Multi-homing sellers and loyal buyers on darknet markets

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June 15, 2018

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Master Thesis for the master of Business Information Management

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Abstract

The trade in illicit drugs via darknet markets has risen vastly over the past years. Forced shutdowns of markets by the government have not deterred buyers and sellers but only displaced them to different markets. This paper analyzed the effect of multi-homing in a shutdown market on a sellers sales performance in a surviving market in the period after a shutdown. The results indicate that multi-homing sellers who multi-homed in the shutdown market significantly increase in sales relative to both multi-homers who were active in other markets and single-homers. This evidence suggests that buyers are loyal to a multi-homing seller even when they have to switch markets. The effect is conditional on the reputation of a seller in the shutdown market, which indicates that reputation influences buyers in their decision to remain loyal.

1 Introduction

Darknet markets orchestrate the anonymous trade of illicit goods of which the majority (70%) are cannabis-, ecstasy- and cocaine-related products (Soska & Christin, 2015). Selling and buying drugs via these online markets have become increasingly popular over the past years. The most popular market in 2013, Silk Road, generated approximately 300,000 US $ in daily revenues, whereas the most popular market in 2017, Alphabay, generated roughly 800,000 US $ a day (Soska & Christin, 2015; Popper, 2017). This trend towards sales via darknet markets could mean a disruptive shift away from current drugs distribution channels and could reduce governments ability to control the drug trade (Décary-Hétu & Giommoni, 2017).

The markets can flourish because they provide superior anonymity to both buyers, sellers and the platform itself (Soska & Christin, 2015). The markets are hosted on the darknet and can only be accessed via the Tor or I2P browser (Singh, 2014). Buyers pay with Bitcoins and communicate via encrypted messages with sellers. Due to these anonymity measures, it is difficult for law enforcement to shut down the platforms or arrest individual sellers.

Law enforcement has succeeded in the shutdown of a few big markets, among others Silk Road 1 in 2013, Silk Road 2 in 2014 and Alphabay in 2017. However, these shutdowns did not deter sellers and buyers from transacting with each other but only lead to displacement and increased activity in other markets (Soska & Christin, 2015; Décary-Hétu & Giommoni, 2017). The darknet market ecosystem as a whole continued to increase in size despite the shutdowns.

International agencies call for better understanding of darknet markets to be able to formulate successful strategies to combat this new form of drug distribution (EUROPOL, 2014; UNODC, 2014). This paper aims to increase the knowledge on buyer and seller behavior on darknet markets. Specifically, this paper is interested in whether buyers who switch market after a shutdown tend to buy at a seller they already bought from in the market which got shut down.

This question has emerged from the combination of multiple topics mentioned in the emerging literature on darknet markets. These topics are multi-homing sellers, loyal buyers, the importance of reputation and the displacement of buyers in the aftermath of shocks.

Multi-homing - the simultaneous participation in multiple (competing) markets or platforms - is common among sellers in darknet markets. Soska and Christin (2015) show, by linking usernames of sellers across different markets, that sellers can be active on one up to six markets. Sellers who affiliate themselves with only one market are defined as single-homers. Multi-homing provides sellers access to a larger share of the total market, especially when the buyers do not multi-home (Rochet & Tirole, 2006), and reduces platform orchestrator dependency (Hyrynsalmi et al., 2016a)[1]. Platform-independent sellers on the darknet markets might be able to continue sales despite market downtime issues or shutdowns (Soska & Christin, 2015). There does not exist any empirical evidence that multi-homing improves seller performance in the context of darknet markets nor in any other context.

Buyer loyalty is the tendency of buyers to repeatedly choose the same seller for purchases, despite the presence of alternative sellers (Décary-Hétu & Quessy-Doré, 2017). In a study focused on the Evolution market, Décary-Hétu and Quessy-Doré (2017), find that buyers purchase on average 60% of the time at the same seller. Although buyer names are entirely anonymous on many darknet markets, the names are partly anonymous on Evolution, allowing the authors to identify buyer-seller ties.[2] Their results further indicate that the level of information provided by the seller increases loyalty, whereas other seller related characteristics, including reputation, do not seem to play a role. However, previous literature suggests that reputation could influence the decision to remain loyal to a seller (Valvi & Fragkos, 2012).

Reputation systems, in the form of ratings and written reviews, are self-enforcing mechanisms which allow spontaneous transactions on the darknet markets to happen (Hardey & Norgaard, 2016). Positive reputations allow sellers to ask a price premium (Janetos & Tilly, 2017) and increases demand (Armona, 2017; Bhaskar et al., 2017). Since all interactions only happen online, the reputation is an essential factor in establishing trust between a seller and buyer (Armona, 2017). A tiny percentage of transactions receive low ratings and sellers with negative reviews will have to face a decrease in sales. Sellers with low reputations eventually tend to leave the market (Bhaskar et al., 2017).

Buyers tend to switch markets in the aftermath of a shutdown, but it is unclear how they choose new markets and sellers. It would be possible that loyal buyers choose for their multi-homing seller in a surviving market. It is not possible to track specific buyers across

[1]Hyrynsalmi et al. (2016a) discuss the multi-homing strategy in their paper and refer to the source Idu, van de Zande & Jansen, 2011 when they mention the benefit of platform orchestrator dependency, without further explaining this benefit. However, when one checks the paper of Idu, van de Zande & Jansen (2011) one cannot find any discussion of this independence. Their paper does discuss how developers on the Apple sub-ecosystem which include the App Store for iPhone, iPad, and Mac, can benefit from portability between these sub-ecosystems.

[2]On Evolution the buyer name in product feedbacks is listed in the following format $a^{**}s$, with the first and last letter revealed while the in-between letters and length of the name are hidden. Based on name and letter distributions Décary-Hétu and Quessy-Doré (2017) calculated the chance that a buyer would be the same buyer.

markets because their usernames are entirely anonymous in most markets. However, it is possible to evaluate weekly sales figures sellers. An influx of new buyers is a likely driver for an increase in sales. This paper hypothesizes that multi-homers who were active in the shutdown market will face an increase in sales in a surviving market in the period after a shutdown. The effect is expected to arise because these sellers had loyal buyers in the shutdown market who continue to be loyal to the seller in a surviving market. The degree to which buyers choose for the multi-homer seller might be depending on the reputation the seller had in the shutdown market before the shutdown.

The research questions of this paper can be summarised as follows:

1. Does multi-homing in a market which gets shutdown lead to an increase in seller performance in a surviving market after the shutdown?

2. Is the effect of multi-homing on performance conditional on the reputation of the seller in the shutdown market?

This paper focuses on the two biggest darknet markets in 2014-2015: Agora and Evolution. The shutdowns utilized are the government take-down of Silk Road 2 on 6 November 2014 and the exit-scam of Evolution on 18 March 2015. Weekly sales revenue and sales quantities are used as performance measures. A difference-in-difference model is used to compare multi-homers in the shutdown market with multi-homers in other markets as well as single-homers in the weeks before and after the shock. These different control groups are used because single-homers might face different growth trends whereas multi-homers who multi-home in other markets might be more similar to the multi-homers who multi-home in the shutdown market. The model also tests whether the impact of multi-homing is conditional on the reputation in the shutdown market.

The main results of this paper indicate that multi-homing sellers, who participated in the shutdown market, increase significantly in sales in a surviving market after the shutdown. These results suggest that buyer loyalty extends across markets and that these sellers have been consciously chosen by buyers in the aftermath of a shutdown. The effect of multi-homing is conditional on the reputation of the seller in the shutdown market. This result suggests that buyers are influenced by reputation in their decision to remain loyal or sellers with lower reputations did not have a large customer base to transfer to a surviving market. Multi-homers who multi-homed in the shutdown market outperformed both multi-homers who multi-homed in other markets and single-homers.

The above-mentioned findings are novel to the academic literature on economic behavior on darknet markets. Although the results imply that shutdowns of markets are not sufficiently effective in removing buyer-seller ties, it does provide some predictability on buyer movements after shutdowns. Governments can use this predictability to track down buyers and sellers more easily. The results suggest that multi-homing sellers are an important type of seller in the online drugs market ecosystem and should receive prioritization in the seller take-down efforts of the government.

This paper contributes to the general literature on multi-homing by being the first to empirically test whether multi-homing contributes to seller performance. The empirical approach used as well as the findings answer the call of Hyrynsalmi et al. (2017) to start building the academic literature on multi-homing and platform participant's performance.

The results imply that multi-homing is a strategy which at least pays off in the context of the darknet markets. The results might be specific to darknet markets in which trust could be more critical and market switching more frequent compared to other platform ecosystems. However, it does imply that firms and sellers in other platform ecosystems could take into account the stability of platforms and the likelihood of switching buyers in their assessment of the strategic choice to multi-home or not.

Furthermore, this paper suggests that firms and sellers should be careful with their reputation in multiple markets because their influence might spillover from one market to the other. Sellers in darknet markets tend to communicate their reputations in other markets via their profile description. Although this paper did not test the role of communication, it could have influenced the extent to which multi-homers were able to reap the benefits of multi-homing and switching buyers.

Platform orchestrators in ecosystems where multi-homing is common could help agents communicate their reputation achieved in other platforms more easily. An example from the darknet is Evolution which verifies sales of its sellers done on other markets and sellers can promote this verification as a signal of trust[3]. The approach of supporting multi-homing sellers in showcasing their multi-homing efforts could counterintuitively increase sales on the platform itself because it could increase trust between buyers and sellers.

The rest of the paper is structured as follows. Section 2 provides an introduction to darknet markets. Section 3 discusses the literature on multi-homing. Section 4 discusses the methodology. Section 5 describes the data. Section 6 explains the results. Section 7 discusses the implications of the results. Section 8 shares the limitations of this study and provides suggestions for future research. Section 9 concludes this paper.

2 Darknet markets

This subsection aims to provide a concise introduction to darknet[4] markets which helps to grasp the context of this study. Darknet markets are two-sided platforms which allow buyers and sellers to exchange goods and money. The difference with a platform like eBay is that a darknet market focuses on illegal goods. The majority (70%) are cannabis-, ecstasy- and cocaine-related products. Most markets offer a wide range of products, but some markets specialize in drugs, weapons or counterfeits (Soska & Christin, 2015). The platform generates revenues through a commission on transactions and an entrance fee for sellers.

The user interface of markets on the darknet mimics the interfaces of legal e-commerce

[3]See page 38 Figure 11 for a screenshot of this function.

[4]Other terms for darknet markets used in the literature are black markets (Baskhar et al, 2017), cryptomarkets (Martin, 2014) or online anonymous marketplaces (Soska & Christin, 2015).

websites (Gilbert & Dasgupta, 2017). See Figure 1 for the interface of the Evolution market. At the same time aggregators such as Grams exist which enable buyers to search through all marketplaces at the same time (Figure 2).

Figure 1: Interface of the Evolution market

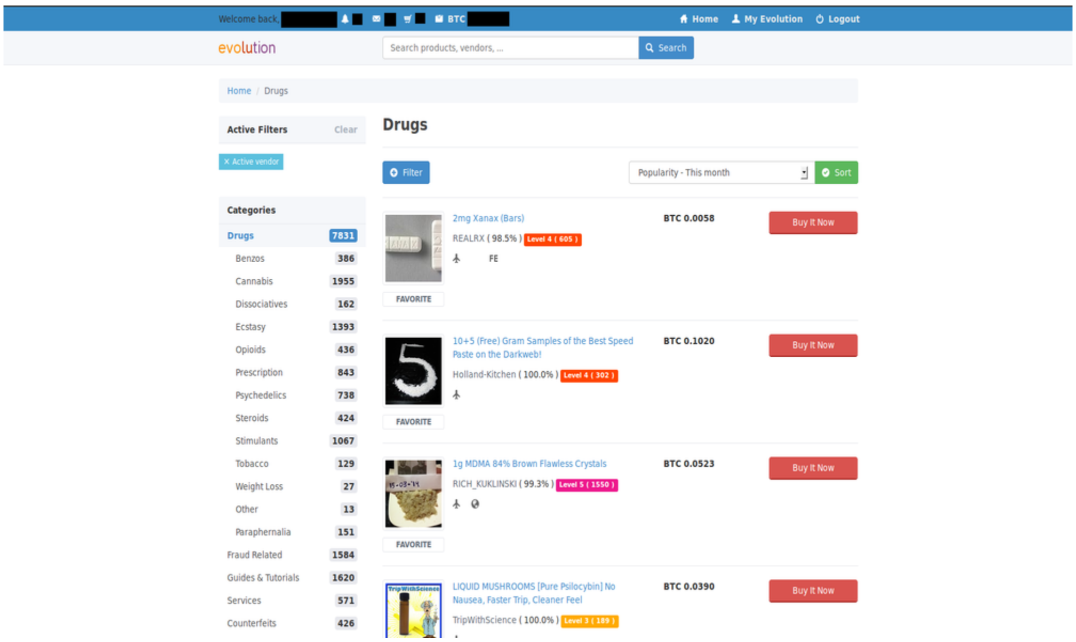
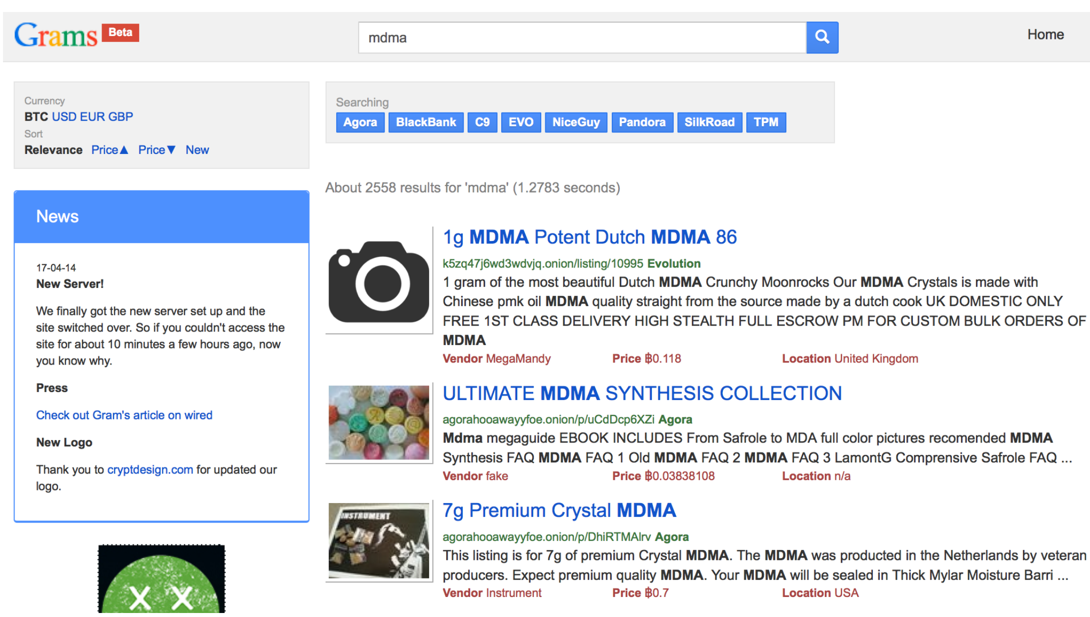


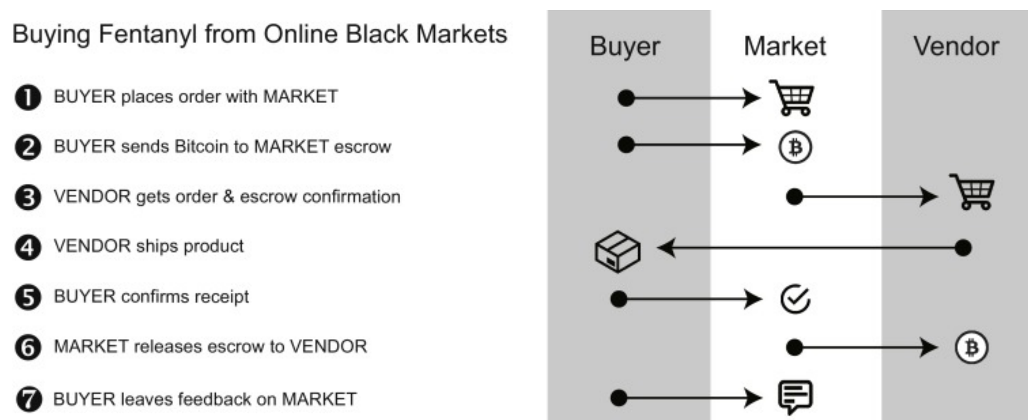
Figure 2: A metasearch engine for the darknet markets



Due to the illegal nature of the products, darknet markets are designed to provide anonymity to its users. The markets operate from the darknet, which is intentionally hidden and inaccessible through standard web browsers. The darknet can be accessed via the Tor or I2P browser (Singh, 2014) and Bitcoin is used as the payment system. Silk Road, which opened in February 2011, was the first darknet market which could provide anonymity in a superior way compared to existing online or offline commerce options (Soska & Christin, 2015).

According to Soska and Christin (2015), the darknet market has as the primary function to manage risks for its users while they participate in transactions. The risk is mitigated in four ways. Firstly, physical interactions are abolished to eliminate physical violence during transactions. Secondly, superior anonymity guarantees are provided, compared to other modes of transactions, which should protect the users from government intervention. Third, financial risk is limited via the use of an escrow system. With an escrow system, payments are stored in a separate account until the receiving party confirms that his order has arrived, after which the market releases the payments to the seller. The process of buying drugs on a darknet market is depicted in Figure 3. Fourth, users are required to provide feedback on the quality of goods received.

Figure 3: The process of buying drugs on a darknet market. *Source: Gilbert and Dasgupta (2017)*



The feedback system is a crucial mechanism for a darknet market to function. The anonymity provided by the marketplace might result in moral hazard from the seller, who would feel more comfortable scamming its customers. However, only a small percentage of all darknet market transactions receive negative ratings. Sellers with bad ratings sell less and eventually exit the market (Bhaskar et al., 2017). At the same time, the feedback system is an opportunity for researchers to estimate the size of the darknet markets. One can build a revenue figure by combining reviews with the selling price of the product on the day of the review[5].

[5]This paper will elaborate on this approach in the data section on page 22.

