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How Search Engine Impacts Market Structure: Empirical Evidence from a Multivendor Darknet Market

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Abstract. Despite the public's familiarity with search engines, little existing research empirically investigates the impact of such a search-cost-reduction tool on online market structure. Knowledge scarcity of this question can mainly be attributed to the challenge of accessing detailed data from a cross-website search engine. Using data from the online illegal transaction platform, the Darknet markets, we manage to empirically evaluate the influence of a cross-website search engine (i.e., GRAMS) on the market structure at the vendor and product category levels. The results show that, although the search engine's entry enhances the overall market performance, the benefit is more significant among leading vendors and popular products, contributing to a more concentrated market. Additional analyses provide empirical evidence that the trustworthiness and the scale-up ability of leading vendors can be the underlying mechanisms for the increased market concentration after the introduction of search engines into Darknet markets. Our study not only contributes to the literature on the dynamics of sales distribution in a multiple-vendor e-commerce market but also provides insights into understanding the operating dynamics of the Darknet markets, which can be helpful for law enforcement policymaking.

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1. Introduction

Search engines are well known and indispensable for consumers in online shopping nowadays because they help significantly reduce search costs in the purchase process. According to an Amazon report in 2022, about 63% of U.S. consumers started their online shopping by searching on Amazon, and 32% of search engine users finally placed an order (Ghosh 2024). Technology upgrades facilitate transaction activities not only on legal e-commerce platforms but also within illicit markets. For example, GRAMS, a Google-like search engine, was designed and deployed in Darknet markets, which are widely regarded as prominent platforms for facilitating online illegal transactions. With GRAMS, consumers can more easily find drug vendors that suit their needs because it provides an easy-to-use search interface where vendors' information, such as reviews and transaction histories, is well aggregated. Knowledge of whether and how such search technology might impact Darknet transactions remains unclear, yet it may play an important role in affecting consumer behavior and reshaping market structures in various ways. Our study aims to fill this research gap through empirical explorations and further unveil the underlying mechanisms.

Search technologies may reshape profit distribution among different stakeholders in the online economy (Brynjolfsson et al. 2010). Scholars adopting analytical approaches have discussed two primary market outcomes that might arise after the introduction of search engines into online markets. One possibility is a more even distribution of sales across different product categories or vendors (Brynjolfsson et al. 2011, Hinz et al. 2011), suggesting that search engines may lead consumers to buy better-suited items from niche vendors and level the playing field. Another potential outcome is a market structure that becomes more concentrated on popular products or vendors (Bar-Isaac et al. 2012), implying that search engines may amplify the success of already well-known or highly sought-after items. Hence, knowledge in prior studies is unable to reach a conclusion about how the introduction of GRAMS-like technology would influence market structure in the illicit Darknet system.

Another gap in prior literature on search engine's impact is the lack of empirical answers derived from real-world market data. Although search engines like Google and Yahoo are well known, their initial deployments largely took place during the early stages of the Internet era. During that time, there was a lack of suitable market data for empirical analyses, which hindered researchers' ability to move beyond analytical modeling and examine the real-world effects of search engines on market structure dynamics (Sundin et al. 2022). Although a few recent studies have emerged to examine the effect of search engines on product sales within a single online store (Brynjolfsson et al. 2011, Hinz et al. 2011), these studies focus on scenarios involving only one vendor and explore how the introduction of a search engine influences the sales of different products offered by that vendor. However, in reality, markets typically consist of multiple vendors offering a variety of products. When search engines are introduced in such multivendor environments, vendors with varying levels of market power may respond differently. Consequently, the findings derived from single-vendor market studies cannot adequately address the impact of search engines in these more complex real-world settings. Additionally, in the context of Darknet markets, conducting vendor-level analysis can provide direct policy implications as vendors are targets of law enforcement. Authorities need to understand how different vendors react to the introduction of search engines into these illicit marketplaces.

The closest related empirical literature could be studies on recommender systems, because both search engines and recommender systems reduce customers' search cost on the platform. However, recommender systems' functions are fundamentally different from search engines and users interact with them in distinct ways. In the context of recommender systems, users are more passively exposed to the system suggestions, which hence tend to limit users' explorations within a specific set of products or sellers, favoring already-popular options (Dellaert and Häubl 2012). On the contrary, with search engines, users more proactively seek products or sellers through their own queries, which can guide them to discover a broader array of products or sellers (Brynjolfsson et al. 2003). This active search behavior facilitated by search engines would hence lead to different market outcomes compared with the passive behavior driven by recommender systems (Hinz et al. 2011). Therefore, there is a need for an independent examination of the impact of search engines on market dynamics.

