.333)	(0.024)	(0.378)	(0.011)	(0.548)	(0.013)	(0.415)
-3	-0.059***	-1.861***	0.015***	0.644**	0.010	-0.045	-0.065***	-0.466	0.015**	-0.223	0.022	0.448
	(0.015)	(0.510)	(0.004)	(0.299)	(0.009)	(0.329)	(0.019)	(0.555)	(0.007)	(0.696)	(0.014)	(0.437)
-2	-0.067***	-1.610***	0.009*	-0.668	-0.002	-0.607*	-0.069***	-0.837**	0.015	-0.964	0.038**	0.387
	(0.018)	(0.224)	(0.005)	(0.463)	(0.009)	(0.365)	(0.025)	(0.339)	(0.009)	(0.722)	(0.016)	(0.463)
-1	-0.046***	-0.468***	0.005	-0.302	0.023**	-0.336	-0.025	-0.173	0.018*	0.101	0.038**	0.087
	(0.010)	(0.120)	(0.004)	(0.354)	(0.009)	(0.301)	(0.017)	(0.140)	(0.009)	(0.301)	(0.016)	(0.469)
Post-event weeks:												
0	-0.085***	-1.013***	0.024***	0.643*	0.040***	-0.298	-0.063***	-0.163	0.031***	0.171	0.057***	0.317
	(0.014)	(0.249)	(0.006)	(0.360)	(0.011)	(0.299)	(0.019)	(0.272)	(0.011)	(0.466)	(0.017)	(0.424)
1	-0.128***	-1.665***	0.024***	-0.452	0.061***	0.291	-0.112***	-0.951**	0.035***	-1.214**	0.062***	0.269
	(0.019)	(0.180)	(0.007)	(0.438)	(0.011)	(0.314)	(0.028)	(0.407)	(0.012)	(0.543)	(0.018)	(0.527)
2	-0.141***	-0.993***	0.024***	-1.091***	0.069***	0.544*	-0.088***	-0.080	0.042***	-0.503	0.067***	0.457
	(0.018)	(0.181)	(0.007)	(0.329)	(0.012)	(0.298)	(0.028)	(0.247)	(0.015)	(0.511)	(0.017)	(0.434)
3	-0.158***	-0.991***	0.046***	0.914***	0.045***	-0.314	-0.137***	-0.452*	0.048***	-0.033	0.088***	0.666
	(0.020)	(0.232)	(0.010)	(0.252)	(0.013)	(0.339)	(0.029)	(0.265)	(0.016)	(0.614)	(0.021)	(0.462)
4	-0.192***	-1.988***	0.050***	0.421	0.054***	-0.287	-0.169***	-1.392***	0.064***	0.156	0.086***	0.276
	(0.020)	(0.220)	(0.009)	(0.269)	(0.012)	(0.250)	(0.029)	(0.331)	(0.017)	(0.524)	(0.018)	(0.318)
5	-0.204***	-1.134***	0.041***	-2.035***	0.079***	0.265	-0.132***	0.096	0.073***	-0.566	0.091***	0.048
	(0.021)	(0.187)	(0.009)	(0.764)	(0.017)	(0.242)	(0.033)	(0.371)	(0.021)	(0.700)	(0.021)	(0.288)
6	-0.280***	-1.101***	0.066***	1.856***	0.080***	-0.092	-0.234***	-0.762***	0.080***	0.015	0.117***	0.417
	(0.030)	(0.166)	(0.014)	(0.374)	(0.017)	(0.296)	(0.041)	(0.239)	(0.023)	(0.349)	(0.026)	(0.531)
7	-0.335***	-2.353***	0.068***	0.058	0.086***	-0.496	-0.287***	-1.335***	0.089***	-0.293	0.124***	-0.003
	(0.029)	(0.218)	(0.012)	(0.319)	(0.019)	(0.313)	(0.042)	(0.361)	(0.022)	(0.623)	(0.027)	(0.401)
Market price	-0.010*	-0.010	0.003	-1.570**	0.002	-0.317	0.000	0.014	0.000*	0.029*	-0.000	-0.015*
	(0.005)	(0.117)	(0.003)	(0.652)	(0.007)	(0.276)	(0.000)	(0.012)	(0.000)	(0.017)	(0.000)	(0.008)
Market supply	0.000***	0.004**	-0.000	0.047***	-0.000	-0.001	0.001	-0.007	-0.001***	-0.066	-0.002**	-0.054**
	(0.000)	(0.002)	(0.000)	(0.011)	(0.000)	(0.004)	(0.001)	(0.028)	(0.000)	(0.053)	(0.001)	(0.024)
Competitors	-0.000	-0.052***	-0.000*	0.139***	0.000	0.053***	-0.001	-0.095***	-0.001**	0.039	-0.000	0.077***
	(0.000)	(0.006)	(0.000)	(0.040)	(0.000)	(0.008)	(0.001)	(0.017)	(0.000)	(0.025)	(0.001)	(0.018)
Number of arrests	0.003	-0.138***	-0.000	1.259***	-0.000	0.053**	-0.003	-0.357**	-0.000	0.536	0.000	0.079***
	(0.002)	(0.045)	(0.001)	(0.314)	(0.001)	(0.023)	(0.002)	(0.175)	(0.001)	(0.343)	(0.001)	(0.028)
Number of arrests lag 1	0.015***	0.354***	-0.004***	-2.290***	0.000	0.084***	0.016***	0.464	-0.006**	-1.112***	-0.001	0.043
	(0.003)	(0.059)	(0.001)	(0.648)	(0.001)	(0.023)	(0.004)	(0.289)	(0.002)	(0.308)	(0.001)	(0.028)
Number of arrests lag 2	-0.020***	-0.092	0.001	-3.412***	-0.000	0.045**	0.003	0.483	-0.009**	-1.934***	-0.000	0.041
	(0.004)	(0.096)	(0.001)	(0.795)	(0.001)	(0.022)	(0.006)	(0.405)	(0.004)	(0.455)	(0.001)	(0.028)
Number of arrests lag 3	-0.037***	-0.193*	0.011***	-3.030***	-0.002**	-0.026	-0.008	0.257	-0.003	-1.553***	-0.001	0.027
	(0.005)	(0.100)	(0.003)	(0.727)	(0.001)	(0.026)	(0.006)	(0.408)	(0.005)	(0.456)	(0.001)	(0.030)
Constant	0.351***		0.004		0.010		0.269***		0.043**		0.212*	
	(0.037)		(0.012)		(0.107)		(0.046)		(0.021)		(0.125)	
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,450	4,027	11,450	1,162	9,859	2,281	6,277	2,152	6,277	840	5,311	1,398
Mean of dep. var.	0.11	0.11	0.01	0.01	0.13	0.13	0.11	0.11	0.01	0.01	0.13	0.13
R-squared	0.123		0.038		0.045		0.103		0.032		0.047	
Pseudo-R-squared		0.345		0.736		0.326		0.399		0.381		0.339

Notes: The fourth week before the event is used as the base period. *Market controls* are binary variables that indicate if the vendor was active on the eight observed markets. *Market price* is a control for the average price of other vendors in week t. *Market supply* is a control for the average quantity offered by other vendors in week t. *Number competitors* controls for the number of vendors selling in the same product category. The mean of the dependent variable refers to the base period. Robust standard errors are clustered on the vendor level and shown in parentheses. Stars indicate statistical significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.