2.1 Market shutdowns and ecosystem growth

Market shutdowns in the darknet market ecosystem happen via government take-downs (e.g., Silk Road), scams (e.g., Evolution), voluntarily retreats (e.g., Agora) or hacks (e.g., Black Market Reloaded). See Bhaskar et al. (2017) for a full list of market entries and exits. Soska and Christin (2015) find that the government take-down of Silk Road in October 2013 sparked the growth of the darknet market ecosystem. The government attention for Silk Road most likely increased public awareness on the possibility to buy drugs via these darknet markets (Bearman, 2015).

Silk Road 2 arose in November 2013 but got shut down by the government in the so-called 'Operation Anonymous' in November 2014. Besides Silk Road 2, also smaller markets where taken down in this police operation. Décary-Hétu and Giommoni, 2017 studied the impact of this take-down, but find a limited impact of Operation Anonymous on sales volumes. They find that prices in the ecosystem remained the same, while few sellers from the shutdown market moved to other markets and many of the sellers retired after the shutdown. Buyers displaced to other markets and concentrated on fewer sellers. The authors suggest that market seizures might not be a worthwhile investment. Agora and Evolution became the new market leaders after the shutdown of Silk Road 2.

The growth of the ecosystem can be captured in the following numbers. In May 2011, Silk Road had 343 drugs listings, and in October 2013 the market featured 13,000 drugs listings (Digital Citizen's Alliance, 2014). Soska and Christin (2015) estimate that Silk Road grossed roughly 300,000 US $ a day in sales in 2013. Agora and Evolution generated together between 500,000 US $ and 6000,000 US $ in daily revenues in the year 2014 (Soska & Christin, 2015).

Evolution exited in March 2015 with a scam, stealing Bitcoins held in escrow, equivalent to 12 million US $. Agora announced in August of 2015 that it would quit and gave its users the opportunity to withdraw their funds before their final exit (Bhaskar et al., 2017). At the time of exit Agora listed 20,000 different products on its website (Greenberg, 2015). Alphabay grew since then, reaching roughly 800,000 US $ in daily transaction revenues and more than 400,000 users (Popper, 2017). In July 2017, the US and Dutch authorities shut down Alphabay. The remaining markets filled its void and exhibited significant increases in traffic (Kelion, 2017).

No one knows the current size of the darknet market ecosystem, but when one reflects on the growth of the ecosystem in the past years and the way that legal commerce has moved to e-commerce, one would expect the significant growth of darknet markets to continue.

2.2 Loyalty

Décary-Hétu and Quessy-Doré (2017) investigate whether buyers are repeatedly buying at the same sellers in the Evolution market. They define loyal behavior as the act of multiple transactions with the same seller in different time periods while the buyer has alternative sellers at its disposal. Sellers can convert their buyers to repeat buyers when a purchase meets the buyer expectations (Oliver, 1997). Sellers on darknet markets tend to generate longer-term relationships by providing favorable shipping and refund policies (Aldridge & Askew, 2016).

On Evolution the buyer name in product feedbacks is listed in the following format $a^{**}s$, with the first and last letter revealed while the in-between letters and length of the name are hidden. See Figure 8 on page 23 for an example of the buyer username in feedback on Evolution. Based on name and letter distributions Décary-Hétu and Quessy-Doré (2017) calculated the chance that a buyer would be the same buyer.

Their research consisted of firstly determining the buyer's loyalty level and secondly to predict the loyalty of the buyers per seller based on the seller's characteristics. They measure buyers loyalty by i) the average number of sellers purchased from and ii) the average largest share of transactions made by repeat buyers at a single seller. Characteristics used to predict a seller's loyalty are the seller's experience as indicated by the number of days since their registration date, the seller's rating, level, length of profile description, length of their product descriptions, whether the seller provided an e-mail address or not, and the number of customers in a sellers network.

Décary-Hétu and Quessy-Doré (2017) find that repeat buyers also make purchases from other sellers but, on average they buy about 60% of their purchases in each product category at the same seller. Loyalty does not necessarily mean a full commitment to only one seller, but a significant proportion of total sales should be concentrated in one seller (Neal, 1999). Few repeat buyers in Evolution seem entirely loyal to one specific vendor.

Buyers might buy at multiple sellers for several reasons. Firstly, a buyer might not be able to buy the product from a seller, because this seller lacks supply. Secondly, a buyer might aim to reduce dependency on one seller. Thirdly, a buyer might switch to cheaper or superior products from a different seller.

At the same time, there are numerous reasons to stick with one seller. First of all, sticking with one seller protects a buyer against the risk of buying from an unknown seller which might scam the buyer. Besides, undercover agents might be part of the seller base, but these agents are unlikely to proceed with running fake drug account for a more extended period. Hence, a long-lasting buyer-seller relationship will most likely not end up in an arrest. Moreover, longer-term relationships reduce information asymmetry and increase the ability of a seller to meet a buyer's needs (Akerlof, 1970).

The results of Décary-Hétu and Quessy-Doré (2017) indicate that a seller can create more loyal buyers by providing more information about products and the seller itself. Also, they found that sellers with a large customer pool did necessarily have a loyal customer base. Reputation in the form of ratings or the time since the seller's registration on the market does not seem to influence the degree of loyalty in the customer base. This result is in contrast to previous research which finds that reputation and past satisfaction increase customer loyalty (Anderson & Srinivasan, 2003; Castaneda, 2010; Oliver, 1997; Valvi & Fragkos, 2012).

Décary-Hétu and Quessy-Doré (2017) argue that the presence of loyal customers, who continue to provide positive feedback to their seller, might explain the high level of positive reviews on darknet markets. The authors conclude that strong seller-buyer ties elevate trust in the market and might, therefore, be a driver of the rise of darknet markets.

2.3 Reputation and seller performance

Soska and Christin (2015) find that there is a large group (70%) of sellers who make a small yearly revenue of maximum $1,000. The authors expect that these sellers are experimenting on the market. The top 1% of the sellers contribute to 51.5% of the sales. They further investigate the sellers who earn more than $10,000 per year. Half of this group specializes in one type of product of which one-third in cannabis, one-third in digital goods and one-third in various product types. Concerning survival rates in the market, they find that half of the sellers are active in the market for 220 days or less and approximately 25% of the sellers remain active for years.

Hardy and Norgaard (2016) find a positive impact of seller rating on the price per gram for cannabis. Hence, higher rated vendors can extract a price premium. They study the Silk Road for an eleven-month period in 2013-2014. To control for other variables influencing the cannabis price per gram they include, whether free-shipping is available, the number of reviews, the weight of the product in gram, and the presence of premium quality related words in advertisement text.

Armona (2017) focuses on product demand and finds that the sentiment in product reviews and messages in the Agora community forum both increase the product demand to a similar extent. The effect of sentiment is stronger when the number of messages is larger.

Surprisingly, the paper also finds that messages of inexperienced users are more influential than experienced users. The messages of inexperienced users are longer and more informative than experienced users which might increase their influence. Agora works with a 0-5 star rating in combination with a text review. Armona (2017) notes that although star ratings are often five stars, the sentiment within these reviews has a wide range. The seller can dampen the reputation effect if he or she signals credibility by not requesting buyers to 'finalize early'. Without the 'finalize early' requirement, a buyer can assess the quality of the product before paying.

Armona (2017) controls for: the number of past deals of the seller, the average seller rating, missing seller rating indication, the price of the product, an indicator for no product rating, product category, product title text and product description text. Time fixed effects are used to control for aggregate market conditions such as stability of the TOR network, Bitcoin exchange rate and seasonal changes in sales. The study focuses on the Agora market in the year 2014.

Janetos and Tilly (2017) find the following three stylized facts: *"(i) there is a positive relationship between the price and rating of the seller. (ii) sellers with more reviews charge higher prices regardless of ratings. (iii) low-rated sellers are more likely to exit the market and make fewer sales"*. The study focuses on the Agora market from 2014-2015 (19 months) for the cannabis, MDMA, heroin, and cocaine products. Controls used are (a.o): dummies for the location the seller ships from, type of product on sale, the age of the vendor and time trends.

Bhaskar et al. (2017) work with a dataset covering the markets Silk Road, Silk Road 2, Agora, Evolution and, Nucleus. Sales revenue per month is used as a performance measure and the proportion of total negative feedback ratings of the previous month is used as the independent variable. Seller and time fixed effects are used as controls. They find that there are little moral hazard problems because only a small proportion of online drug purchases receive negative reviews. Low ratings lead to fewer sales for the seller and eventually a market exit. They note that the effect of rating on sales is most likely an underestimate because bad-rated sellers eventually exit the market and are not taken into account anymore. Furthermore, they conclude that the take-down of Silk Road 1 and 2, as well as the Evolution exit-scam, did not deter buyers and sellers from darknet markets.

Nurmi et al. (2017) test the impact of reputation and seller capacity on daily drug sales revenue. Reputation is measured as the difference between positive and negative reviews. Seller capacity is calculated as the sum of the values of all the seller's listed stock. The market investigated is the Finnish version of Silk Road studied, Silkkitie, in 2014-2015 (11 months). They find that reputation and seller capacity both have a positive impact on sales revenue. In addition, they note that many products were not sold at all and that a seller was active for on average 62 days.

3 Multi-homing

The literature on multi-homing tends to focus on the impact of multi-homing on the ecosystem. The literature provides arguments for benefits and cost of multi-homing on the firm level, but only Hyrynsalmi et al. (2016b, 2017) try to examine whether multi-homing firms outperform single-homing firms.

In an ecosystem where multiple platforms are available, platform participants can join only one platform or multiple platforms. These scenarios are respectively referred to as single-homing or multi-homing (Rochet & Tirole, 2003; Sun & Tse, 2009). Sun and Tse (2009) show, using systems models, that when all participants single-home, there will be only one large platform which survives. The platform participants become a crucial resource in this case. The platform orchestrator can pursue participants to be exclusively related to one platform (Eisenmann et al., 2006). Gabszewicz and Wauthy (2004) show, in a model of two platforms, that when all participants are allowed to participate on both platforms, multi-homing will take place, but only at one side of the market. When multi-homing is present, multiple platforms can be sustained. Multi-homing can reduce the resource advantage of a platform because the heterogeneity which the platform participant brings is also spread to the other platforms (Sun & Tse, 2009). Multi-homing hence undermines the ability of a platform to dominate the ecosystem. Landsman and Stremersch (2011) find that the multi-homing of games, in the video game industry, negatively affects the sales of the platform. This effect is dampened by platform maturity or market share. This study differentiates between seller-level multi-homing, where a seller participates in multiple markets, and platform-level multihoming, where the same product is offered at multiple markets, but the product is offered by different parties.

Eisenmann et al. (2006) state that for at least one participant side the multi-homing cost is high. They define homing costs as the expenses the participant faces to be able to maintain two platforms affiliations. Examples are product adoption, administrative, marketing cost as well as opportunity cost of time. Benefits are access to larger potential markets, especially if the other side of the market does not multi-home (Rochet & Tirole, 2006) and a reduction in platform orchestrator dependency (Hyrynsalmi et al. 2016).

Idu, van de Zande and Jansen (2011) research multi-homing behavior on the Apple sub-ecosystems. The authors sent surveys to developers in these ecosystems to understand why they are multi-homing. The primary strategic motivation for developers to multi-home was the increased customer base and the ease of portability between the platform. An app for the iPhone App Store can be ported with little resources to the iPad App Store for example. Additional benefits are that customers of the Apple sub-ecosystems tend to move between the platforms because they often own more than one device. In this way, the same customers can be supported across different platforms. Because customers are active on multiple platforms, the developer can increase its sales on one platform by entering another platform. Difficulties of multi-homing include that users expect the same product and benefits across platforms, but this might not be the case, resulting in unsatisfied customers. Negative reviews in one platform could influence the performance in another platform.

A few studies estimate the proportion of sellers who multi-home within a specific ecosystem. Boudreau (2008) finds that 1% of the developers in the mobile application ecosystem during 1999-2004 multi-homes. Hyrynsalmi et al. (2016a) study the mobile application ecosystem, consisting of Google Play, Apple App Store, and Windows Phone Store, for 2012-2013. They find multi-homing rates of 1.7-3.2% for applications and 5.8-7.2% for developers. An important finding is that for the top performing apps, 41-58% of the applications were multi-homing and 42-69% of the developers. Burkard et al. (2011) find that a small number of developers multi-home in the SaaS CRM Solution ecosystem.

For the darknet markets, Soska and Christin (2015) show that sellers participate in up to six different markets. They observe that a large number of seller participates in only one market, but note that a large number of sellers sells very small quantities. They suggest verifying whether top sellers are more diversified across marketplaces.

The literature on multi-homing and seller or firm performance is scarce. Hyrynsalmi et al. (2016b, 2017) are the only two papers which try to estimate whether multi-homing provides benefits to the firm. However, they state that they do look for an association, but do not examine causality. In a study on Finnish game industry, Hyrynsalmi et al. (2016b) classify firms into four groups based on their assets and revenues values and look within these groups which companies single-home and multi-home. Subsequently, they employ the Mann-Whitney U test to verify whether there is a significant difference between the single-homers and multi-homers. They do not find any significant difference and can therefore not state that multi-homing has a positive impact (on return on assets).

Hyrynsalmi et al. (2017) review the revenue growth of single-homers and multi-homers in a group of mobile application developers. They find that revenue growth is faster for single-homers. However, the number of multi-homers in their dataset is too low to draw any conclusion. They state that their paper serves as a starting point towards a research agenda examining the impact of multi-homing on the performance of a platform participant.

4 Methodology

Previous research has not tested a causal effect between multi-homing and seller or firm performance. Hyrynsalmi et al. (2016b, 2017) try to test whether there is an association, but not causation. Although they do not discuss the reasons why it is difficult to study for a causal relation, it might be important to shortly state these challenges in order to understand how this paper overcomes them.

Studying the impact of multi-homing on performance faces, regardless of the context, two major challenges which make the explanatory variable to be correlated with the error term. Firstly, there might exist reverse causation, i.e., seller performance might influence the decision to multi-home. High performing sellers might build up more savings which makes it easier to expand to additional markets. Secondly, there could be omitted variables which influence both multi-homing and performance. Examples are the seller's skills or long-term vision.

These endogeneity problems might be tackled if one can find an instrumental variable which influences multi-homing and not seller performance, create an experiment or leverage the presence of exogenous shocks. The literature does not provide suggestions for an instrumental variable, nor seems running an experiment where one assigns multi-homers and single-homers a feasible option.

This paper's focus is on the effect of multi-homing during shutdowns in the darknet market ecosystem and uses inherently to this focus the method of an external shock to solve the endogeneity problem. With the perspective of a surviving market after a shutdown, the shutdown creates three groups. The first group is the multi-homers who were present in the shutdown market and are hence the treatment group. The second groups are multi-homers who were not active in the shutdown market, but because they are multi-homers they provide a relevant control group. The third group is the single-homers who where, due to their nature of single-homing, not in the shutdown market and can also serve as an additional control group. Single-homers, however, can be regarded as different sellers because they did not choose to multi-home at all and might possess different unobserved characteristics.

After a shutdown buyers seem to switch to new markets (Soska & Christin, 2015; Décary-Hétu & Giommoni, 2017). Within a market, buyers are loyal to a specific seller on darknet markets (Décary-Hétu & Quessy-Doré, 2017). If the multi-homers who where multi-homing in the shutdown market increase in performance after the shock relative more than the control groups, it suggests that they saw a higher increase of buyers which might have shifted away from the shutdown market. This finding would provide evidence for a buyer loyalty stretching across markets.

Reputation is an important factor in steering transactions on the darknet market (Hardy & Norgaard, 2015; Armona, 2017; Bhaskar et al., 2017) and previous research suggests that reputation can a be factor which influences buyers in their decision to remain loyal (Valvi & Fragkos, 2012). Therefore, it might be that the relation between multi-homing in the shutdown market and sales in the surviving market after the shock is dependent on the reputation of the seller.

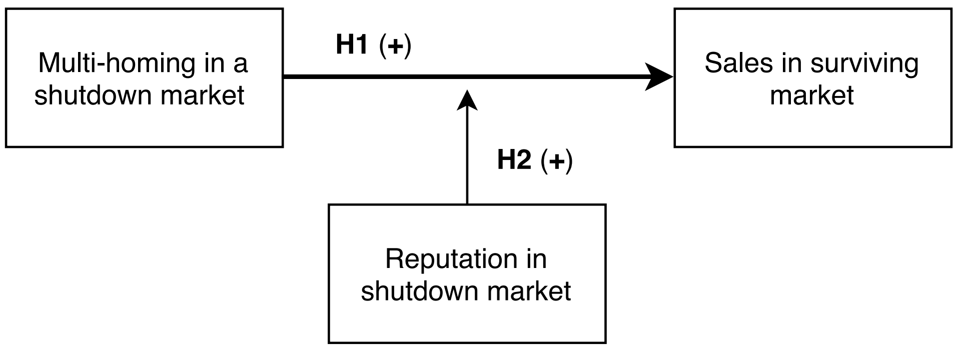
This paper has the goal to test the following hypotheses:

H1 Multi-homing in a market which gets shutdown causes an increase in seller performance in a surviving market after a shutdown.

H2 Multi-homing in a market which gets shutdown causes an increase in seller performance in a surviving market after a shutdown, conditional on the reputation of the seller in the shutdown market.

The conceptual model depicting these hypotheses can be found in Figure 4.

Figure 4: Conceptual Model



Where multi-homing in a shutdown market refers to whether a seller is active in the market which gets shut down as well as in the surviving market. Reputation in the shutdown market could be regarded as the rating or the total number of deals of a seller. The literature suggests that seller performance can be captured by sales revenue, sales count or survival of the seller.