Last but not least, consumers behave differently on Darknet markets compared with regular commercial websites, highlighting another significant reason to separately study the impact of search engines on Darknet market structures. Specifically, when purchasing online, consumers often consider multiple factors in selecting product suppliers (Chen et al. 2018). In traditional markets, consumers primarily seek to match product quality with the lowest price. In illegal trading markets, a higher-priority concern may emerge: minimizing the risk of being detected and avoiding legal sanctions. To trade safely, consumers would place greater emphasis on the trustworthiness of vendors, as dealing with unreliable sellers can increase their risk of exposure to law enforcement. This risk concern plays an important role in shaping the impact of search engines on these Darknet markets. These differences make it more challenging to apply findings from existing studies to directly infer the impact of search engines on Darknet market structures.

Motivated by these existing research gaps, our study aims to examine two questions. (1) How does the introduction of a search engine influence the structure of a multivendor illegal market? (2) What are the underlying mechanisms that drive the observed market dynamics? To answer the research questions, we leverage the entry of a search intermediary in an online multivendor commercial market (i.e., the Darknet market) as our empirical context. With a unique data set and different levels of analysis (websites, drug categories, and vendors), we empirically demonstrate that introduction of the search engine shows a boosting effect on the entire market and leads to a more concentrated market structure. Our findings reveal that leading vendors experience a disproportionately large increase in sales after the search engine is introduced. Through detailed vendor-level analysis, we explore the underlying mechanisms driving this concentration from two perspectives. Firstly, customers prefer more reliable vendors in the market due to the higher risk associated with illegal transactions. The introduction of the search engine facilitates this preference by making it easier for customers to identify reputable vendors. As a result, leading vendors, which demonstrate higher levels of trustworthiness, benefit more from the presence of search engines in the market compared with their nonleading counterparts. This is evidenced by our observation that leading vendors experience a more significant increase in high-risk transactions following the entry of a search engine. Secondly, leading vendors have the capacity to scale up quickly, particularly by expanding offerings in popular drug categories to fully leverage the benefits of search engines.

The introduction of the search engine increases the popularity of top drug categories and attracts significant consumer traffic to vendors who offer a wider range of products within these popular categories. As only leading vendors, with the necessary resources and market dominance, can provide a broader selection of popular drug products and offer a "one-stop" shopping experience for consumers, it's unsurprising to observe a concentration of sales shifting toward these leading vendors after the introduction of search engines. We believe these findings provide a comprehensive interpretation of the concentrated market distribution resulting from the adoption of search engines.

This study makes significant contributions. As far as we know, this study is the first empirical analysis to investigate the effect of search engines on the market structure of a multivendor online economy. Our detailed analyses from multiple aspects find that the search engines' entry leads to a more concentrated market, which is contradictory to the long-tail effect observed in existing empirical studies based on single-vendor data. More importantly, we propose and verify two mechanisms to explain such an effect: Leading vendors are regarded to be more trustworthy and have a better capacity to scale up. These findings significantly deepen the understanding of Darknet market operations, particularly regarding the influence of technological advancements. This study also uncovers key operational characteristics such as price stickiness and strong consumer loyalty to leading vendors on illicit markets, which advances the understanding of consumer behaviors and vendor strategies in this unique market.

The rest of this paper is organized as follows. In Section 2, we review the relevant literature. In Section 3, we describe the empirical context and data used in this study. Section 4 presents our main empirical analysis and estimation results. The underlying mechanisms are discussed in Section 5. Section 6 lists the validity checks and robustness tests we have conducted. We conclude the paper in Section 7.

2. Literature Review

2.1. Impact of Search Cost Reduction on Online Markets

Existing literature has documented various effective ways to reduce search costs and facilitate online market prosperity, such as sufficient information disclosure (Jung et al. 2022), effective layouts of search results (Gu and Wang 2022), and proper product-buyer matching procedures (Zhong 2023). Among these efforts, recommender systems and search engines are the most widely applied techniques, casting significant influence on consumers' behavior and market structure (Brynjolfsson et al. 2010). Nevertheless, they affect consumers' search behavior in distinct ways.

Specifically, recommender systems work by actively providing information to consumers and guiding them toward specific products or sellers. These recommendations are based on the customer's previous purchase patterns and peers' purchase behaviors (Brynjolfsson et al. 2010). Although this approach simplifies customers' search process, it can also reduce their motivation to actively search for items independently (Tam and Ho 2006, Dellaert and HÄubl 2012). As a result, consumers' product selection decisions are more likely to be influenced by the personalized recommendations received, which may affect market structures (Sun et al. 2023, Zhong 2023). Existing studies have shown that such an effect can vary based on the design of recommender systems' underlying algorithms. For example, when systems are designed based on historical sales and ratings, already-popular vendors or items are likely to be recommended more frequently, potentially leading to a concentrated market where a few dominant players emerge (Fleder and Hosanagar 2009, Lee and Hosanagar 2019). In collaborative filtering designs, when similar customers favor niche products or new vendors, the distribution of sales can become more flattened (Hinz et al. 2011). This is because these recommendations often expand beyond individuals' initial consideration set, promoting a broader range of products and sellers to consumers (Li et al. 2022).