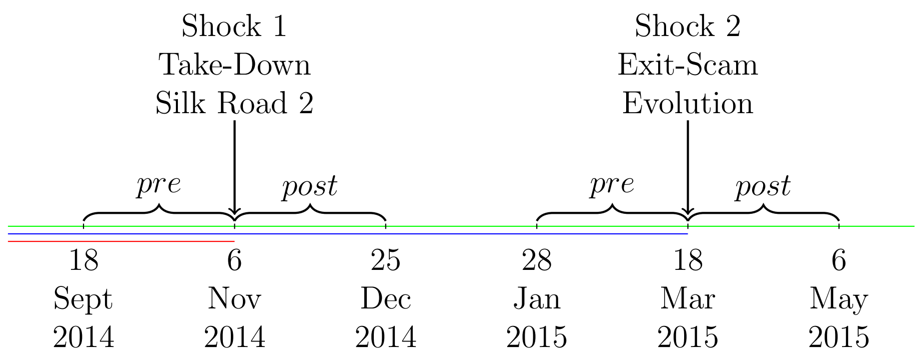
The literature provides several factors which should be used as control variables for seller performance. The seller's rating, seller capacity, product category, the ship from and ship to location of the seller and the total number of deals of the seller all contribute to performance. Ratings and the total number of deals signal trust to potential buyers (Armona, 2017). Nurmi et al. (2017) argue that a seller which showcases a large capacity also signals trust. However, one could argue that a large capacity leads to high performance, just because a seller has more to sell. The ship from or to location might influence trust, shipping times or shipping possibilities and could, therefore, influence seller performance. Product category influences performance, because specific categories might be sold more often or for higher prices.

This paper does not test the impact of multi-homing from a larger customer pool perspective. The performance of a multi-homer within a market is compared to test whether buyers have a tendency after a shock to pick a specific type of seller. In order to study the customer pool benefit, one should aggregate performances over different markets. This paper does also not test the degree to which profile description text length influences the degree of loyalty. This finding has been put forward by Décary-Hétu and Quessy-Doré

(2017). This variable could be taken into account in the conceptual model as well as the econometric model. However, due to time constraints, this paper does not control for that relation.

4.1 Shocks

Figure 5: Timeline



In the timeline presented in Figure 5 one can see two unexpected shocks in the darknet market ecosystem during the years 2014-2015. The first shock is the government take-down of Silk Road 2 on 6 November 2014. The pre- and post-shock performances of sellers in the surviving Agora and Evolution market can be used to test the hypotheses of this paper. The second shock is the exit-scam of Evolution on 18 March 2015[6] The surviving market Agora can be used as the entity of analysis. There are in total three shock-market pairs: Agora around Shock 1, Evolution around Shock 1, and Agora around shock 2. The rest of this paper sometimes refers sometimes to Shock 1 data or Shock 2 data instead of using the full sentence the data in the Agora and Evolution market around the Silk Road 2 shutdown or the Agora market data around the Evolution shutdown.

Although other markets exist around these shocks or are shutting down in these periods, this paper focuses on Silk Road 2, Agora and Evolution because they are the most important markets around at that time. Figure 6 depicts the percentage of drugs listings in these markets in the entire darknet market ecosystem. During most of 2014-2015, the three markets provide more than 80% of the listings of the whole darknet market ecosystem.

Table 1 summarises the opening and close date of the markets and the reason for their closure.

[6] The last feedback recorded in the webscrape is on March 17 and the Evolution community seemed to notice on March 18 that the owners of the platform exited with the money held in escrow (Greenberg, 2015).

Figure 6: Listings of three major darknet markets. *Source: Armona (2017).*

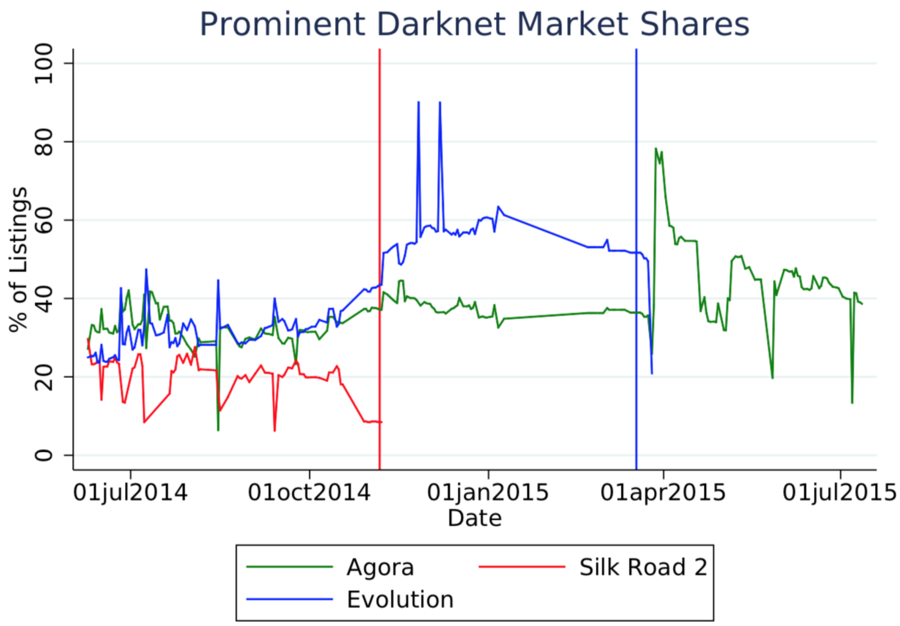


Table 1: Markets opening and closure dates

Market	Opened	Closed	Days Open	Reason For Closure
Silk Road 2	6/11/2013	6/11/2014	365	Take-Down
Agora	3/12/2013	6/09/2015	642	Voluntary
Evolution	14/01/2014	18/03/2015	428	Exit-Scam

4.2 Econometric specification

The following difference-in-difference model (Equation 1) is employed to test whether sellers, who multi-homed in a market which got shut down, increase in sales in a surviving market in the period after the shutdown. The model looks at sellers and their performance before and after a shutdown in the surviving market.

$$\begin{aligned} Sales_{i,t} = {} & \beta_0 + \beta_1 Mh\_in\_shutdown_{i,t} + \beta_2 (Mh\_in\_shutdown_{i,t} \times Time_{i,t}) \\ & + \beta_3 X_{i,t} + \beta_4 Evolution_{i,t} + \mu_t + \epsilon_{i,t} \end{aligned} \tag{1}$$

$Sales_{i,t}$ refers to the log of sales revenue in US \$ or the log of sales count (quantity) of seller i in week t. $Mh\_in\_shutdown_{i,t} = 1$ if the seller is multi-homing in the market which gets shut down, 0 otherwise. $Mh\_in\_shutdown_{i,t} \times Time_{i,t} = 1$ if a seller is a multi-homer in the shutdown market in the weeks after the market has been shut down, 0 if the seller was not multi-homing or the seller is in a week before the shutdown. $Time_{i,t}$ is not included as a single dummy, because time fixed effects are included with μ_t to control for variations across weeks.

$X_{i,t}$ is a vector which captures all control variables, including the rating of the seller and the log sales capacity. $Evolution_{i,t}$ is a dummy which takes the value 1 if the seller is in Evolution market and 0 if the seller is active in Agora. This dummy controls for market specific effects. $\epsilon_{i,t}$ is the error term.

The coefficient interpretations are as follows: β_0 captures the value of the intercept. β_1 captures the effect of multi-homing in the shutdown market before the shutdown. β_2 captures the average weekly effect of multi-homing after the shutdown. For this study, the sign and significance of β_2 are of most interest and the hypothesis is that this coefficient will be positive and statistically significant. β_3 is a vector of coefficients for the control variables. β_4 indicates the average performance difference between sellers in Agora and Evolution.

Instead of using only a dummy variable to indicate whether a seller was active in the shutdown market or not, one can also control for the reputation the seller had in the shutdown market. The reputation in the shutdown market is relevant because one would expect buyers to switch to sellers conditionally on the strength of a seller's reputation. Similarly, one could expect sellers with a lower reputation to have a smaller customer base which could switch. This paper focuses on rating as a proxy for reputation but will also experiment with the total number of deals in the shutdown market. Equation 2, where reputation is included as conditioning factor, can be stated as follows:

$$\begin{aligned} Sales_{i,t} = &\beta_0 + \beta_1 Mh\_in\_shutdown_{i,t} + \beta_2(Rating\_in\_shutdown_{i,t} \times Mh\_in\_shutdown_{i,t}) \\ &+ \beta_3(Mh\_in\_shutdown_{i,t} \times Time_{i,t}) \\ &+ \beta_4(Rating\_in\_shutdown_{i,t} \times Mh\_in\_shutdown_{i,t} \times Time_{i,t}) \\ &+ \beta_5 X_{i,t} + \beta_6 Evolution_{i,t} + \mu_t + \epsilon_{i,t} \end{aligned} \tag{2}$$

Where *Rating_in_shutdown* refers to the rating a seller has in the market which gets shut down. In this equation β_4 and β_3 are the coefficients of interest. Although a three-way interaction is created in the regression, the variables *Rating_in_shutdown* and $Rating\_in\_shutdown \times Time_{i,t}$ are not included because these would be perfectly collinear with $Rating\_in\_shutdown_{i,t} \times Mh\_in\_shutdown_{i,t}$ and $Rating\_in\_shutdown_{i,t} \times Mh\_in\_shutdown_{i,t} \times Time_{i,t}$. Therefore, these variables would drop out of the regression.

4.3 Control groups

This paper conducts three comparisons with respect to the sample groups:

- Multi-homers who multi-homed in the shutdown market compared with the combination of sellers who multi-homed in other markets and single-homers.
- Multi-homers who multi-homed in the shutdown market *including sellers who are at the same time multi-homing on another market* compared with sellers who multi-homed in another market.

- Multi-homers who multi-homed in the shutdown market *only* compared with sellers who multi-homed in another market

Since the difference-in-difference model relies on similar trend assumption between treatment and control group one can doubt whether single-homers are a fair comparison group. Therefore the second and third comparisons which only takes into account multi-homers might be the more strict and appropriate test. A complication might arise because multi-homers who multi-home in the shutdown market can also multi-home at the same time in another market. The sellers who multi-home on multiple big markets might be different sellers. Therefore, it might be appropriate to test for variations of the treatment group consisting of multi-homers who only multi-homed in the shutdown market. In the data section, examples of the sample groups per market are provided, and these examples might ease understanding of the different comparisons.

4.4 Multiple periods

The pre- and post-periods are created seven weeks around the shocks. Seven weeks are chosen because one can expect buyers to take some time to switch to another market. The effect will most likely not be visible in week one. On the other hand, choosing a very long period might not be preferable because the chances increase that other factors start to influence performance.

4.5 Seller inclusion

Sellers' 'start-week' in the panel is the first week of the panel, if the seller was already present on the market before the start of the panel, or the start-week is the first week that the seller joined the market, if the seller joined later than the panel started. Sellers who joined after the shocks are not included, because firstly, these sellers can only be part of the control group since the shutdown market is already gone and secondly, these sellers are unlikely to quit just after they joined and therefore bias positive sales towards the post-shock period.

Each seller is kept in the panel until the last week of the panel, even though they might have left the market or did not sell anything. The above-mentioned decisions lead to an unbalanced panel with slightly more observations after the shock than before the shock. It is difficult to determine when a seller is not active anymore. If one would remove inactive or missing sellers after the shock, it might bias the results towards the 'survivors' of the shock.

4.6 Combining shocks data

Regressions can be run on three levels. First, Shock 1 and Shock 2 data can be combined. Second, Shocks can be studied separately. Third, individual regressions can be run for each shock-market pair to verify changes across markets.

5 Data

The data section has the goal to explain where the data for the econometric model comes from and how the data is transformed. The data definitions table can be found in Appendix A. The structure of this section is as follows. First, the raw data sources are discussed. Second, the data for the explanatory variable, the multi-homing variable is explained, and the resulting sample groups are discussed. Third, the data and approach for the dependent variable, seller performance, is discussed. Fourth, the control variables are elaborated on. Fifth, the descriptive statistics of the sample groups are presented.

5.1 Data sources

This section explains the sources, HTML-scrapes, and Grams CSV-files, which are used to build the different variables of this study. The datasets are uploaded online by Branwen (2015) and are accessible to everyone.

5.1.1 HTML-scrapes

HTML-scrapes are available for many markets and include Silk Road 2, Agora and Evolution. The scrapes appear mostly twice a week and provide unstructured data on product listings as well as seller pages per market. Branwen (2015) explains the shortcomings of these scrapes: *"No matter how much work one puts into it, one will never get an exact snapshot of a market at a particular instant: listings will go up or down as one crawls, vendors will be banned, and their entire profile & listings & all feedback vanish instantly, Tor connection errors will cause a nontrivial % of page requests to fail, the site itself will go down (Agora especially), and Internet connections are imperfect. Scrapes can get bogged down in a backwater of irrelevant pages, spend all their time downloading a morass of on-demand generated pages, the user login expire or be banned by site administrators, etc. If a page is present in a scrape, then it probably existed at some point; but if a page is not present, then it may not have existed or existed but did not get downloaded for any of a myriad of reasons. At best, a scrape is a lower bound on how much was there."*

The crawling procedure can be found here: https://www.gwern.net/DNM-archives. Armona (2017) states that this crawling procedure follows more or less a recursively defined random walk. Therefore, the listings observed can be treated as independent and identically distributed (i.i.d.) observations. The absence of a listing will be unrelated to unobservable characteristics of the product. This reasoning can be extended to the seller level, which is the entity of focus in this paper.

5.1.2 Grams CSV-files

The Grams dataset is an export of the search engine Grams which was specialized in searching darknet market listings. This Grams engine was used by drugs buyers to search for a product and have prices and different markets as a result returned. The listings have been exported to CSV on a near-daily basis. Grams acquired the listings information via APIs provided by the markets (Evolution) or via own custom crawls (Agora, Silk Road 2). Especially for Evolution this means that the prices listed are quite accurate. There are some gaps however in this dataset of several days. This paper fills an empty date with the Grams export of the most recent date.

5.2 Explanatory variable

5.2.1 Multi-homing dummy variable (*mh_in_shutdown*)

The HTML scrapes can be used to identify unique seller names per week per market. With seller names, this paper refers to the username the sellers use on the platform. Exact case-insensitive matching is applied to verify whether the same seller name exists during the same week in another market. It is expected that this matching strategy contains a few false positive and false negatives, but that most of the matches are correct. Sellers have an incentive to choose the same seller name in a different market for recognisability.

Furthermore, Wang et al. (2018) comment that in their research towards weapon sellers on the darknet markets, that most of the exact matches appear to be correct matches. They conclude this after further investigation of profile descriptions, pictures of products and PGP-encryption keys used by the sellers to verify whether it is indeed a match. For efficiency sake, this study does not use additional information to verify the correctness of a match.

5.2.2 Sample groups

This section illustrates the different sample groups created in this study. The different sample groups are coded in this section with a type label A, B, C or D. To increase readability of some in-text elements or table descriptions the type labels are used instead of repeating the lengthy description of each sample group.

For the scenario of Agora around the shutdown of Silk Road 2, a dummy variable is created which takes the value of 1 for sellers in Agora who were multi-homing in Silk Road 2 and 0 for sellers who did not. The name for this variable is *mh_in_shutdown*. Similarly, with a *mh_other* dummy variable, it is indicated whether the seller was multi-homing in Evolution or not. Four different combinations of the *mh_in_shutdown* and *mh_other* dummy can be made. These combinations give for Agora in Shock 1 the sample groups as presented in Table 2. Note that:

A - multi-homing in Silk Road 2 AND Evolution are in dummy variable terms where $mh\_in\_shutdown = 1$ & $mh\_other = 1$.

B - multi-homing in Silk Road 2 only is where $mh\_in\_shutdown = 1$ & $mh\_other = 0$.

C - multi-homing in Evolution only is where $mh\_in\_shutdown = 0$ & $mh\_other = 1$.

D - single-homing is where $mh\_in\_shutdown = 0$ & $mh\_other = 0$.

Table 2: Agora, Shock 1, sample groups

Type of seller	**Unique sellers**
A - Multi-homing in Silk Road 2 & Evolution	155
B - Multi-homing in Silk Road 2 only	167
C - Multi-homing in Evolution only	315
D - Single-homing	632
Total unique sellers*	1102
Sum of groups*	1269

*Some sellers are in multiple groups due to weekly changes.

Table 3: Evolution, Shock 1, sample groups

Type of seller	**Unique sellers**
A - Multi-homing in Silk Road 2 & Agora	107
B - Multi-homing in Silk Road 2 only	49
C - Multi-homing in Agora only	272
D - Single-homing	739
Total unique sellers*	1105
Sum of groups*	1167

*Some sellers are in multiple groups due to weekly changes.

It is important to note that a seller can also multi-home on more markets (e.g., Nucleus Market). However, this paper only focuses on analyzing the most important markets and hence did not match seller names with seller names in other markets.

For Evolution around Shock 1 (see Table 3) the sample groups are similar only one has to replace in type A and type C "Evolution" with "Agora". For Agora Shock 2 (see Table 4) the types of sellers are more limited because at this shock, Silk Road 2 is not in the ecosystem anymore and only data from Agora and Evolution is analyzed. A dummy for sellers multi-homing in another market than the shutdown market is not created. Therefore, at this shock the multi-homing in Evolution ($mh\_in\_shutdown = 1$) and single-homing ($mh\_in\_shutdown = 0$) are the only sample-groups.

Table 4: Agora, Shock 2, sample groups

Type of seller	**Unique sellers**
B - Multi-homing in Evolution	522
D - Single-homing	689
Total unique sellers*	1184
Sum of groups*	1211

*Some sellers are in multiple groups due to weekly changes.

The different types of treatment-control comparisons discussed in the methodology can now be explained as follows:

1. multi-homers of type A and B compared with multi-homers of type C and single-homers of type D
2. multi-homers of type A and B compared with multi-homers of type C
3. multi-homers of type B compared with multi-homers of type C

This paper suggests that the comparison of type B and type C is the most strict and appropriate comparison. Both seller types are multi-homing in only one other big market and might, therefore, be most similar. For robustness, all versions will be tested.

It is unclear whether multi-homers of type B from the Agora market at Shock 2 should be included in the multi-homer only comparisons with all shock-markets compared because Agora at Shock 2 does not contribute any multi-homers to the regression which multi-home in another market. Therefore, the default set-up will be to compare B and C for Shock 1 only and provide as robustness test the comparison of B and C for both shocks in the appendix.

5.2.3 Multi-homing reputation variable *(Rating_in_shutdown, Deals_in_shutdown)*

Two variables could be used to control for reputation in the shutdown market: the average feedback rating of a seller and the total deals of a seller. A seller with a high rating or many total deals is more trusted by buyers (Armona, 2017). At Silk Road 2 and Evolution the average feedback rating per seller is used to construct the *Rating_in_shutdown* variable.

At Silk Road 2 this is a 1-5 scale with 1 being the lowest score and 5 the highest. At Evolution a seller receives either a positive, neutral or negative rating. $(Positive + 1)/(Positive + Negative + 1)$ is the formula used to transform that information to a score between 0-1 where 1 means a fully positive rating, and with every negative rating, the score moves to 0. To be able to run a regression with Shock 1 and Shock 2 combined the data needs to be transformed to the same scale. The Silk Road 2 rating is by divided by 5 to create a 0-1 rating score. The latest rating in the shutdown market before the shutdown is taken as a variable, which means the variable enters as a constant in the regression in the surviving market.

Since every feedback includes the same number of feedbacks, at Silk Road 2 the number of feedback pages can be used as an indication of the number of deals of a seller, without spending time on parsing each feedback from the HTML-scrapes. Evolution provides the total number of deals as information with each seller. These deals can be divided by the average number of feedbacks per page to be of the same scale as the data from Silk Road 2. The log of total feedback pages in the shutdown market is used as *Deals_in_shutdown* variable. Again here the latest figure of deals before the market shuts down is taken as a constant in the regression. Both versions of reputation are used to test for robustness.

5.3 Dependent variable: seller performance

For seller performance, the focus in this study is on weekly sales revenue and total sales. The probability of survival is not analyzed because of time constraints.

Sales revenue is highly related to sales count and is created by multiplying individual sales of products with the related product sales price. Using both versions of seller performance might provide a broader perspective on performance. Sales count can go up, but revenues can go down, due to fallen prices, or vice-versa. In addition, there is some uncertainty and missing values in the price data, making the sales revenue variable less reliable. Mistakes in the sales revenue variable could bias results. Décary-Hétu & Giommoni (2017) test the change of prices after the shutdown of Silk Road 2 and indicate that prices remained similar. This finding suggests that changes in the sales count variable would be a good proxy for sales revenue changes and might serve more like an extra test rather than providing a different perspective.

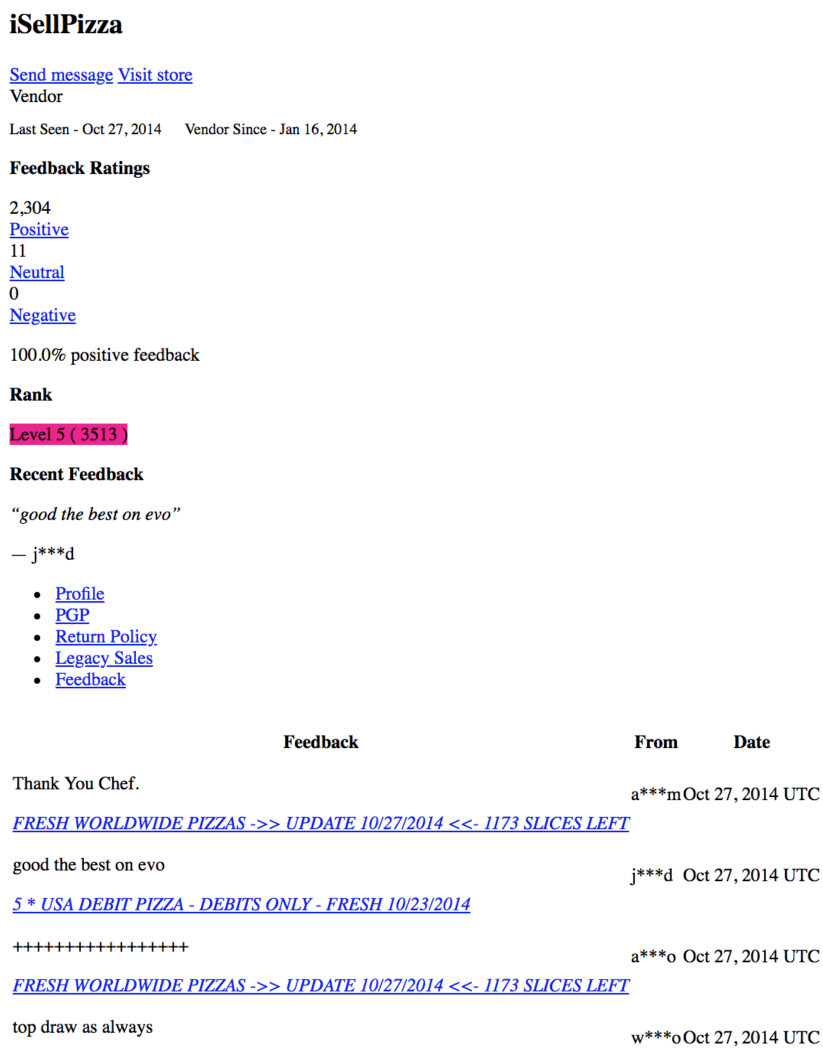
5.3.1 Sales count

The HTML-files provide per seller and product a list of feedbacks. See Figure 7 and 8 for examples.

Figure 7: Product feedback page on Agora loaded from a local HTML-file

Feedback is given when a product is bought. The presence of feedback allows the construction of a sales variable per seller. Daily feedbacks can be counted and averaged to arrive at a weekly sales count variable. The log of this variable is taken because the data is skewed to the right.

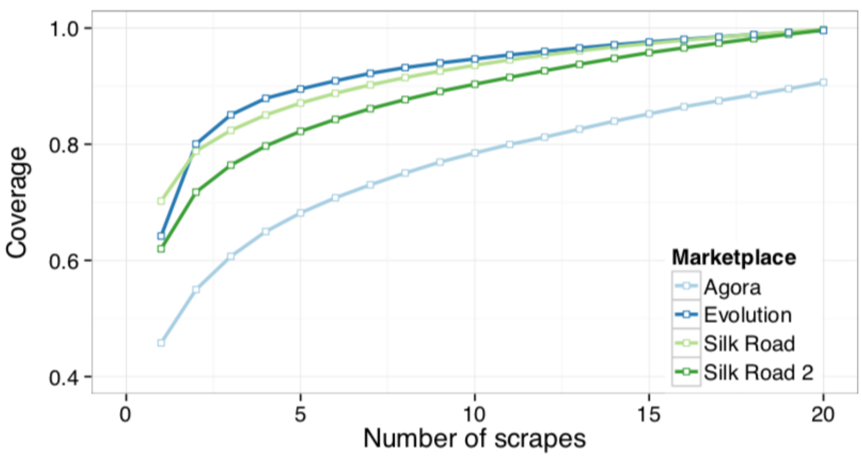
Figure 8: Seller feedback page on Evolution loaded from a local HTML-file



This sales count is a lower limit on the actual sales count. First of all, the actual sales count depends on to what extent feedback is mandatory at a purchase. Bhaskar et al. (2017) suggest that feedback is not always required, whereas Soska and Christin (2015) argue that providing feedback is mandatory. Secondly, a buyer might be able to buy different quantities of the product in one purchase. See for example Bhaskar et al. (2017) for a discussion on calculating sales revenue or counts in darknet markets. For this analysis, it is not a problem if providing feedback is not mandatory all the time, but it should be that feedbacks are required in similar proportion per product or seller. If the proportion of feedbacks to total actual purchases would be similar, then one could still show performance differences per seller group. Third, scrapes are not always able to retrieve all the website pages. Therefore, the number of feedbacks found in one scrape is a lower limit of the total number of feedbacks. Since subsequent scrapes contain feedback lists with feedbacks from the past, the estimate of the number of feedbacks at a certain becomes more complete by combining information from multiple scrape dates.

Figure 9 shows the estimation by Soska and Christin (2015) on the increase in completeness per market with every additional website scrape for their research.

Figure 9: This graph can be found in Soska and Christin (2015). The plot estimates the fraction of all feedback they obtain for a given time, as a function of the number of scrapes they collect.



5.3.2 Sales revenue

A sales price needs to be added to each product feedback to create a sales revenue variable. For this, the Grams CSV-files are used which list prices per date per product. The prices can also be parsed from the HTML-files, but it would cost more time and the parsing would most likely extract fewer data.

The prices are listed in Bitcoins and are converted to US $ with the historical exchange rates from https://www.coindesk.com/price/. The product feedbacks are matched with the selling price of that product on the date of sale. The product link and date are used as matching key. Summing all the product sales revenue per week and seller gives the sales revenue variable. The log of weekly revenues is taken because the data is skewed to the right.

The above-mentioned process comes with two problems: extreme and missing prices. Sellers can adjust their price throughout the day. Therefore, prices found in the Grams dataset or HTML-files might not be the price at which the product was sold. Sellers are known to use hold-out prices when they are out of stock (Soska & Christin, 2015). Hold-out prices are high prices used by sellers to indicate they are not able to sell anymore. Another reason why the price might not reflect the selling price is if the seller accidentally entered the US $ value instead of the Bitcoin value. Both deliberate and in-deliberate price adjustments create prices in the dataset which are often higher than the selling price.

After manual inspection of outlier prices and the corresponding products, this paper finds that products sold above 20,000 US $ are for sure incorrect prices. Below that price, it was difficult to decide whether a price could have been the true selling price or not. Prices above 20,000 US $ are replaced with 'NAs', and subsequently, the NA-values are imputed with the mean of the product prices. Another strategy to deal with extreme prices would be to create a formula which decides that a price is an outlier with respect to the other prices in that category or historical prices from the same product. This paper continues with the ruder 20,000 US $ cutoff point for outliers, which is easily implementable and captures the most significant outliers.

The dataset has roughly 15% missing price values in the Agora market and 10% missing values in the Evolution market. First, missing values are replaced with the mean of the prices of that specific product. Hence, if a seller who sells product X which has price data on date Y and Z, but not on date A, the missing price on date A is imputed with the mean of the price on date Y and Z. This problem arises because not all prices can be found in the Grams dataset at the exact date the product was sold. This strategy reduces missing prices percentage of the total dataset is roughly 5%.

Second, the remaining missing values are removed. Since the missing values are spread evenly over different weeks, and the percentage is not very high, this deletion of observations should not pose a large problem for the analysis. Another strategy would be to impute the mean of a sellers prices of all products. However, this could inflate revenue for example for a seller with a few high priced sales of one product and many unknown priced sales of a different product.

The above discussion on prices explains why the sales revenue variable might be further away from the true values than the sales count variable.

Appendix I provide graphs which show the total sales revenue and sales count per week per market.

5.4 Control variables

As control variables, the rating, number of deals, sales capacity, ship from, ship to and product category variables are created.

5.4.1 Rating

Rating is the overall feedback rating which a seller received on all its products. At Agora this is a 1-5 scale with 1 being the lowest score and 5 the highest. At Evolution a seller receives either a positive, neutral or negative rating. $(Positive + 1)/(Positive + Negative + 1)$ is the formula used to transform that information to a score between 0-1 where 1 means a fully positive rating, and with every negative rating, the score moves to 0. A missing rating indicator is used when no rating could be found.

To be able to run a regression with the Evolution and Agora market combined, the data needs to be transformed to the same scale. The Agora rating is by divided by 5 to create a 0-1 rating score. For the weekly panel data, ratings are averaged per seller per week.

5.4.2 Deals

The seller page indicates how many deals a seller has completed in its lifetime on the platform. On Agora this is a range can be, for example, 200-300 deals, of which the starting number 200 is saved for this study. On Evolution the deals variable is an exact number. Since the total number of deals is highly correlated with sales count, only the total number of deals at panel entrance is used as control variable. If the deals variable is allowed to vary across weeks, then an increase in deals must mean an increase in sales and sales revenue. The log of this variable is taken because the data is skewed to the right.

5.4.3 Capacity

Capacity is the worth in US $ of a seller's products for sale. The sum of the prices of the products available per sale at a specific date. The data is derived from the Grams files. Note that extreme prices problem mentioned earlier also applies for this variable. Corrected data is used as input for the capacity variable. The daily capacities are summed by week. The log of this variable is taken because the data is skewed to the right.

5.4.4 Ship from

The ship from location indicates the location the seller ships its product from. The product pages in the HTML-files as well as in the Grams files provide this information. In Agora sellers can write their own 'ship from' location while in Evolution there are predefined country choices. For this reason, the Agora data is messy. To deal with all the variations of locations, the most frequent used location per seller is stored and the name is replaced to create uniform names. This approach causes that the data to show for Agora sellers only has one ship from location (the most frequent occurring), whereas at Evolution multiple locations are shown. The full list of ship from locations for Agora and Evolution is provided in Appendix B.

5.4.5 Ship to

The ship to location is the locations to which a seller ships and is only applicable in the Agora market. The same procedure is followed as for the ship from variable. The Evolution market does not show where sellers are shipping to. The ship to locations can be found in Appendix B.

5.4.6 Product category

Each product belongs to a category and most of the times a sub or sub-subcategory of a category. The product categories are added as dummy variables, and a seller can be active in multiple categories. The categories are reduced to higher levels giving roughly 26 categories for Agora and 39 for Evolution. The category names can be found in Appendix B.

5.5 Descriptive statistics

Table 5 shows the descriptive statistics of the above-mentioned variables for the sellers who multi-home in the market which gets shut down, (sellers of type A and B) as discussed in section Sample Groups on page 19. Table 6 shows the descriptive statistics of the sellers who are not multi-homing in the market which gets shut down, (sellers of type C and D). Note that the data in the tables includes sellers from both Shock 1 and 2.

Table 7 presents the descriptive statistics of the sellers which multi-home only in the shutdown market and not in any other market (type B). Table 8 presents the descriptive statistics of the sellers who multi-home only in another market (type C). Note that these tables only focus on Agora and Evolution during Shock 1 where there is also data available on sellers multi-homing in another market than the shutdown market.

Table 5: Type A & B, Shock 1 and 2

Statistic	N	Mean	St. Dev.	Min	Max
Week	12,630	59.416	10.184	42	74
Mh_in_shutdown	12,630	1.000	0.000	1	1
Mh_other	12,630	0.235	0.424	0	1
Time	12,630	0.556	0.497	0	1
Sales revenue	12,630	5.353	3.589	0.000	12.094
Sales count	12,630	2.126	1.591	0.000	6.205
Rating	12,432	0.983	0.027	0.390	1.000
No-rating	12,630	0.020	0.139	0.000	1.000
Deals_in_shutdown	12,630	2.462	1.425	0.000	6.512
Rating_in_shutdown	12,630	0.908	0.255	0.000	1.000
Evolution	12,630	0.149	0.356	0	1
Deals	12,432	4.630	1.511	0.000	8.517
Capacity	12,616	9.622	2.024	0.537	15.567

Type A sellers the sellers multi-homing in the shutdown market and another market
Type B sellers are the sellers multi-homing in the shutdown market only

Table 6: Type C & D, Shock 1 and 2

Statistic	N	Mean	St. Dev.	Min	Max
Week	33,194	53.885	9.312	42	74
Mh_in_shutdown	33,194	0.000	0.000	0	0
Mh_other	33,194	0.209	0.406	0	1
Time	33,194	0.539	0.498	0	1
Sales revenue	33,194	4.384	3.532	0.000	13.726
Sales count	33,194	1.764	1.535	0.000	6.282
Rating	32,204	0.982	0.043	0.050	1.000
No-rating	33,194	0.035	0.182	0.000	1.000
Deals_in_shutdown	33,194	0.000	0.000	0	0
Rating_in_shutdown	33,194	0.000	0.000	0	0
deals	32,204	145.478	291.816	0.000	5,000.000
Evolution	33,194	0.387	0.487	0	1
Deals	32,204	3.956	1.511	0.000	8.517
Capacity	33,026	8.798	2.228	0.000	16.458

Type C sellers the sellers multi-homing in another market
Type D sellers are the sellers who single-home

Table 7: Type B, Shock 1

Statistic	N	Mean	St. Dev.	Min	Max
Week	2,505	48.165	3.906	42	55
Mh_in_shutdown	2,505	1.000	0.000	1	1
Mh_other	2,505	0.000	0.000	0	0
Time	2,505	0.461	0.499	0	1
Sales revenue	2,505	4.720	3.795	0.000	12.094
Sales Count	2,505	1.776	1.570	0.000	6.100
Rating	2,463	0.982	0.038	0.390	1.000
No-rating	2,505	0.035	0.182	0.000	1.000
Deals_in_shutdown	2,505	1.843	1.439	0.000	4.905
Rating_in_shutdown	2,505	0.772	0.397	0.000	1.000
Evolution	2,505	0.225	0.418	0	1
Deals	2,463	3.942	1.507	0.000	6.909
Capacity	2,505	9.326	2.076	3.039	15.500

Type B sellers are the sellers multi-homing in the shutdown market only

Table 8: Type C, Shock 1

Statistic	N	Mean	St. Dev.	Min	Max
Week	6,561	48.662	3.987	42	55
Mh_in_shutdown	6,561	0.000	0.000	0	0
Mh_other	6,561	1.000	0.000	1	1
Time	6,561	0.516	0.500	0	1
Sales revenue	6,561	5.308	3.523	0.000	13.726
Sales count	6,561	2.107	1.570	0.000	6.198
Rating	6,458	0.986	0.025	0.775	1.000
No-rating	6,561	0.022	0.144	0.000	1.000
Deals_in_shutdown	6,561	0.000	0.000	0	0
Rating_in_shutdown	6,561	0.000	0.000	0	0
Evolution	6,561	0.505	0.500	0	1
Deals	6,458	4.096	1.529	0.000	8.072
Capacity	6,519	9.628	2.025	0.000	15.441

Type C sellers the sellers multi-homing in another market

6 Results

This section first explains the results found and the next section discuss their implications.

The regression results for Shock 1 and 2 combined, can be found in Table 9 and 10. Multi-homers who multi-home in the shutdown market (Type A and B) are compared with both multi-homers in other markets and single-homers together (Type C and D). Column (1) to (3) show the coefficients and significance of the regressions with sales revenue as the dependent variable and (4) to (6) with sales count as the dependent variable.