Unlike recommender systems that analyze purchase patterns to predict users' buying intentions, the interaction between search engines and users is more intentional (Bronnenberg et al. 2016). When using search engines, users actively seek content by entering specific queries to find information or products that meet their needs. Search engines meet users' information needs by directly providing search results that reflect customers' true preferences, without interference from peers' behaviors (Hinz et al. 2011). Hence, users' preferences are more transparently reflected when using search engines, especially in the early deployment stages of a search engine, when fewer algorithms or advertising systems are yet involved. These distinctions between search engines and recommender systems underscore the importance of a separate study to comprehend how search engines affect consumer behavior and the online market structure.

More importantly, current discussions on the impact of search engines on market structure are primarily theoretical using analytical models. Based on existing analytical studies, the introduction of search engines can lead to either a more flattened or concentrated sales distribution. On the one hand, lower search costs encourage customers to engage in more extensive searches, enabling them to find products from niche markets where less-advantageous vendors operate

(Bar-Isaac et al. 2012). Furthermore, the deployment of search tools enhances consumers' search efficiency by improving search targetability, effectively guiding customers to most suitable product categories. This increased search accuracy boosts the visibility of vendors offering niche products, driving more traffic to their offerings, increasing sales, and ultimately flattening the market share distribution (Yang 2013). Therefore, the entry of search engines could benefit niche vendors more and potentially bring a more balanced market structure.

On the other hand, leading vendors might benefit more from search engine adoption, which leads to a more concentrated structure. The use of search engines can intensify the competition among vendors. Dominant vendors, leveraging economies of scale, can employ competitive pricing strategies to seize larger market shares and maintain financial sustainability (Goldmanis et al. 2010). Lower manufacturing costs further empower these leading vendors to expand their product lineup, thereby attracting more customers (Rhodes and Zhou 2019). Such competitive dynamics would consequently shift the market further toward leading vendors following the entry of search engines. In addition, leading vendors also have financial advantages in investing in search engine marketing campaigns to boost their traffic and enhance visibility (Ghose and Yang 2009, Ghose et al. 2013).

Considering the various theoretical perspectives on how search engines may affect market structures, it is crucial to seek empirical evidence to determine the actual impact. As search engines were typically introduced during the early stages of the Internet (e.g., Google, Yahoo), when detailed market data were scarce, there are only a few empirical studies exploring this research question. Furthermore, they primarily concentrate on the impact on the distribution of product sales within a single vendor. For example, Hinz and Eckert (2010), using an analysis of data from a single-vendor video-on-demand store, demonstrate that search engines diversify sales by increasing niche product purchases, driven by both new and shifted consumer demand. Brynjolfsson et al. (2011) further verify this in another single-vendor scenario where the market becomes less centralized, resulting from a boost in sales of niche products, with the use of online search tools. Hinz et al. (2011) provide a more comprehensive interpretation of the impact of search tools on product demand distribution by examining three functional adjustments to an online movie search tool. Specifically, upgrades on the pure search functionality, such as the introduction of additional filtering options, result in a more flattened demand distribution. Despite these empirical explorations that shed light on market structure dynamics, there is a research gap in understanding the impact of search engines from a multivendor view, which is a better reflection of real-world scenarios (Sundin et al. 2022). Our study seeks to fill this research gap by empirically testing the impact of search engines on vendors' sales distribution and exploring the underlying mechanisms driving market structure dynamics.

2.2. Darknet Market

The Darknet market has attracted much attention from academia, underscoring the necessity for a comprehensive understanding of an effective regulation of cybercrime to ensure society's safety (Benjamin et al. 2019). Relevant studies include topics such as the effectiveness of law enforcement actions (Chan et al. 2023) and illegal vendors' strategic adaptations to reputation shocks (Batikas and Kretschmer 2018). These studies reveal individuals' behavior changes but are less concerned about the economic impacts of technical advancements that determine the efficiency of resource allocation in anticrime enforcement actions (Davies 2020).

Thus far, very few studies have previously examined this issue, although some existing work has investigated the market features of Darknet with descriptive statistics. For instance, Christin (2013) documents a limited number of "big-fish" vendors dominating a disproportionally large share of transactions. In many marketplaces, a large number of small drug vendors constitute a long tail but only take a tiny or even zero share of the sales (Soska and Christin 2015). Using agent-based simulation methods, Norgaard et al. (2018) also analytically demonstrate that the Darknet supply chains show a hierarchical structure with many lower-level vendors benefiting little. To summarize, a typical feature of Darknet sales distribution is the coexistence of a top-heavy and long-tail structure. However, how search technologies, which decrease consumers' search costs, can influence this market structure is currently poorly understood. Our study thus contributes to Darknet literature from this perspective.

3. Context and Data

3.1. GRAMS

Our empirical context is the Darknet marketplaces with an introduction of the search engine GRAMS. GRAMS was released in mid-April 2014 and recognized as the first search tool available to Darknet markets. Similar to mainstream search engines like Google on the regular Internet, GRAMS indexes listings from various Darknet markets. This technology allows users to search for products across multiple Darknet markets through a single interface. For example, before the introduction of GRAMS, consumers who were interested in a drug product had to visit each Darknet market individually to check information such as available vendors, prices, and shipping origins, which was time-consuming. GRAMS provides a more convenient and aggregated channel for consumers to collect such information. With this technology, consumers can easily discover desirable products and available vendors on Darknet markets, leading to a substantial decline in search costs (Zetter 2014, Stone 2017).

In addition to indexing product information, another significant convenience that GRAMS offers is to provide profiles for all indexed vendors. Vendor profile is an aggregated information panel that compiles vendors' information from all GRAMS-indexed markets.[1] We use the vendor "Bungee54" as an example to showcase the available information, including active marketplaces, Pretty Good Privacy (PGP) encryption keys, available products (see Figure A.1 in the Online Appendix), and recent feedback from multiple markets (see Figure A.2 in the Online Appendix). There are two ways that consumers can easily retrieve vendor profiles through GRAMS. First, when consumers search for products, each returned search result includes a vendor profile link allowing them to click and browse this vendor's details (see Figure A.3 in the Online Appendix). Second, GRAMS enables consumers to search for vendors directly through its tool "InfoDesk" (see Figure A.4 in the Online Appendix), which guides users straight to vendors' profile. Therefore, GRAMS provides convenient ways for consumers to efficiently evaluate vendors through integrated information.[2] When a market is searchable via GRAMS, it considerably lowers the effort required for consumers to find satisfactory vendors that offer the desired products.

3.2. Darknet Website Archives

To empirically evaluate the effect of search engines on market structure dynamics and the underlying mechanisms, we collect data to generate proxies for vendors' transactions. The data source we use is a Darknet website archive generated by Branwen et al. (2015), documenting transaction feedback and relevant vendor information (see Figure A.5 in the Online Appendix). To extract the necessary information, two research assistants were recruited to process the daily snapshots of consumer feedback in the archive. Each piece of feedback includes the product name, vendor name, feedback time, numerical rating, textual content, and the website where the transaction took place. To facilitate our analysis, we also collect vendors' unique identity labels, that is, PGP keys, from vendors' profile pages in the website archive (see Figure A.6 in the Online Appendix).

We employ several ways to validate the reliability of the archival data used in our study. First, it has been widely used in various research topics, including the impact of public policing (Chan et al. 2023), forum content analysis (Li et al. 2021), vendor careers (Booij et al. 2021), and online advertisements (Ursani et al. 2021). Its extensive use across multiple research domains demonstrates its validity and suitability for academic purposes. Second, the original snapshot archives were scraped daily to minimize the likelihood of missing data. These frequently crawled snapshots ensure the best recovery of vendors' feedback profiles. Additionally, several researchers have verified the similarity between this Darknet archive and actual transaction records. For example, Soska and Christin (2015) compare the archives with several trial cases and law enforcement records, finding that the sales data captured in website snapshots are reasonably aligned with the ground truth. Chan et al. (2023) compare feedback data with real-time transaction records provided by GRAMS and find that they are consistent.

Following previous studies (Soska and Christin 2015, Paquet-Clouston et al. 2018, Chan et al. 2023), we use the number of feedback as a proxy for a vendor's transaction volume. With the implementation of an escrow system, one transaction in Darknet markets will be finalized only after the buyer leaves a comment, at which point the payment is released to vendors (Christin 2013, Dittus et al. 2018). Such a setting ensures the validity of using feedback numbers as a measurement for vendors' transaction volumes. Based on the feedback, we are able to identify the associated vendor, website, product, and estimated trading time of each transaction. In this study, we mainly investigate transactions of drug products. The focus on drug-related transactions is driven by two key reasons. (1) In the Darknet, most transactions are drug relevant, whereas nondrug transactions account for only around 15% of all transactions during our study period. (2) There is a standard drug category schema that enables easy comparison across websites, whereas non–drug-related transactions do not have such a unified categorization system. Therefore, we primarily use drug-relevant transactions in our empirical analysis and conduct robustness checks with full data.

3.3. Panel Construction

Recall that our research goal is to estimate the impact of search engines on market structure dynamics. As GRAMS is developed and introduced to the Darknet market by an anonymous user, such an exogenous event offers us a good chance to evaluate the influence of search engines by leveraging a differences-in-differences (DID) framework, where we label websites searchable on GRAMS as treated websites and those not supported by GRAMS as the control group for comparison. Accordingly, vendors (drug categories) on the treated websites are labeled as treated vendors (drug categories), whereas those from nonindexed websites are labeled as control vendors (drug categories). We collect data from different Darknet markets over time, both before and after the introduction of GRAMS for the DID analysis. On November 5, 2014, a large-scale international law enforcement operation known as Operation Onymous was conducted by multiple authorities to target illegal Darknet markets. This operation led to the shutdown of numerous websites and had a significant impact on Darknet transactions. To eliminate the potential influence of Operation Onymous on our analysis, we limit our study period to end on October 31, 2014, before the operation's occurrence. The identification strategy is shown in Figure 1. The final data set for our empirical analysis consists of feedback records from five GRAMS-indexed websites and five nonindexed websites, covering the period from December 15, 2013, to October 31, 2014. A website-level meta data description can be found in Table A.1 of the Online Appendix, and a detailed data processing explanation can be found in Part II of the Online Appendix.