The results of Table 9 indicate that multi-homing in a shutdown market contributes to the average weekly sales revenue and sales count after a shutdown. The coefficients of *Mh_in_shutdown*× *Time* are positive and significant at the 1%-level. Multi-homers in the shutdown market do not significantly differ from other sellers in the baseline which can be derived from the most of the times statistically insignificant coefficients of *Mh_in_shutdown*. *Capacity*, *Deals*, and *Rating* all positively contribute to sales revenue and sales count. Sellers in Evolution have on average fewer sales revenue and sales count than Agora sellers given the negative and statistically significant coefficient of *Evolution* in most regressions. The *No-rating* dummy happens to switch from negative effects on performance to positive effects.

The results of Table 10 test the same data as used for 9, but now the effect of multi-homing interacts with the rating of the seller in the shutdown market. *Rating_in_shutdown*× *Mh_in_shutdown*× *Time* is positive but statistically insignificant in most regressions, and *Mh_in_shutdown*× *Time* both turned statistically insignificant in all regres-

Table 9: Type A and B compared with Type C and D, Shock 1 and 2, Equation 1

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	0.635***	0.167	0.016	0.203***	0.057	−0.041
	(0.117)	(0.107)	(0.099)	(0.054)	(0.053)	(0.046)
Mh_in_shutdown×Time	0.306***	0.278***	0.249**	0.193***	0.184***	0.165***
	(0.109)	(0.104)	(0.104)	(0.046)	(0.044)	(0.044)
Capacity		0.576***	0.534***		0.179***	0.151***
		(0.018)	(0.017)		(0.010)	(0.009)
Deals			0.511***			0.333***
			(0.027)			(0.014)
Evolution	−0.812***	−0.747***	−0.403***	−0.170***	−0.150***	0.074
	(0.116)	(0.104)	(0.099)	(0.055)	(0.052)	(0.049)
Rating	14.659***	15.878***	14.500***	6.153***	6.526***	5.628***
	(1.824)	(1.944)	(1.910)	(0.723)	(0.761)	(0.737)
No-rating	−1.042***	−0.430	1.035***	−0.809***	−0.618***	0.337***
	(0.400)	(0.337)	(0.330)	(0.139)	(0.126)	(0.118)
Observations	44,636	44,538	44,538	44,636	44,538	44,538
R^2	0.060	0.183	0.225	0.050	0.113	0.205
Adjusted R^2	0.059	0.183	0.224	0.049	0.112	0.204

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

sions. This insignificance might arise because both variables are highly correlated with each other. Their correlation coefficient is 0.96 (See Appendix C Table 15). The high correlation occurs because the rating variable in the shutdown market ranges from 0 to 1 with many observations close to 1. Since *Mh_in_shutdown* is a dummy and *Time* as well, the interaction of a 1×1 dummy is similar to 1×1×[close to 1].

In Appendix D two variations of this regression are shown for robustness. Table 17 runs the same regression (Equation 2) but includes only Shock 1 data. The coefficient of *Rating_in_shutdown*×*Mh_in_shutdown*×*Time* is here positive and statistically significant with respect sales count. The correlation coefficient with *Mh_in_shutdown*×*Time* is 0.91 in Shock 1. Table 16 runs the same regression for Shock 1 and 2 again, but without the highly correlated *Mh_in_shutdown*×*Time*, which results in a positive and statistically significant coefficient of the variable *Rating_in_shutdown*×*Mh_in_shutdown*×*Time* with

Table 10: Type A and B compared with Type C and D, Shock 1 and 2, Equation 2

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	0.428	−0.019	−0.212	0.140	0.0004	−0.125
	(0.394)	(0.334)	(0.316)	(0.167)	(0.153)	(0.137)
Rating_in_shutdown×Mh_in_shutdown	0.231	0.208	0.255	0.070	0.063	0.094
	(0.416)	(0.352)	(0.332)	(0.177)	(0.162)	(0.144)
Mh_in_shutdown×Time	0.022	0.018	−0.026	−0.002	−0.004	−0.033
	(0.350)	(0.331)	(0.330)	(0.131)	(0.124)	(0.122)
Rating_in_shutdown×Mh_in_shutdown×Time	0.313	0.287	0.302	0.216	0.209	0.219*
	(0.373)	(0.352)	(0.352)	(0.140)	(0.133)	(0.131)
Capacity		0.576***	0.533***		0.179***	0.151***
		(0.018)	(0.017)		(0.010)	(0.009)
Deals			0.512***			0.333***
			(0.027)			(0.014)
Evolution	−0.820***	−0.754***	−0.410***	−0.173***	−0.154***	0.070
	(0.116)	(0.104)	(0.100)	(0.055)	(0.052)	(0.049)
Rating	14.609***	15.833***	14.446***	6.131***	6.505***	5.601***
	(1.817)	(1.939)	(1.903)	(0.720)	(0.758)	(0.734)
No-rating	−1.023***	−0.412	1.056***	−0.799***	−0.609***	0.348***
	(0.389)	(0.330)	(0.321)	(0.135)	(0.124)	(0.114)
Observations	44,636	44,538	44,538	44,636	44,538	44,538
R^2	0.060	0.183	0.225	0.050	0.113	0.205
Adjusted R^2	0.059	0.183	0.224	0.050	0.112	0.204

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

respect sales count. Either the results of Agora during Shock 2 remove significance or the high correlation between variables removes significance. Table 29 in Appendix G runs a regression for Agora during Shock 2 only, with more control variables included, and here the effect of multi-homing in the shutdown conditionally on reputation can be found. This result suggests that high correlation between variables might have been the issue.

The results of Table 11 and 12 focus on the multi-homers who multi-home in the shutdown market only (Type B), compared to multi-homers who only multi-home in another market (Type C). In Table 11 and 12 the effect of multi-homing in the shutdown market on performance after the shutdown cannot be found. However, Table 12 shows a positive and statistically significant effect of *Rating_in_shutdown*× *Mh_in_shutdown*× *Time* on sales count, indicating that multi-homing in the shutdown market does contribute to performance after the shutdown conditionally on the rating of a seller. The same regression without *Mh_in_shutdown*× *Time* can be found in Appendix E Table 18, but results stay

Table 11: Type B compared with Type C, Shock 1, Equation 1

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	−0.785***	−0.625***	−0.411*	−0.422***	−0.363***	−0.219**
	(0.263)	(0.232)	(0.215)	(0.116)	(0.108)	(0.095)
Mh_in_shutdown×Time	0.318	0.281	0.261	0.173	0.155	0.142
	(0.268)	(0.252)	(0.251)	(0.107)	(0.101)	(0.101)
Capacity		0.717***	0.657***		0.260***	0.220***
		(0.043)	(0.041)		(0.022)	(0.020)
Deals			0.538***			0.361***
			(0.063)			(0.031)
Evolution	−0.525**	−0.638***	−0.088	−0.204*	−0.246**	0.123
	(0.222)	(0.197)	(0.193)	(0.106)	(0.100)	(0.095)
Rating	20.972***	23.683***	21.773***	8.720***	9.654***	8.372***
	(3.436)	(3.667)	(3.745)	(1.421)	(1.504)	(1.557)
No-rating	−2.120***	−0.907**	0.394	−1.075***	−0.634***	0.240
	(0.597)	(0.407)	(0.448)	(0.188)	(0.149)	(0.155)
Observations	8,921	8,879	8,879	8,921	8,879	8,879
R^2	0.044	0.209	0.253	0.042	0.155	0.258
Adjusted R^2	0.042	0.208	0.252	0.040	0.153	0.256

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

the same.

The question is why the results for sales count are statistically significant while the results for sales revenue are often positive, but not significant. An explanation would be that multi-homing sellers in the shutdown market sell more, but have decreased their prices relative to other sellers. A different reason would be that the revenue variable includes more mistakes because of wrong prices and missing values which increase noise in the data and influence the coefficient and its standard error.

The economic significance of the results is not discussed because with the multiple interactions and log-transformed dependent variables the exact interpretation of the coefficient becomes tricky. In addition, the quality of the data is not perfect due to the potential incompleteness of scrapes. For these reasons, it might be safer to look for the sign and direction of the coefficients rather than the exact effect.

Table 12: Type B compared with Type C, Shock 1, Equation 1

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	−0.491	−0.254	−0.273	−0.158	−0.072	−0.084
	(0.493)	(0.403)	(0.386)	(0.221)	(0.198)	(0.179)
Rating_in_shutdown×Mh_in_shutdown	−0.376	−0.473	−0.177	−0.337	−0.372*	−0.173
	(0.549)	(0.450)	(0.426)	(0.241)	(0.215)	(0.192)
Mh_in_shutdown×Time	−0.405	−0.254	−0.308	−0.203	−0.152	−0.188
	(0.529)	(0.488)	(0.482)	(0.180)	(0.162)	(0.156)
Rating_in_shutdown×Mh_in_shutdown×Time	0.938	0.689	0.741	0.484**	0.393**	0.428**
	(0.599)	(0.556)	(0.551)	(0.210)	(0.193)	(0.188)
Capacity		0.716***	0.655***		0.260***	0.219***
		(0.043)	(0.041)		(0.022)	(0.020)
Deals			0.541***			0.362***
			(0.063)			(0.031)
Evolution	−0.530**	−0.641***	−0.089	−0.207*	−0.248**	0.122
	(0.222)	(0.197)	(0.194)	(0.106)	(0.100)	(0.095)
Rating	20.970***	23.828***	21.667***	8.826***	9.814***	8.368***
	(3.445)	(3.723)	(3.763)	(1.441)	(1.538)	(1.569)
No-rating	−2.096***	−0.903**	0.426	−1.073***	−0.638***	0.252
	(0.596)	(0.414)	(0.441)	(0.195)	(0.155)	(0.154)
Observations	8,921	8,879	8,879	8,921	8,879	8,879
R^2	0.045	0.210	0.254	0.043	0.156	0.259
Adjusted R^2	0.043	0.208	0.252	0.041	0.154	0.257

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

Mh_in_shutdown is in Table 11 negative and statistically significant, while in Table 12 this variable is statistically insignificant. The negative and statistically significant coefficient means that multi-homers in who multi-home in the shutdown market perform worse at baseline compared to multi-homers in who multi-home in other markets when one does not control for the reputation of a seller in the shutdown market.

Different treatment and control group variations are used to test the robustness of this paper's results. The results can be found in Appendix E. Multi-homers who multi-home in the shutdown market (Type B) of both Shock 1 and 2 are included and compared against multi-homers who multi-home in other markets (Type C) during Shock 1 (Table 20 and 22). Furthermore, one can increase the treatment group by adding sellers who multi-home in both shutdown and other markets (Type A). These regressions for Shock 1 data are found in Table 19 and for Shock 1 and 2 data in Table 21 and 23. These results show a mix between statistically significant and insignificant unconditional effect of multi-homing in the shutdown market on sales after the shutdown. However, all accept the hypothesis that multi-homing in the shutdown market conditionally on reputation improves sales after a shutdown.

As an additional test, Equation 2 runs with the total number of deals in the shutdown market as a variable for reputation instead of rating (See Table 24 in Appendix E). The number of deals signal competence to buyers and having many deals might be regarded as having a high reputation. Apart from reputation, the number of deals might give an insight in the size of the customer base and hence a higher customer base might lead to a higher influx of buyer for this seller in the surviving market. The results are similar and indicate that multi-homing, conditional on the total number of deals a seller had in the shutdown market, positively impacts sales count in the surviving market.

Whether to included time fixed effects in a difference-in-difference regression can be subject to debate. A test without fixed effects and with a *Time* dummy indicating the post-shock period does provide the same results (See Table 25). The results suggest that on average the performance of sellers slightly decreases over time, which is likely driven by the drop-outs of the market and the research set-up that new sellers who join after the shock are not included.

The seller's rating has been found in all above-mentioned regression to drive performance of sellers positively. A regression (see Appendix F Table 26) which interacts *Rating* with *Time* shows that reputation after a shock becomes increasingly important. This result might be due to buyers concentrate their purchases more on a few sellers, behavior suggested by Décary-Hétu & Giommoni (2017) after the shock. The sellers with a positive reputation might benefit from this concentration and the increased uncertainty in the ecosystem created by the shutdown. At the same time, the results might be driven by 'bad' sellers who have exited the market or stop selling, but these sellers are still kept in this panel.

Tests are run on individual market-shock combinations to verify whether differences exist among markets and shocks. The results per market can be found in Appendix G Tables 27-29. One should note that on the hand the sample size decreases which might make it more difficult to find an effect. On the other hand, more control variables can be included which could improve the regression. Product category and ship from and ship to locations are the additional included control variables.

For Agora the multi-homers who multi-home only in Silk Road 2 (Type B) are compared with multi-homers who multi-home only in Evolution (Type C). Some regressions show the positive and statistically significant effect of multi-homing in the shutdown market conditionally on the rating. For Evolution the multi-homers who multi-home only in Silk Road 2 (Type B) are compared with multi-homers who multi-home only in Agora (Type C). The results are positive but insignificant. The insignificance might likely be the result of a drop in sample size for this regression. For Agora in Shock 2, only the comparison can be made between multi-homers in the shutdown market (Type B) and single-homers (Type D). The effect of multi-homing conditionally on the rating is positive and statistically significant.

A regression is run with *Mh_in_shutdown* replaced for *Mh_general* to show that multi-homers, in general, outperform single-homers. The results can be found in Table 30. Multi-homers seem to perform better at baseline and this difference with single-homers increases after the shock. Note that this regression does not imply causation. Multi-homers seem to be a different type of sellers than single-homers. They perform better and are better able to benefit from a shock. It might also reveal that single-homers tend to drop out more because they might be more afraid and multi-homers, who are more committed to their drugs business, stay in the market.

The key findings of this study can be summarized as follows:

- There are robust results that multi-homing in the shutdown market, conditionally on the reputation in this market, increases performance in the surviving market. Therefore, hypothesis 2 is accepted. These results suggest that buyers who switch markets have a tendency to choose multi-homing sellers but are conditioned in this decision by the reputation this seller had in the shutdown market.
- There is weak evidence that multi-homing in the shutdown market on itself increases performance in a surviving market. The evidence is weak because both positive and statistically significant and insignificant coefficients are found. In the most strict comparison (Type B compared with Type C) the results are insignificant. Therefore, hypothesis 1 cannot be accepted.
- Multi-homers in the shutdown market outperform both other multi-homers and single-homers
- Robust effects can be found of multi-homing in the shutdown market on sales count, but weak results are found for the impact on sales revenue
- The conditional effect of reputation is found when reputation is measured as average feedback rating as well as total deals of the seller in the shutdown market
- It is difficult to state whether there is a difference between shocks and markets because of changing sample sizes and sample groups[7]
- Rating, capacity and the total number of deals all positively contribute to sales performance.
- The effect of rating seems to become more important after a shock
- There is a positive association between multi-homing in general and seller performance before and after the shock.

[7]For Agora at shock 2 there are not other multi-homers to compare with. The insignificant finding of the multi-homing comparison in Evolution can or cannot stem from the significantly reduced sample size.

7 Discussion

The results show that sellers who multi-homed in a shutdown market improve in performance in the surviving market after a shock. This relation is conditional on the reputation in the shutdown market. This paper suggests that the increase in performance for multi-homers who were active in the shutdown market stems from loyal buyers switching markets.

However, this paper does not prove that buyer-loyalty is the mechanism which benefits this type of multi-homer. Another scenario might be that the sellers who multi-homed in the shutdown market have an excess capacity after the closure of one of their markets. Because they shift their capacity entirely to the surviving market their performance might increase. This study does control for capacity fluctuations of sellers. However, this measure of capacity might be imperfect because it only measures the sum of the prices of the goods for sale and cannot count the total inventory of a seller. Still, an increase in demand is needed for a seller to get rid of any excess capacity and attracting and winning the trust of new buyers might be difficult, especially after a shutdown. Therefore, the rise in demand for sellers who multi-home is most likely to be explained by buyers specifically targeting multi-homers whom they transacted with in the shutdown market.

Buyer-seller ties seem to extend across markets and do not seem to be dependent on a specific market. The findings of this paper illustrate the limited effectiveness of take-downs of the markets by the government and suggest that resources spent by the government on these take-downs might be wasted. Different strategies should be employed by the government to deter buyers and sellers from buying and selling drugs on darknet markets. This paper suggests that government focus should be directed especially to multi-homing sellers because they are high-performing sellers who serve buyers in multiple markets and seem to benefit or be resistant to shocks as opposed to single-homers. The understanding that buyers move to the same seller in a different market could be useful for the anti-drug trade strategies of international agencies.

In 2017, the Dutch and US law enforcement first closed down Alphabay which led to an influx of buyers on the Hansa Market. However, the law enforcement had already infiltrated in Hansa but decided to log data on buyers and sellers before shutting this market down (Greenberg, 2017). It is still difficult for law enforcement to find out true identities based on seller or buyer usernames and account information. The findings of this paper suggest that specific buyer-seller relationships move to different markets and this finding might help the law enforcement better map the information they have on darknet market users which consequently increases the chances of tracking these users down.

This paper supports the existing literature which shows that trust is an important mechanism in darknet markets. Rating, the number of deals and capacity size are all strong predictors of seller performance. Furthermore, the idea that buyer loyalty exceeds market boundaries conditional on reputation in the shutdown market suggests that buyers prefer a trusted seller over the risk of buying from a new seller. Reputation in the shutdown market, in the form of ratings as well as the total number of deals, both influence the decision to remain loyal or showcase that these sellers already had a small client base in the shutdown market. This study stresses the importance of reputation in online markets and raises awareness for firms and sellers that positive or negative spillover effects of reputation from one market to the other might happen. Multi-homing might be a beneficial strategy if one expects to achieve and maintain a positive reputation.

Reputation in the surviving market seems to become increasingly important after the shock which might be a result of increased uncertainty in the platform ecosystem and the move towards fewer high rated sellers. Previous research (Décary-Hétu & Laferrière, 2015) shows how the distortion of reputation system on darknet market can destabilize the market. The government could look into ways on how to break the trust in the market as a way to reduce trade.

This paper is the first in the literature to find a causal effect of multi-homing on seller performance. The empirical approach used as well as the findings answer the call of Hyrynsalmi et al. (2017) to start building the academic literature on multi-homing and platform participant's performance. With the rise of platform mediated transactions in the economy, the need for platform participants to understand whether to multi-home or single-home increases. This study showcases that multi-homers, in general, outperform single-homers. Furthermore, multi-homing sellers who were active in the shutdown market can quickly increase sales in a surviving market. Both findings indicate that a multi-homing can pay-off.

Soska and Christin (2015) suggested furthering the research on whether multi-homing sellers are the high-performing sellers in the darknet market ecosystem. This paper provides evidence that multi-homing sellers play an essential role in the darknet market, especially in the aftermath of shocks. In addition, Soska and Christin (2015) suggested that multi-homers on the darknet might be multi-homing in order not to be harmed by platform downtimes and shutdowns. The high percentage of multi-homers on the Agora[8] market could support this motivation. Agora faced significant more downtime issues than for example Evolution (Soska & Christin, 2015) which might have driven more sellers on Agora to multi-home than in Evolution.

Although the specific darknet market circumstances might reduce generalisability of the findings, the darknet markets might provide some insights relevant for firms, sellers or platform orchestrators in other ecosystems. First of all, the instability of platforms and the likelihood that buyers might switch between markets could be taken into account by firms and sellers in their decision to multi-home or not. Multi-homing might be a valuable diversification strategy in an uncertain ecosystem with the possibility to have one's buyers remain loyal to the firm or seller even when they need to switch market. Secondly, sellers or firms could communicate their presence on multiple markets better towards their customers. Multi-homing sellers on the darknet tend to communicate about their multi-homing efforts (See Figure 10). Although this paper did not test the influence of different communication strategies, firms and sellers might experiment with their communication efforts to raise awareness with new and existing buyers of their competence in other markets. Thirdly, a platform orchestrator in an ecosystem where multi-homing is common could counterintuitively raise the value of the platform for both

[8]See subsection 5.2.2 on page 19 for the distribution of multi-homers per market

sellers and buyers by showcasing the reputation a seller has in other markets. Evolution supports multi-homers in their communications by providing verification of seller's sales in other markets (See Figure 11). The verification might help loyal buyers to find their multi-homing seller in new markets.

Figure 10: Profile description text of a seller on Silk Road 2 who describes its presence on multiple markets

If you must have escrow then i am afraid i can only point you to our other Stores over on Evolution or Agora (links below) as Silkroad still has not implemented any escrow system yet. We will always use the sites escrow systems where and when they are available.

Be aware of imitators. We only operate on 3 marketplaces Silkroad, Evolution and Agora.. All using the same name - UkNextDay. So if someone is claiming to be us with a simeler name on a different marketplace, IT ISN'T US. Always check our pgp key for verification, we use the same key for all of our business across the 3 marketplaces.

http://agorahooawayyfoe.onion/register/oRtLPKE6zy
http://k5zq47j6wd3wdvjq.onion/store/12337
http://silkroad6ownowfk.onion/users/uknextday

Figure 11: Snapshot of the legacy sales functionality of Evolution which allows sellers to showcase verified competence in other markets

- Profile
- PGP
- Return Policy
- Legacy Sales
- Feedback

- Jun 15, 2014 — Confirmed 300 sales on **Agora**.

- Jun 15, 2014 — Confirmed 395 sales on **SilkRoad**.

8 Limitations

This study evaluates seller performance and assumes that improvements after a shock arise due to loyal buyers who switch markets after a shutdown. To proof this case one should be able to know which buyers switch markets, at which seller they bought from in the shutdown market and at which seller the buyer starts buying from in the surviving market. Usernames of buyers are hidden in reviews on darknet markets and do not enter the scrapes.

This study cannot be certain on the exact channel through multi-homing contributes to better performance due to the lack of this data. Future research could evaluate discussions on darknet (market) fora for clues on buyer behavior. If one can conduct interviews with buyers, one could get qualitative insights into the behavior and decisions of buyers after a shutdown.

A second limitation is that the multi-homing variable used in this study is crudely created. Firstly, the variable does not capture all the markets a seller could be multi-homing in nor does it take into account the smaller markets which also disappeared during Shock 1. Secondly, the variable is based on username matching which could create false positives and false negatives. Future research could expand the markets included in the research design and use additional elements such as pictures and profile descriptions to match sellers.

The time window of seven weeks might paint a limited picture of the effects of multi-homing after a shutdown, and long-term effects are currently ignored. Future research could tweak the empirical approach and extend the panel period to look for long-term effects after the shutdown.

Future research could increase the variables controlled for. The merged regressions are currently limited by a lack of category and ship from controls. Besides, Décary-Hétu and Quessy-Doré (2017) mention that information provided by the seller might induce more loyalty for buyers. This paper currently does not control for information provided by the seller. The profile information might provide two additional elements which could be essential. Firstly, the seller can communicate that it is multi-homing on a different platform. The communication strategy might influence the extent to which buyers locate the seller in a surviving market. Secondly, some sellers indicate when they have temporarily left the market because of holidays for example. The regression will be fairer if it controls for sellers on holiday because these sellers add zero sales to the equation for a different reason than the lack of performance of other sellers.

An additional limitation is the potential incompleteness of the scrapes and the presence of missing price data. Especially the sales revenue variable might be of weak quality. The variable could be improved via smarter outlier detection and missing values imputation methods

A final limitation is that this study cannot define seller performance as profits. Revenue and sales quantities only provide one picture of performance, but costs should be incorporated to be able to discuss the impact of multi-homing on profits. Future research could explore the costs of multi-homing on multiple platforms on the darknet.

9 Conclusion

The past years have witnessed the rise of darknet markets which orchestrate trades in illicit products on online platforms. The darknet market ecosystem is growing despite government take-downs (Soska & Christin, 2015). International agencies call for a better understanding of this new distribution platforms for drugs.

Buyers seem to move to surviving markets when one market shuts down (Décary-Hétu & Giommoni, 2017). Some sellers are multi-homing, they are participating in multiple markets at the same time. These sellers might be motivated to multi-home because of the instability of the markets (Soska & Christin, 2015). Buyers on darknet markets show loyal behavior: they tend to purchase most products at the same seller (Décary-Hétu & Quessy-Doré, 2017).

This paper studied weekly seller sales in Agora and Evolution before and after the government take-down of Silk Road 2 and the exit-scam of Evolution. The results of this paper indicate that multi-homing sellers in a shutdown market improve in sales in a surviving market conditionally on the reputation in the shutdown market. Sellers who multi-homed in a shutdown market outperform both other multi-homers as well as single-homers.

These results suggest that loyal buyers who need to switch markets remain loyal to the same seller in the surviving market. With buyer-seller ties being independent of the specific market available one could argue that the policy of shutting down markets would not be effective. This paper suggests that multi-homing sellers should receive prioritization in seller take-down efforts from law enforcement.

This paper contributed to the academic literature on the behavior of buyers and sellers in darknet markets. This papers' results on the relation between multi-homing, reputation and seller performance in surviving markets after a shutdown are novel to the academic literature. Furthermore, the paper supports previous findings which indicate that reputation is an essential driver of transactions in darknet markets.

The empirical literature on the impact of multi-homing and seller or firm performance is non-existent. This paper contributes to the literature by providing an empirical approach which utilizes different shocks to analyze the causal effect of multi-homing. This method could be used in different environments to increase the understanding of multi-homing benefits.

This paper adds the first empirically tested results to the literature on the benefits of multi-homing. Platform participants in other platforms can use these insights in their evaluation of the strategic choice to multi-home. When multi-homing is prevalent, a platform orchestrator might raise the value of its platform by allowing buyers to find a multi-homing seller on their platform more easily.

Future research could qualitatively investigate how buyers make their decision to switch markets and sellers on the darknet market. Furthermore, future research could investigate whether communication strategies used by multi-homers to promote their reputation in different markets influence their performance across markets.

10 References

Akerlof, G. A. (1970). The market for lemons: Qualitative uncertainty and the market mechanism. *Quarterly Journal of Economics*, 84, 488-500.

Aldridge, J., & Askew, R. (2016). When drug dealers can advertise: how drug cryptomarkets enable drug dealers to advertise. In *10th Annual Conference of the International Society for the Study of Drug Policy*, Sydney.

Anderson, R. E., & Srinivasan, S. S. (2003). E-satisfaction and e-loyalty: a contingency framework. *Psychology & Marketing*, 20, 123-138.

Bearman, J. (2015). The Untold Story of Silk Road, Part 1. *Wired*. Accessed at: https://www.wired.com/2015/04/silk-road-1/

Armona, L. (2017). Measuring the impact of formal and informal communication on electronic commerce demand.

Bhaskar, V., Linacre, R., & Machin, S. (2017). The economic functioning of online drugs markets. *Journal of Economic Behavior & Organization.*

Boudreau, K. (2008). Too many complementors? Evidence on software developers.

Burkard, C., Draisbach, T., Widjaja, T., & Buxmann, P. (2011). Software ecosystems: Vendor-sided characteristics of online marketplaces. *Inst. fr Betriebswirtschaftslehre.*

Castaneda, J. A. (2010). Relationship between customer satisfaction and loyalty on the internet. *Journal of Business & Psychology*, 26, 371-383.

Décary-Hétu, D., & 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., & Laferrière, D. (2015). Discrediting vendors in online criminal markets. In *Disrupting criminal networks: Network analysis in crime prevention*, 129-152

Décary-Hétu, D., & 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.

Digital Citizens Alliance (2014). Busted but not Broken: The State of Silk Road and the Darknet Marketplaces.

Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard business review*, 84(10), 92.

EUROPOL. (2014). The Internet Organised Crime Threat Assessment. Retrieved at: https://www.europol.europa.eu/content/internet-organised-crime-threat-assesment-iocta.

Gabszewicz, J. J., & Wauthy, X. (2004). Two-sided markets and price competition with multi-homing.

Gilbert, M., & Dasgupta, N. (2017). Silicon to syringe: Cryptomarkets and disruptive innovation in opioid supply chains. *International Journal of Drug Policy*, 46, 160-167.

Greenberg, A. (2015). Agora, the dark web's biggest drug market, is going offline. *Wired*. Accessed at: https://www.wired.com/2015/08/agora-dark-webs-biggest-drug-market-going-offline/

Greenberg, A. (2017). Global police spring a trap on thousands of dark web users. *Wired*.

Accessed at: https://www.wired.com/story/alphabay-hansa-takedown-dark-web-trap/
Gwern Branwen, Nicolas Christin, David Dcary-Htu, Rasmus Munks- gaard Andersen, StExo, El Presidente, Anonymous, Daryl Lau, Sohhlz, Delyan Kratunov, Vince Cakic, Van Buskirk & Whom. Dark net market archives, 2011-2015, 12 July 2015. Web. [accessed 24 January 2018] https://www.gwern.net/DNM-archives
Hardy, R. A., & Norgaard, J. R. (2016). Reputation in the internet black market: an empirical and theoretical analysis of the deep web. *Journal of Institutional Economics*, 12(3), 515-539.
Hyrynsalmi, S., Suominen, A., & Mntymki, M. (2016a). The influence of developer multi-homing on competition between software ecosystems. *Journal of Systems and Software*, 111, 119-127.
Hyrynsalmi, S., Suominen, A., Jansen, S., & Yrjnkoski, K. (2016b). Multi-homing in ecosystems and firm performance: Does it improve software companies' ROA? In *IWSECO@ ICIS*, 56-69.
Hyrynsalmi, S., Mntymki, M., & Baur, A. W. (2017). Multi-homing and software firm performance. In *Conference on e-Business, e-Services and e-Society*, 442-452.
Idu, A., van de Zande, T., & Jansen, S. (2011, November). Multi-homing in the Apple ecosystem: why and how developers target multiple apple app stores. In *Proceedings of the International Conference on Management of Emergent Digital EcoSystems*, 122-128.
Janetos, N., & Tilly, J. (2017). Reputation Dynamics in a Market for Illicit Drugs. *arXiv preprint arXiv:1703.01937.*
Kelion, L. (2017). Dark web markets boom after AlphaBay and Hansa busts. *BBC*. Accessed at: http://www.bbc.com/news/technology-40788266
Landsman, V., & Stremersch, S. (2011). Multihoming in two-sided markets: An empirical inquiry in the video game console industry. *Journal of Marketing*, 75(6), 39-54.
Martin, J. (2014). Lost on the Silk Road: Online drug distribution and the 'cryptomarket'. *Criminology & Criminal Justice*, 14(3), 351-367.
Neal, W. D. (1999). Satisfaction is nice, but value drives loyalty. *Marketing Research*, 11, 20-23.
Nurmi, J., Kaskela, T., Perala, J., & Oksanen, A. (2017). Seller's reputation and capacity on the illicit drug markets: 11-month study on the Finnish version of the Silk Road. *Drug & Alcohol Dependence*, 178, 201-207.
Oliver, R. L. (1997). Satisfaction: A behavioural perspective on the consumer. New York, NY: McGraw-Hill.
Popper N., (2017). AlphaBay, biggest online drug bazaar, goes dark, and questions swirl. *New York Times.*
Rochet, J. C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European economic association*, 1(4), 990-1029.
Rochet, J. C., & Tirole, J. (2006). Two-sided markets: a progress report. *The RAND journal of economics*, 37(3), 645-667.
Singh, M. (2014). Clearing up confusion - deep web vs. dark web. Accessed at: https://brightplanet.com/2014/03/clearing-confusion-deep-web-vs-dark-web/

Soska, K., & Christin, N. (2015). Measuring the longitudinal evolution of the online anonymous marketplace ecosystem. In *USENIX Security Symposium*, 33-48.
Sun, M., & Tse, E. (2009). The Resource-Based View of Competitive Advantage in Two-Sided Markets. *Journal of Management Studies*, 46(1), 45-64.
UNODC. (2014). World Drug Report 2014. Retrieved at: http://www.unodc.org/wdr2014/.
Valvi, A. C., & Fragkos, K. C. (2012). Critical review or the e-loyalty literature: A purchase-centred framework. *Electronic Commerce Research*, 12, 331-378.
Wang, X., Peng, P., Wang, C., & Wang, G. (2018). You are your photographs: Detecting multiple identities of vendors in the darknet marketplaces. In *Proceedings of the 2018 on Asia Conference on Computer and Communications Security*, 431-442.

A Data definition table

Table 13: Variable definitions

Variable/Code	**Description**
Type A	Sellers who multi-home in the shutdown market and another market
Type B	Sellers who multi-home in the shutdown market only
Type C	Sellers who multi-home in another market only
Type D	Sellers who single-home
Shock 1	Take-down of Silk Road 2 and the related pre- and post-shock data for Agora and Evolution
Shock 2	Exit-scam of Evolution and the related pre- and post-shock data for Agora
Sales revenue	The log of revenue calculated as the sum of product sales times the product price
Sales count	The log of products sold
Mh_in_shutdown	A dummy taking the value 1 for sellers who were multi-homing in the shutdown market
Mh_other	A dummy taking the value 1 for sellers who were multi-homing in another market
Mh_general	A dummy taking the value 1 for sellers who were multi-homing
Time	A dummy taking the value 1 for weeks in the post-shock period
Rating_in_shutdown*	The latest rating of a seller before a shock ranging from 0 (low) to 1 (high)
Deals_in_shutdown*	The log of the latest total number of deals of a seller before a shock
Rating	The average rating of a seller ranging from 0 (low) to 1 (high)
No-rating	A dummy taking the value of 1 for a seller where no rating could be found
Deals*	The log of total number of deals at the beginning of the panel
Capacity	The log of the sum of the prices of the product listed for sale by a seller
Evolution*	A dummy taking the value of 1 for an observation in the Evolution market
Ship from*	The location a seller ships its product from
Ship to*	The location a seller ships its product to
Product category*	The product categories in which a seller is active in

*Constant variables. Other variables can fluctuate per week.

B Ship from, ship to locations and product categories

Agora

Ship from and **ship to**:
usa, germany, australia, other, netherlands, uk, europe, canada, asia, world

Product categories:
Chemicals, Counterfeits, Data, Drug_Paraphernalia, Drugs_Barbiturates, Drugs_Benzos, Drugs_Cannabis, Drugs_Dissociatives, Drugs_Ecstasy, Drugs_Opioids, Drugs_Other, Drugs_Prescription, Drugs_Psychedelics, Drugs_RCs, Drugs_Steroids, Drugs_Stimulants, Drugs_Weightloss, Electronics, Forgeries, Info, Jewelry, Other, Services, Tobacco, Weapons

Evolution

Ship from:
Afghanistan, Andorra, Argentina, Aruba, Australia, Austria, Azerbaijan, Bangladesh, Belgium, Bolivia, Bosnia.and.Herzegovi, Brazil, Bulgaria, Cambodia, Canada, Cayman.Islands, Chile, China, Christmas.Island, Colombia, Cuba, Czech.Republic, Denmark, Djibouti, Ecuador, Egypt, El.Salvador, Estonia, Fiji, Finland, France, Gambia, Georgia, Germany, Ghana, Greece, Guatemala, Guernsey, Hong.Kong.SAR.China, Hungary, India, Ireland, Italy, Jamaica, Kenya, Latvia, Lithuania, Luxembourg, Malaysia, Mexico, Nepal, Netherlands, Netherlands.Antilles, New.Zealand, North.Korea, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Russia, Saudi.Arabia, Serbia, Singapore, Slovakia, Slovenia, South.Africa, Spain, Sri.Lanka, Svalbard.and.Jan.May, Swaziland, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Togo, Turkey, Ukraine, United.Kingdom, United.States, Uruguay, Western.Sahara, Worldwide

Product categories:
CounterfeitsAccessories, CounterfeitsApparel, CounterfeitsMoney, CounterfeitsOther, DigitalGoodsE.Books, DigitalGoodsOther, DigitalGoodsSoftware, DrugsBenzos, DrugsCannabis, DrugsDissociatives, DrugsEcstasy, DrugsOpioids, DrugsOther, DrugsParaphernalia, DrugsPrescription, DrugsPsychedelics, DrugsSteroids, DrugsStimulants, DrugsTobacco, DrugsWeightLoss, ElectronicsSIMCards, FraudRelatedAccounts, FraudRelatedCC.CVV, FraudRelatedDocuments.Data, FraudRelatedDumps, Guides.TutorialsDrugs, Guides.TutorialsFraud, Guides.TutorialsHacking, Guides.TutorialsOther, Guides.TutorialsSecurity, ServicesHacking, ServicesIDs.Passports, ServicesOther, ServicesPaypal, WeaponsAmmunition, WeaponsExplosives, WeaponsGuns, WeaponsMelee, WeaponsOther,