To achieve our research purpose, we leverage the feedback records contained in the Darknet archives to measure transactions on Darknet markets. Specifically, we construct three weekly panel data sets by aggregating feedback at the vendor, category, and website levels separately. First, we use vendor and website names to uniquely identify vendors in the Darknet market and aggregate feedback at the vendor level to generate a vendor-weekly panel. This data set enables us to assess the overall impact of search engines and to uncover the mechanisms underlying any observed changes in market structure. Similarly, we create a category-weekly panel by aggregating feedback using a category identifier (i.e., a combination of category and website names), offering additional evidence of GRAMS' effect. Last, we further construct a website-weekly panel by aggregating feedback at the website level, which helps us capture the change in market distributions among vendors (or categories) at the marketplace level.

One concern of the DID model might be the potential differences between treated and control groups during the pretreatment period. Because we mainly focus on vendor-level analysis to reveal how the market structure changes among vendors, we apply propensity score matching (PSM) to pair each vendor on the control website with at least one similar vendor on the treated websites.[3] Specifically, for the matching purpose, we choose five pre-GRAMS variables, as shown in Table A.2 in the Online Appendix. These variables measure vendors' accumulated reputation from different angles because reputation is widely considered as crucial for business success on the Darknet (Batikas and Kretschmer 2018). A detailed explanation of pre-GRAMS matching variables can be found in Part III of the Online Appendix. To evaluate the performance of the matching, we apply the *t*-test and Kolmogorov–Smirnov test (KS-test) for the balance check, with results shown in Table A.2 of the Online Appendix. After matching, we observe that the treated and control vendors do not show significant differences across pretreatment characteristics, indicating the validity of using the matched sample for further DID analysis.

For these matched vendors, we aggregate their transactions on a weekly basis. One concern for the validity of the DID identification is vendors' potential multihoming behavior. Following other Darknet studies (Soska and Christin 2015, Broséus et al. 2017, Chan et al. 2023), we rely on PGP keys to identify vendors with accounts in both treated and control marketplaces. Although one vendor can have multiple names across websites, the PGP key of a vendor's blockchain account, which is used to receive payments in Darknet markets, serves as a unique identifier. Thus, the PGP key is an effective tool to help identify multihoming vendors.[4] Employing this method, we have identified all multihoming vendors, which only occupy a very small percentage of our data. We then drop these multihoming vendors from the transaction samples in all our empirical analyses. The final matched vendor panel contains 166 treated vendors and 92 control vendors. As discussed above, to offer more empirical insights, we also conduct analysis at the drug category level and website level. The summary statistics of primary variables in these three weekly panels are reported in Table 1.

4. Main Analysis

4.1. Overall Market Performance

We first investigate the impact of GRAMS' entry on transactions of indexed vendors. As GRAMS only indexes some websites, we thereby leverage a DID

Figure 1. Identification Strategy

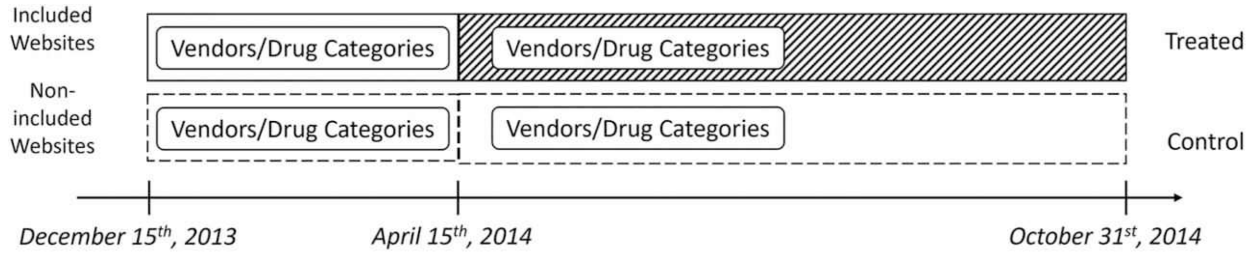


Table 1. Summary Statistics

	(1) Mean	(2) Standard deviation	(3) Minimum	(4) Maximum
Vendor-weekly panel				
Dependent variables				
Transaction Number	10.50	51.02	0.00	2,605.00
Category Number	0.48	0.90	0.00	11.00
PSM matching variables				
Average Weekly Sales	7.56	18.91	0.06	174.24
Average Weekly Category Number	0.58	0.62	0.06	3.00
Average Weekly Drug Number	1.10	1.75	0.06	13.76
Tenue Length	11.66	4.97	1.00	17.00
Number of Active Weeks	4.71	5.11	1.00	17.00
Category-weekly panel				
Transaction Number	579.11	1,491.62	0.00	26,002.00
Vendor Number	35.38	50.64	0.00	323.00
Website-weekly panel				
Transaction Number	3,792.47	10,570.68	0.00	135,568.00
Category Number	5.54	4.72	0.00	12.00
Vendor Number	149.47	224.09	0.00	873.00
Gini (vendor)	0.44	0.33	0.00	1.00
Gini (category)	0.38	0.30	0.00	1.00

model to estimate the impact as follows:

$$\log(y_{ijt}) = \beta_0 + \beta_1 * Treat_j * After_t + \delta_j t + \eta_i + \tau_t + \epsilon_{ijt}, \quad (1)$$

where y_{ijt} is the dependent variable, which represents the transaction volume or the number of drug categories that each vendor i sells in week t from website j. A natural log transformation is applied to account for the overdispersion of the count variables. $Treat_j$ is defined as one if vendors comes from a website that can be searchable using GRAMS, and zero otherwise. $After_t$ is a time dummy, which equals one when the referred time is after the launch of GRAMS, and zero otherwise. The coefficient β_1 is of main interest, because it measures how the introduction of GRAMS affects transactions on the treated vendors relative to those of the control vendors. To account for the possibility that different websites might experience different rates of market change, we include a website-specific time trend $\delta_j t$, where δ_j is a website dummy variable and t is a time trend. We also include a vendor-level fixed effect η_i to control for unobserved time-invariant characteristics of a vendor and a time-fixed effect term τ_t to account for common temporal factors. Hence, the $Treat_j$ dummy and the $After_t$ dummy are absorbed in the regression. We cluster the standard error by vendors to deal with potential concerns for serial correlation.

The estimation results can be seen in columns (1) and (2) of Table 2. When vendors are indexed by GRAMS, their weekly transaction number can increase by 87.76% (column (1)).[5] Overall, the results indicate a strong boosting effect of search engines on Darknet transactions, given that vendors see a significant transaction increase when they are indexable by search engines compared with control vendors. Furthermore, previous studies indicate that the introduction of search engines may lead to a change in consumers' preferred products (Bar-Isaac et al. 2012). As a search engine encourages consumers to delve deeper into

Table 2. Average Treatment Effect of GRAMS

	Vendor level		Category level	
	(1) No. of transactions	(2) No. of categories	(3) No. of transactions	(4) No. of vendors
After × *Treat*	0.63***	0.21***	0.53**	0.42***
	(0.13)	(0.04)	(0.22)	(0.10)
No. of observations	9,610	9,610	2,452	2,452
Website-specific time trend	Yes	Yes	Yes	Yes
Vendor fixed effect	Yes	Yes		
Drug category fixed effect			Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes

Note. All dependent variables are log-transformed.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

exploration prior to making purchases, this increases the exposure for a broader range of items (Brynjolfsson et al. 2011). Accordingly, vendors are also incentivized to expand their drug offerings (Benner and Waldfogel 2020). Such an expansion of the business scope can effectively meet consumers' needs, foster consumers' loyalty, and enhance appeal to new consumers. Therefore, we conduct another set of analyses using the number of drug categories as the dependent variable and report the results in column (2) of Table 2. The empirical evidence aligns with previous literature, showing that the number of drug categories increases by 23.37% in transactions involving vendors who are searchable by GRAMS compared with those not indexed by GRAMS.

In addition to the vendor-level analysis, we also conduct DID estimations at the drug category level to provide further evidence on the effect of GRAMS. We use a model similar to Equation (1) but apply it to the drug category-weekly panel. The dependent variable represents the transaction volume of drug category k or the number of vendors selling drug category k in week t from website j. $Treat_j$ is a dummy variable that equals one if the observation under investigation represents trading in a treated website. Similarly, we include category-level and time-level fixed effects and cluster the standard error by drug categories to deal with potential concerns for serial correlation. The estimation results, summarized in columns (3) and (4) of Table 2, consistently support the boosting effect of search engines on the online economy. For drug categories indexed by GRAMS, we observe an average 69.89% increase in transaction volume (column (3)) compared with a drug category from a control website. Moreover, the introduction of the search engine leads to a significant increase in the number of vendors, with an average increase of around 52.20% in vendor size (column (4)).

Furthermore, we also examine the impact of GRAMS at a website level. Empirically, we leverage a similar model as described in Equation (1), with dependent variables defined as the weekly transaction volumes, the number of transacted drug categories, and the number of active vendors in each week for a certain website. $Treat_j$ is defined as one if the website j under investigation is searchable using GRAMS, and zero otherwise. Similarly, we include website-level and time-level fixed effects and cluster the standard error by websites to deal with potential concerns for serial correlation. From the estimated results in Table 3, it is evident that GRAMS boosts illegal economic activities in those indexed marketplaces by facilitating more transactions (column (1)), diversifying product offerings (column (2)), and activating more vendors (column (3)), indicating a market expansion effect driven by the upgrade in search technology within online illegal transaction economies. By combining estimations at vendor, drug category, and website levels, we conclude that the introduction of a search engine significantly boosts the online illegal economy.