C Correlation matrices

Table 14: Correlation matrix

	Mh_ in_ shutdown	Mh_ other	Mh_ general	Time	Sales revenue	Sales count	Rating	No-rating	Deals in_ shutdown	Rating_ in_ shutdown	Deals	Evo-lution
Mh_in_shutdown	1	0.028	0.715	0.015	0.121	0.081	0.016	-0.039	0.827	0.950	0.144	-0.227
Mh_other	0.028	1	0.608	0.007	0.126	0.083	0.059	-0.045	0.022	0.010	-0.027	0.176
Mh_general	0.715	0.608	1	0.013	0.171	0.116	0.046	-0.051	0.591	0.679	0.112	-0.094
Time	0.015	0.007	0.013	1	-0.018	0.001	-0.034	-0.070	0.009	0.018	-0.006	-0.035
Sales revenue	0.121	0.126	0.171	-0.018	1	0.510	0.160	-0.182	0.146	0.121	0.227	-0.094
Sales count	0.081	0.083	0.116	0.001	0.510	1	0.091	-0.079	0.156	0.080	0.484	-0.002
Rating	0.016	0.059	0.046	-0.034	0.160	0.091	1	0.033	0.018	0.026	0.056	0.061
No-rating	-0.039	-0.045	-0.051	-0.070	-0.182	-0.079	0.033	1	-0.059	-0.051	-0.038	0.015
Deals_in_shutdown	0.827	0.022	0.591	0.009	0.146	0.156	0.018	-0.059	1	0.870	0.240	-0.200
Rating_in_shutdown	0.950	0.010	0.679	0.018	0.121	0.080	0.026	-0.051	0.870	1	0.148	-0.226
Deals	0.144	-0.027	0.112	-0.006	0.227	0.484	0.056	-0.038	0.240	0.148	1	-0.119
Evolution	-0.227	0.176	-0.094	-0.035	-0.094	-0.002	0.061	0.015	-0.200	-0.226	-0.119	1

Table 15: Correlation matrix for the interaction terms

Mh_in_shutdown×Time	Rating_in_shutdown×Mh_in_shutdown×Time	Rating_in_shutdown×Mh_in_shutdown	
Mh_in_shutdown×Time	1	0.959	0.659
Rating_in_shutdown×Mh_in_shutdown×Time	0.959	1	0.697
Rating_in_shutdown×Mh_in_shutdown	0.659	0.697	1

D Variations Type A and B compared with Type C and D, Shock 1 and 2

Table 16: Type A and B compared with Type C and D, Shock 1 and 2, Equation 2 without interaction Mh_in_shutdown×Time

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	0.440	−0.010	−0.226	0.139	−0.002	−0.142
	(0.379)	(0.324)	(0.309)	(0.166)	(0.152)	(0.138)
Rating_in_shutdown× Mh_in_shutdown	0.220	0.199	0.269	0.071	0.066	0.111
	(0.401)	(0.342)	(0.326)	(0.176)	(0.161)	(0.145)
Rating_in_shutdown×Mh_in_shutdown×Time	0.335***	0.305***	0.276**	0.214***	0.205***	0.186***
	(0.116)	(0.111)	(0.111)	(0.049)	(0.047)	(0.047)
Capacity		0.576***	0.533***		0.179***	0.151***
		(0.018)	(0.017)		(0.010)	(0.009)
Deals			0.512***			0.333***
			(0.027)			(0.014)
Evolution	−0.820***	−0.754***	−0.410***	−0.173***	−0.154***	0.070
	(0.116)	(0.104)	(0.100)	(0.055)	(0.052)	(0.049)
Rating	14.610***	15.833***	14.446***	6.131***	6.505***	5.601***
	(1.817)	(1.939)	(1.903)	(0.720)	(0.758)	(0.734)
No-rating	−1.023***	−0.412	1.056***	−0.799***	−0.609***	0.348***
	(0.390)	(0.330)	(0.321)	(0.135)	(0.124)	(0.114)
Observations	44,636	44,538	44,538	44,636	44,538	44,538
R^2	0.060	0.183	0.225	0.050	0.113	0.205
Adjusted R^2	0.059	0.183	0.224	0.050	0.112	0.204

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

Table 17: Type A and B compared with Type C and D, Shock 1, Equation 2

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	0.402	−0.011	−0.122	0.110	−0.015	−0.096
	(0.401)	(0.338)	(0.321)	(0.169)	(0.156)	(0.140)
Rating_in_shutdown×Mh_in_shutdown	0.097	0.079	0.195	−0.054	−0.059	0.026
	(0.437)	(0.369)	(0.349)	(0.185)	(0.171)	(0.152)
Mh_in_shutdown×Time	−0.092	−0.080	−0.209	−0.025	−0.022	−0.116
	(0.355)	(0.334)	(0.333)	(0.132)	(0.126)	(0.123)
Rating_in_shutdown×Mh_in_shutdown×Time	0.430	0.342	0.364	0.295**	0.268*	0.284**
	(0.393)	(0.369)	(0.369)	(0.149)	(0.142)	(0.140)
Capacity		0.606***	0.584***		0.183***	0.167***
		(0.020)	(0.019)		(0.011)	(0.010)
Deals			0.382***			0.279***
			(0.029)			(0.016)
Evolution	−0.742***	−0.673***	−0.368***	−0.156***	−0.136***	0.086*
	(0.109)	(0.098)	(0.096)	(0.051)	(0.049)	(0.047)
Rating	13.968***	14.837***	14.387***	5.759***	6.015***	5.687***
	(1.989)	(2.034)	(2.092)	(0.775)	(0.789)	(0.832)
No-rating	−0.082	0.272	1.285***	−0.477***	−0.370***	0.368***
	(0.238)	(0.190)	(0.197)	(0.084)	(0.076)	(0.078)
Observations	31,932	31,827	31,827	31,932	31,827	31,827
R^2	0.046	0.188	0.214	0.033	0.100	0.174
Adjusted R^2	0.045	0.187	0.214	0.032	0.100	0.174

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

E Variations on Type B compared with Type C

Table 18: Type B compared with Type C, Shock 1, without interaction Mh_in_shutdown×Time

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	−0.689	−0.378	−0.423	−0.257	−0.146	−0.176
	(0.458)	(0.406)	(0.382)	(0.217)	(0.201)	(0.180)
Rating_in_shutdown×Mh_in_shutdown	−0.189	−0.356	−0.035	−0.244	−0.302	−0.087
	(0.517)	(0.449)	(0.419)	(0.237)	(0.218)	(0.192)
Rating_in_shutdown×Mh_in_shutdown×Time	0.554*	0.448	0.449	0.291**	0.249**	0.250**
	(0.302)	(0.286)	(0.287)	(0.123)	(0.118)	(0.118)
Capacity		0.717***	0.656***		0.260***	0.219***
		(0.043)	(0.041)		(0.022)	(0.020)
Deals			0.540***			0.362***
			(0.063)			(0.031)
Evolution	−0.529**	−0.641***	−0.089	−0.206*	−0.248**	0.122
	(0.222)	(0.197)	(0.194)	(0.106)	(0.100)	(0.095)
Rating	20.970***	23.828***	21.669***	8.825***	9.814***	8.368***
	(3.444)	(3.722)	(3.761)	(1.440)	(1.538)	(1.567)
No-rating	−2.101***	−0.906**	0.422	−1.075***	−0.640***	0.249
	(0.594)	(0.413)	(0.439)	(0.194)	(0.155)	(0.154)
Observations	8,921	8,879	8,879	8,921	8,879	8,879
R^2	0.044	0.210	0.254	0.043	0.156	0.258
Adjusted R^2	0.042	0.208	0.252	0.041	0.154	0.257

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

Table 19: Type A and B compared with Type C, Shock 1, Equation 1

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	-0.339^{*}	-0.340^{**}	-0.228	-0.226^{**}	-0.225^{***}	-0.148^{**}
	(0.192)	(0.170)	(0.159)	(0.090)	(0.085)	(0.075)
Mh_in_shutdown×Time	0.517^{***}	0.441^{***}	0.428^{**}	0.261^{***}	0.231^{***}	0.221^{***}
	(0.183)	(0.169)	(0.169)	(0.077)	(0.072)	(0.072)
Capacity		0.700^{***}	0.646^{***}		0.244^{***}	0.207^{***}
		(0.038)	(0.036)		(0.020)	(0.018)
Deals			0.521^{***}			0.358^{***}
			(0.053)			(0.028)
Evolution	-0.595^{***}	-0.725^{***}	-0.136	-0.229^{**}	-0.274^{***}	0.130
	(0.188)	(0.168)	(0.167)	(0.090)	(0.086)	(0.084)
Rating	21.600^{***}	24.214^{***}	22.648^{***}	8.520^{***}	9.390^{***}	8.314^{***}
	(3.173)	(3.321)	(3.372)	(1.313)	(1.363)	(1.386)
No-rating	-2.164^{***}	-0.958^{**}	0.365	-1.103^{***}	-0.681^{***}	0.228
	(0.620)	(0.413)	(0.446)	(0.200)	(0.151)	(0.155)
Observations	11,887	11,845	11,845	11,887	11,845	11,845
R^2	0.037	0.196	0.239	0.031	0.130	0.232
Adjusted R^2	0.035	0.195	0.237	0.029	0.128	0.231

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

Table 20: Type B compared with Type C, Shock 1 and 2, Equation 1

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	−0.784***	−0.645***	−0.415*	−0.422***	−0.372***	−0.219**
	(0.263)	(0.232)	(0.213)	(0.116)	(0.108)	(0.094)
Mh_in_shutdown×Time	0.319	0.290	0.267	0.173	0.159	0.144
	(0.268)	(0.253)	(0.253)	(0.107)	(0.102)	(0.102)
Capacity		0.633***	0.567***		0.222***	0.177***
		(0.033)	(0.032)		(0.017)	(0.016)
Deals			0.578***			0.387***
			(0.050)			(0.025)
Evolution	−0.527**	−0.639***	−0.045	−0.206*	−0.246**	0.152
	(0.221)	(0.197)	(0.189)	(0.106)	(0.100)	(0.093)
Rating	21.251***	24.823***	22.324***	8.899***	10.122***	8.449***
	(2.649)	(2.717)	(2.710)	(1.126)	(1.152)	(1.136)
No-rating	−2.123***	−1.062**	0.337	−1.077***	−0.704***	0.233
	(0.596)	(0.415)	(0.457)	(0.187)	(0.147)	(0.156)
Observations	15,924	15,882	15,882	15,924	15,882	15,882
R^2	0.047	0.175	0.223	0.049	0.128	0.237
Adjusted R^2	0.045	0.173	0.221	0.047	0.127	0.236

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

Table 21: Type A and B compared with Type C, Shock 1 and 2, Equation 1

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	-0.343^{*}	-0.350^{**}	-0.234	-0.227^{**}	-0.228^{***}	-0.149^{**}
	(0.191)	(0.170)	(0.158)	(0.089)	(0.085)	(0.074)
Mh_in_shutdown×Time	0.390^{**}	0.306^{*}	0.266	0.206^{***}	0.173^{**}	0.146^{**}
	(0.181)	(0.169)	(0.169)	(0.077)	(0.073)	(0.073)
Capacity		0.633^{***}	0.573^{***}		0.217^{***}	0.176^{***}
		(0.031)	(0.029)		(0.016)	(0.014)
Deals			0.549^{***}			0.374^{***}
			(0.044)			(0.022)
Evolution	-0.618^{***}	-0.767^{***}	-0.156	-0.235^{***}	-0.287^{***}	0.130
	(0.183)	(0.163)	(0.159)	(0.088)	(0.084)	(0.080)
Rating	21.433^{***}	25.036^{***}	22.870^{***}	8.724^{***}	9.933^{***}	8.456^{***}
	(2.500)	(2.532)	(2.520)	(1.064)	(1.077)	(1.053)
No-rating	-2.149^{***}	-1.056^{**}	0.342	-1.102^{***}	-0.727^{***}	0.227
	(0.618)	(0.422)	(0.457)	(0.199)	(0.151)	(0.159)
Observations	19,249	19,207	19,207	19,249	19,207	19,207
R^2	0.040	0.169	0.214	0.039	0.115	0.220
Adjusted R^2	0.038	0.168	0.213	0.037	0.113	0.218

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

Table 22: Type B compared with Type C, Shock 1 and 2, Equation 2

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	−0.471	−0.325	−0.354	−0.148	−0.097	−0.117
	(0.485)	(0.399)	(0.381)	(0.218)	(0.196)	(0.176)
Rating_in_shutdown×Mh_in_shutdown	−0.402	−0.410	−0.079	−0.349	-0.352^{*}	−0.131
	(0.537)	(0.444)	(0.419)	(0.236)	(0.212)	(0.188)
Mh_in_shutdown×Time	−0.508	−0.400	−0.471	−0.239	−0.205	−0.252
	(0.520)	(0.483)	(0.477)	(0.177)	(0.162)	(0.156)
Rating_in_shutdown×Mh_in_shutdown×Time	1.075^{*}	0.894	0.966^{*}	0.531^{***}	0.468^{**}	0.516^{***}
	(0.586)	(0.547)	(0.541)	(0.206)	(0.191)	(0.186)
Capacity		0.633^{***}	0.566^{***}		0.222^{***}	0.177^{***}
		(0.033)	(0.032)		(0.017)	(0.016)
Deals			0.582^{***}			0.388^{***}
			(0.050)			(0.025)
Evolution	-0.532^{**}	-0.643^{***}	−0.046	-0.208^{**}	-0.248^{**}	0.150
	(0.221)	(0.197)	(0.190)	(0.106)	(0.100)	(0.093)
Rating	21.208^{***}	24.829^{***}	22.101^{***}	8.965^{***}	10.206^{***}	8.385^{***}
	(2.654)	(2.736)	(2.709)	(1.135)	(1.165)	(1.139)
No-rating	-2.093^{***}	-1.043^{**}	0.391	-1.073^{***}	-0.703^{***}	0.254^{*}
	(0.593)	(0.415)	(0.440)	(0.194)	(0.152)	(0.152)
Observations	15,924	15,882	15,882	15,924	15,882	15,882
R^2	0.047	0.175	0.224	0.050	0.129	0.238
Adjusted R^2	0.045	0.173	0.222	0.048	0.127	0.236

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

Table 23: Type A and B compared with Type C, Shock 1 and 2, Equation 2

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	−0.308	−0.333	−0.366	−0.145	−0.153	−0.175
	(0.397)	(0.330)	(0.313)	(0.172)	(0.156)	(0.140)
Rating_in_shutdown×Mh_in_shutdown	−0.045	−0.022	0.160	−0.100	−0.092	0.031
	(0.417)	(0.348)	(0.327)	(0.180)	(0.164)	(0.145)
Mh_in_shutdown×Time	−0.027	−0.053	−0.115	−0.059	−0.072	−0.114
	(0.363)	(0.340)	(0.340)	(0.137)	(0.129)	(0.127)
Rating_in_shutdown×Mh_in_shutdown×Time	0.508	0.438	0.463	0.323**	0.299**	0.316**
	(0.387)	(0.362)	(0.362)	(0.147)	(0.138)	(0.137)
Capacity		0.633***	0.572***		0.217***	0.175***
		(0.031)	(0.029)		(0.016)	(0.014)
Deals			0.552***			0.376***
			(0.044)			(0.022)
Evolution	−0.622***	−0.772***	−0.161	−0.237***	−0.289***	0.127
	(0.183)	(0.163)	(0.160)	(0.088)	(0.084)	(0.080)
Rating	21.303***	24.912***	22.600***	8.691***	9.902***	8.328***
	(2.499)	(2.536)	(2.518)	(1.067)	(1.080)	(1.054)
No-rating	−2.122***	−1.032**	0.391	−1.091***	−0.717***	0.252*
	(0.608)	(0.413)	(0.438)	(0.197)	(0.149)	(0.151)
Observations	19,249	19,207	19,207	19,249	19,207	19,207
R^2	0.040	0.169	0.215	0.039	0.115	0.221
Adjusted R^2	0.038	0.168	0.213	0.038	0.114	0.219

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

Table 24: Type B compared with Type C, Shock 1, Equation 2, Rating_in_shutdown replaced with Deals_in_shutdown

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	-1.115^{***}	-0.811^{**}	-0.492	-0.504^{***}	-0.393^{**}	-0.178
	(0.391)	(0.349)	(0.326)	(0.168)	(0.159)	(0.140)
Deals_in_shutdown×Mh_in_shutdown	0.168	0.094	0.040	0.041	0.015	-0.021
	(0.153)	(0.130)	(0.123)	(0.066)	(0.060)	(0.053)
Mh_in_shutdown×Time	-0.061	0.015	-0.058	-0.081	-0.057	-0.107
	(0.403)	(0.370)	(0.368)	(0.148)	(0.135)	(0.133)
Deals_in_shutdown×Mh_in_shutdown×Time	0.243	0.167	0.191	0.153^{**}	0.125^{*}	0.141^{**}
	(0.173)	(0.162)	(0.164)	(0.070)	(0.067)	(0.069)
Capacity		0.713^{***}	0.654^{***}		0.258^{***}	0.218^{***}
		(0.043)	(0.041)		(0.022)	(0.020)
Deals			0.536^{***}			0.361^{***}
			(0.063)			(0.031)
Evolution	-0.517^{**}	-0.633^{***}	-0.087	-0.202^{*}	-0.244^{**}	0.123
	(0.221)	(0.197)	(0.193)	(0.106)	(0.100)	(0.095)
Rating	20.497^{***}	23.377^{***}	21.546^{***}	8.526^{***}	9.520^{***}	8.287^{***}
	(3.410)	(3.663)	(3.747)	(1.417)	(1.505)	(1.561)
No-rating	-1.973^{***}	-0.823^{**}	0.454	-1.014^{***}	-0.596^{***}	0.265^{*}
	(0.550)	(0.393)	(0.434)	(0.173)	(0.147)	(0.151)
Observations	8,921	8,879	8,879	8,921	8,879	8,879
R^2	0.048	0.211	0.254	0.046	0.157	0.259
Adjusted R^2	0.046	0.209	0.253	0.044	0.155	0.258

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

Table 25: Type B compared with Type C, Shock 1, Equation 2, Time dummy included instead of week fixed effects