4.2. Market Structure Change

After observing the overall boosting effect on the indexed markets, we continue to investigate the impact of GRAMS on market structure, which is the focus of our study. Although niche vendors can be targeted by customers more easily, search engines also increase the visibility of popular vendors and drug categories. Consumers may exhibit a preference for predominant vendors over niche sellers because the former ones have accumulated reputation and trustworthiness on the Darknet markets. Therefore, it is not clear who might benefit more and how the market structure may change following search engine entry. To answer this question, we conduct several analyses. First, we explore the impact on market structure based on the website-level Gini index, using the DID model and the website-weekly panel introduced in Section 3.3. The Gini index has been widely applied to measure market share concentration levels in the market structure literature (Fleder and Hosanagar 2009, Brynjolfsson et al. 2010, Park et al. 2020). The higher the Gini index is, the greater the level of market concentration indicated. Building on the approach of Brynjolfsson et al. (2011), we calculate the Gini coefficient at the vendor (category) level for each website using the weekly sales of active vendors (categories) on each website during week t. Table 4 summarizes the results from the DID estimation, indicating that the introduction of a search engine leads to

Table 3. Average Treatment Effect of GRAMS at Website Level

	(1) No. of transactions	(2) No. of categories	(3) No. of vendors
After × *Treat*	2.15***	0.58**	1.59***
	(0.79)	(0.29)	(0.58)
No. of observations	378	378	378
Website fixed effects	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes

Note. All dependent variables are log-transformed.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4. Effect of GRAMS on Market Structure at Website Level

	(1) Gini index value (vendor level)	(2) Gini index value (category level)
After × *Treat*	0.12**	0.10**
	(0.06)	(0.05)
No. of observations	378	378
Website fixed effects	Yes	Yes
Time fixed effect	Yes	Yes

Note. Dependent variables are log-transformed.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

a more concentrated market structure at both vendor and category levels. Specifically, we find that, compared with marketplaces not indexed by search engines, searchable websites show an increase in the vendor-level Gini index by 12.75% and the category-level Gini index by 10.52% after the introduction of GRAMS. For better visualization, we provide plots using raw data of vendor (category) Gini coefficients on GRAMS-indexed/nonindexed websites. The plots can be found in Figure A.7 of the Online Appendix. In previous studies (Brynjolfsson et al. 2011, Hinz et al. 2011), empirical analyses with data from a single vendor's sales generally show a flattened distribution among different products after the implementation of search tools. In contrast, our results show that sales distribution concentrates at both vendor and product levels. Such divergence between our findings and those of earlier studies also highlights the necessity and contribution of our research.

Secondly, to better understand the market-concentration effect, we conduct two additional analyses using the vendor-weekly panel. First, we evaluate the disparity in GRAMS' effect between leading vendors and nonleading vendors. Specifically, we divide all vendors into two subsamples based on their pre-GRAMS average weekly sales: vendors whose pre-GRAMS sales performance is above the median are categorized as leading vendors and nonleading vendors otherwise. Applying Equation (1), we estimate the effect of GRAMS separately for leading and nonleading vendors, with the results shown in columns (1)–(3) of Table 5. We discover that, despite the significant boosting effect on both leading (column (1)) and nonleading (column (2)) vendors, leading vendors benefit substantially more based on the chi-square test results presented in column (3). Similarly, we also explore which type of products, popular versus nonpopular drug categories, see a larger increase in sales following the search engine's entry. Popular categories are defined as those whose sales are higher than the median value. We then partition vendors' total transactions into sales from popular and nonpopular categories, determined by the pre-GRAMS total sales volume of each category. The same DID estimation is applied, and the results are summarized in columns (4)–(6) of Table 5. We find that, despite the significant boosting effect on transactions in both popular (column (4)) and nonpopular (column (5)) categories, popular categories experience a significantly higher increase in transactions following GRAMS' introduction (column (6)). These two analyses further support the overall positive effect of GRAMS and its role in driving increased market concentration.

To provide more evidence for the impact of GRAMS on the market structure, we also develop an econometric model with interaction terms to capture the heterogeneous responses of vendors to the introduction of GRAMS. In particular, we add a moderator into the DID model as follows:

$$\begin{aligned}\log(y_{ijt}) = \beta_0 + \beta_1 * Treat_j * After_t + \beta_2 * Moderator_i \\ * After_t + \beta_3 * Treat_j * After_t * Moderator_i \\ + \delta_j t + \eta_i + \tau_t + \epsilon_{ijt},\end{aligned} \tag{2}$$

where all the variables are defined similarly as in Equation (1). $Moderator_i$ represents the leadership of a vendor, and we use three pre-GRAMS leadership proxies as moderators. Specifically, the first leadership proxy, *Leadership I*, is defined as the average weekly