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_in_shutdown	−0.490	−0.254	−0.274	−0.158	−0.073	−0.086
	(0.493)	(0.403)	(0.385)	(0.221)	(0.198)	(0.179)
Time	−0.418***	−0.429***	−0.333***	−0.082*	−0.082*	−0.018
	(0.116)	(0.107)	(0.107)	(0.049)	(0.046)	(0.046)
Rating_in_shutdown×Mh_in_shutdown	−0.377	−0.474	−0.175	−0.337	−0.371*	−0.172
	(0.549)	(0.449)	(0.426)	(0.241)	(0.215)	(0.192)
Mh_in_shutdown×Time	−0.399	−0.251	−0.304	−0.201	−0.152	−0.187
	(0.528)	(0.488)	(0.481)	(0.179)	(0.162)	(0.156)
Rating_in_shutdown×Mh_in_shutdown×Time	0.958	0.708	0.759	0.490**	0.400**	0.434**
	(0.598)	(0.555)	(0.550)	(0.210)	(0.193)	(0.188)
Capacity		0.714***	0.653***		0.257***	0.217***
		(0.043)	(0.041)		(0.022)	(0.020)
Deals			0.544***			0.363***
			(0.063)			(0.031)
Evolution	−0.533**	−0.646***	−0.090	−0.208*	−0.249**	0.122
	(0.221)	(0.197)	(0.193)	(0.106)	(0.100)	(0.095)
Rating	21.015***	23.862***	21.675***	8.831***	9.807***	8.348***
	(3.471)	(3.750)	(3.789)	(1.448)	(1.544)	(1.574)
No-rating	−2.055***	−0.853**	0.475	−1.055***	−0.620***	0.266*
	(0.595)	(0.417)	(0.441)	(0.195)	(0.156)	(0.155)
Constant	−14.862***	−24.463***	−24.293***	−6.422***	−9.833***	−9.720***
	(3.406)	(3.739)	(3.751)	(1.418)	(1.550)	(1.565)
Observations	8,921	8,879	8,879	8,921	8,879	8,879
R^2	0.042	0.208	0.252	0.042	0.153	0.256
Adjusted R^2	0.041	0.207	0.251	0.041	0.152	0.255

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

F Reputation and Time interaction, Shock 1 and 2

Table 26: Reputation and Time interaction

	Dependent variable:	
	Sales revenue	Sales count
	(1)	(2)
Rating	13.166***	5.225***
	(1.798)	(0.659)
Time	−2.835**	−0.880*
	(1.157)	(0.459)
Capacity	0.541***	0.154***
	(0.017)	(0.009)
Deals	0.502***	0.329***
	(0.027)	(0.014)
Evolution	−0.239***	0.135***
	(0.086)	(0.043)
No-rating	1.003***	0.299***
	(0.321)	(0.116)
Rating×Time	2.505**	0.772*
	(1.177)	(0.469)
Constant	−14.900***	−5.969***
	(1.780)	(0.654)
Observations	44,538	44,538
R^2	0.217	0.194
Adjusted R^2	0.217	0.194

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses
No time fixed effects included.
All sellers included

G Breakdown per market

Table 27: Type B compared with Type C, Agora Shock 1, Equation 2

	Dependent variable:			
	Sales revenue		Sales count	
	(1)	(2)	(3)	(4)
Mh_in_shutdown	−0.458	−0.477	−0.068	−0.105
	(0.448)	(0.423)	(0.199)	(0.190)
Rating_in_shutdown×Mh_in_shutdown	−0.009	−0.006	−0.039	−0.032
	(0.095)	(0.090)	(0.042)	(0.040)
Mh_in_shutdown×Time	−0.037		−0.077	
	(0.549)		(0.212)	
Rating_in_shutdown×Mh_in_shutdown×Time	0.148	0.141*	0.082*	0.068**
	(0.126)	(0.073)	(0.049)	(0.030)
Rating	3.099***	3.099***	0.988***	0.989***
	(0.786)	(0.786)	(0.315)	(0.315)
Deals	1.010***	1.010***	0.609***	0.609***
	(0.109)	(0.109)	(0.048)	(0.048)
Observations	4,200	4,200	4,200	4,200
R^2	0.366	0.366	0.411	0.411
Adjusted R^2	0.356	0.357	0.402	0.403

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses
Product category controls, ship from and ship to controls hidden from table output

Table 28: Type B compared with Type C, Evolution Shock 1, Equation 2

	Dependent variable:			
	Sales revenue		Sales count	
	(1)	(2)	(3)	(4)
Mh_in_shutdown	0.083	0.642	-0.038	0.145
	(0.784)	(0.597)	(0.331)	(0.295)
Rating_in_shutdown×Mh_in_shutdown	0.032	-0.079	0.048	0.012
	(0.170)	(0.137)	(0.072)	(0.065)
Mh_in_shutdown×Time		-1.199		-0.392
		(0.735)		(0.257)
Rating_in_shutdown×Mh_in_shutdown×Time	-0.019	0.220	0.011	0.089
	(0.098)	(0.175)	(0.038)	(0.062)
Rating	20.040**	20.031**	7.667**	7.664**
	(8.311)	(8.399)	(3.743)	(3.772)
No-rating	2.105***	2.108***	1.136***	1.137***
	(0.520)	(0.522)	(0.193)	(0.193)
Capacity	0.470***	0.468***	0.133***	0.132***
	(0.063)	(0.063)	(0.030)	(0.030)
Deals	1.375***	1.374***	0.754***	0.753***
	(0.081)	(0.081)	(0.037)	(0.037)
Observations	3,832	3,832	3,832	3,832
R^2	0.473	0.474	0.562	0.563
Adjusted R^2	0.461	0.461	0.552	0.552

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses
Product category controls and ship from controls hidden from table output

Table 29: Type B compared with Type C, Agora Shock 2, Equation 2

	Dependent variable:			
	Sales revenue		Sales count	
	(1)	(2)	(3)	(4)
Mh_in_shutdown	-2.332	-5.008^{*}	-1.218	-2.213^{*}
	(2.225)	(2.935)	(1.000)	(1.267)
Rating_in_shutdown×Mh_in_shutdown	2.198	4.917^{*}	1.151	2.162^{*}
	(2.267)	(2.980)	(1.017)	(1.286)
Mh_in_shutdown×Time	-4.668^{*}		-1.736	
	(2.661)		(1.109)	
Rating_in_shutdown×Mh_in_shutdown×Time	4.959^{*}	0.218	1.896^{*}	0.133^{*}
	(2.712)	(0.168)	(1.132)	(0.071)
Rating	2.454^{***}	2.458^{***}	0.958^{***}	0.959^{***}
	(0.761)	(0.762)	(0.277)	(0.277)
Deals	0.919^{***}	0.919^{***}	0.528^{***}	0.528^{***}
	(0.053)	(0.053)	(0.026)	(0.026)
Observations	13,264	13,264	13,264	13,264
R^2	0.273	0.273	0.331	0.331
Adjusted R^2	0.270	0.270	0.328	0.328

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses
Product category controls, ship from and ship to controls hidden from table output

H Mhgeneral

Table 30: Type A, B and C (Mh_general) compared with Type D, Shock 1 and 2, Equation 1

	Dependent variable:					
	Sales revenue			Sales count		
	(1)	(2)	(3)	(4)	(5)	(6)
Mh_general	0.964***	0.402***	0.233***	0.324***	0.150***	0.039
	(0.099)	(0.092)	(0.086)	(0.046)	(0.046)	(0.040)
Mh_general×Time	0.229**	0.219**	0.203**	0.164***	0.163***	0.153***
	(0.092)	(0.088)	(0.087)	(0.040)	(0.038)	(0.038)
Capacity		0.560***	0.522***		0.172***	0.147***
		(0.018)	(0.017)		(0.010)	(0.009)
Deals			0.502***			0.330***
			(0.027)			(0.014)
Evolution	−0.763***	−0.718***	−0.383***	−0.151***	−0.138***	0.082*
	(0.114)	(0.103)	(0.099)	(0.054)	(0.052)	(0.048)
Rating	14.194***	15.601***	14.318***	5.975***	6.401***	5.558***
	(1.812)	(1.937)	(1.906)	(0.719)	(0.757)	(0.736)
No-rating	−1.021**	−0.443	0.992***	−0.800***	−0.622***	0.321***
	(0.402)	(0.339)	(0.335)	(0.139)	(0.126)	(0.120)
Observations	44,636	44,538	44,538	44,636	44,538	44,538
R^2	0.073	0.187	0.226	0.060	0.116	0.206
Adjusted R^2	0.072	0.186	0.226	0.059	0.115	0.205

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by seller are in parentheses

I Total sales revenue and count per market

Figure 12: Weekly sales revenue Agora

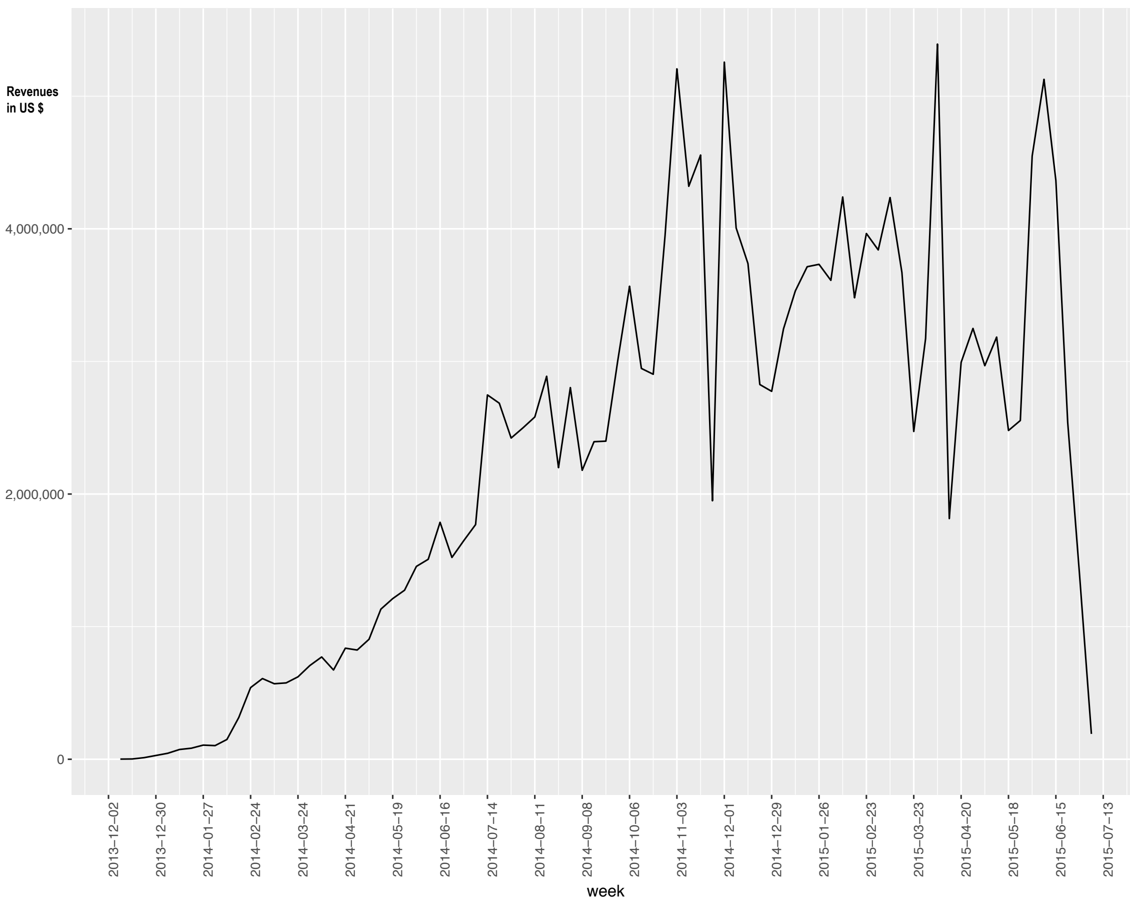


Figure 13: Weekly sales count Agora

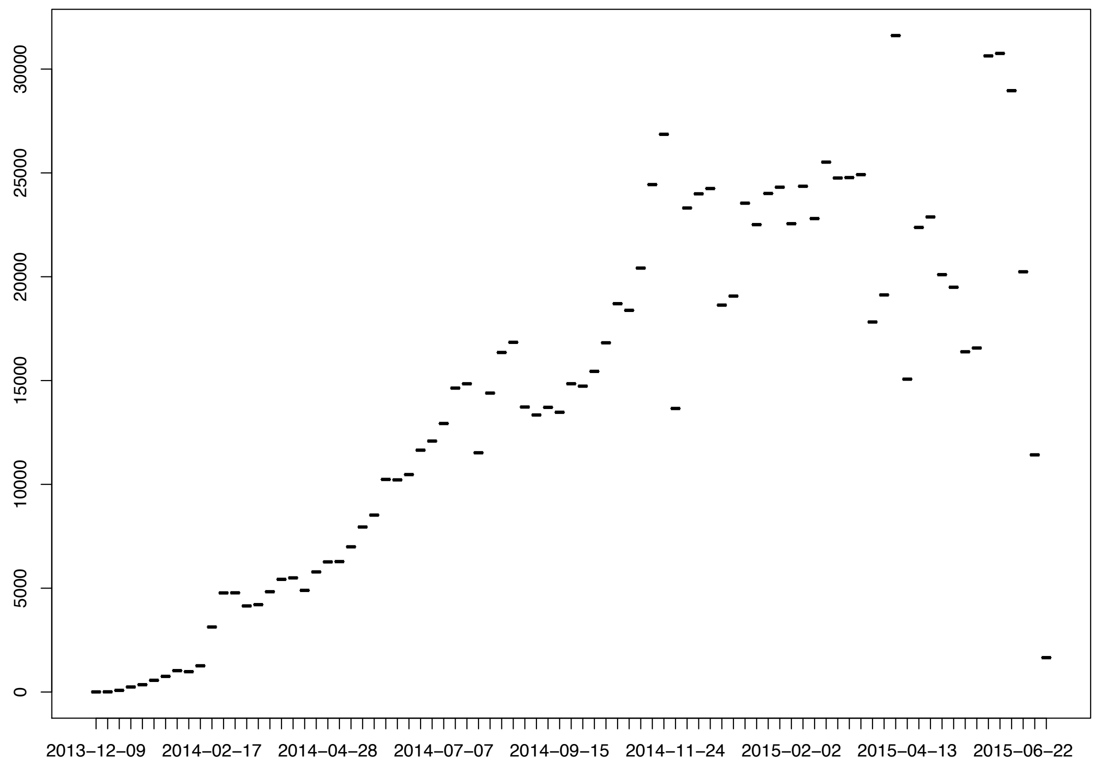


Figure 14: Weekly sales revenue Evolution

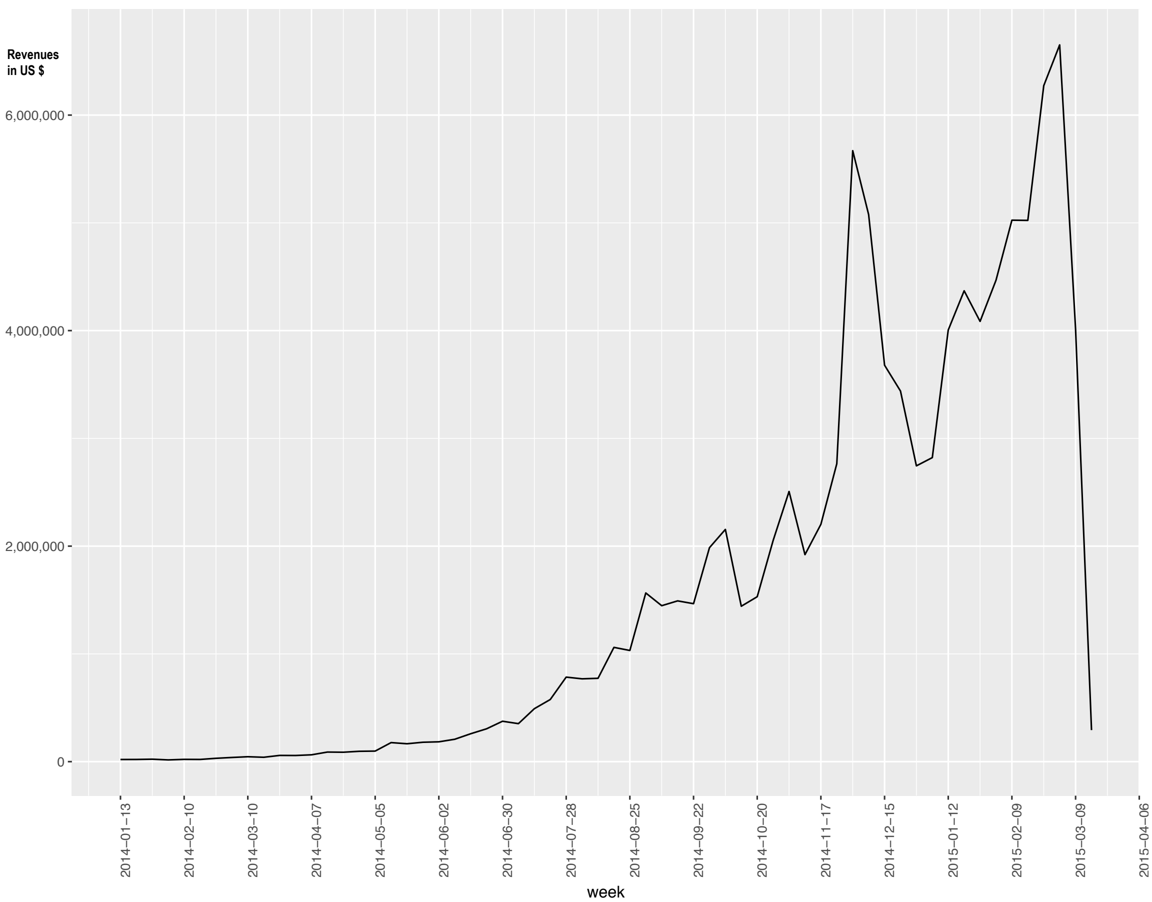


Figure 15: Weekly sales count Evolution