Table 5. Effect of GRAMS on Different Vendors and Categories

	Leading vs. nonleading vendors			Popular vs. niche categories		
	(1) No. of transactions (leading)	(2) No. of transactions (nonleading)	(3) Coefficient difference	(4) No. of transactions (popular)	(5) No. of transactions (niche)	(6) Coefficient difference
After × *Treat*	0.97***	0.33***	0.64***	0.58***	0.18***	0.40***
	(0.24)	(0.08)	6.26	0.13	0.05	8.33
No. of observations	4,632	4,978	—	9,610	9,610	—
Website-specific time trend	Yes	Yes	—	Yes	Yes	—
Vendor fixed effect	Yes	Yes	—	Yes	Yes	—
Time fixed effect	Yes	Yes	—	Yes	Yes	—

Notes. Dependent variables are log-transformed. We calculate the coefficient difference by subtracting the coefficient of nonleading vendors (niche categories) from that of leading vendors (popular categories). The significance of this comparison is then assessed using a chi-square test. The values in column (3) and column (6) report chi-square statistics associated with the significance for two groups of comparisons, respectively.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

number of transactions vendors had in pre-GRAMS periods. It is the most direct reflection of vendors' dominance in the market (Goldmanis et al. 2010, Kumar and Hosanagar 2019). The second proxy, *Leadership II*, is defined as the average number of unique drug categories vendors had sold per week in the pretreatment periods. This proxy measures the diversity of vendors' products. According to prior literature, product diversity is associated with vendors' manufacturing power and therefore signals the capacity to quickly expand, seize market share, and maintain dominance in the market competition (Bar-Isaac et al. 2012, Rhodes and Zhou 2019). The third leadership proxy, *Leadership III*, is defined as the number of active weeks that vendors had transacted before the introduction of GRAMS. This is an insightful measure, because the longer vendors remain active, the more likely they are to accumulate a higher reputation, marketing experience, and competitive advantage. Using these different leadership measures as the moderating variables, we report our estimation results in Table 6, which provides evidence that the search engine enhances consumers' preference for the leading vendors in the indexable Darknet markets. Regardless of how we measure leadership, a more significant increase in transaction volumes can be observed for leading vendors after the search intermediary is introduced to markets. This implies that search engines' entry, by reducing consumers' search costs, has facilitated the creation of a more concentrated market.

5. Mechanism Analysis

Thus far, our empirical findings indicate that the introduction of a search engine results in a more concentrated market structure instead of a more even distribution of profits. To better understand the underlying mechanism, we undertake additional empirical analyses in this section.

5.1. Trustworthiness Advantage

Marketing literature suggests that the accumulated trustworthiness and higher reputation of vendors play a crucial role in increasing sales, fostering brand loyalty, and ultimately prevailing in the intensified market competition (Gutt et al. 2019). The importance of trustworthiness is especially prominent in online illegal transaction markets (Batikas and Kretschmer 2018). With the introduction of search tools (e.g., GRAMS), Darknet markets provide consumers with convenience in purchasing products from a broader range of vendors. However, the scrutiny from law enforcement in online illegal trading compels consumers to prioritize trustworthiness during their purchase process instead of simply comparing vendors' prices (Tzanetakis et al. 2016). To minimize the risk of detection, consumers tend to be cautious when transacting with niche vendors, who are usually less experienced. Consumers might exercise greater caution when determining whether to switch to searchable vendors who may offer better-fitted items but with whom they are not familiar. In such circumstances, leading vendors, compared with nonleading vendors, show richer experience that reflects higher trustworthiness in secure trading, making them preferred choices among consumers (Paquet-Clouston et al. 2018). Therefore, one of the underlying mechanisms for the intensified market concentration induced by the search engine's entry is consumers' desire for trustworthiness in illicit trading.

To verify our conjecture for the trustworthiness mechanism, we conduct heterogeneous analyses by classifying drug products into two genres, that is, high-risk versus low-risk drugs. Generally, engaging in high-risk transactions carries more severe legal consequences compared with dealings involving lower-risk drugs. To empirically test this proposed mechanism, we rely on two measures to classify the drugs. The first measure is the level of danger they pose to human health. Specifically, we rely on the definition of drug dependency released by the Drug Enforcement Administration (DEA) to define high-risk versus low-risk drugs.[6] High-risk drugs are typically those highly addictive drugs that are associated with more severe abuse conditions

Table 6. Heterogeneous Treatment Effect of GRAMS on Vendors' Leadership

	(1) Moderator = *Leadership I*	(2) Moderator = *Leadership II*	(3) Moderator = *Leadership III*
After × Treat	0.36***	0.30**	−0.00
	(0.12)	(0.14)	(0.17)
After × Treat × Moderator	0.24**	0.85**	0.42***
	(0.11)	(0.37)	(0.14)
No. of observations	9,610	9,610	9,610
Vendor fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Website-specific time trend	Yes	Yes	Yes

Notes. The dependent variable is weekly sales. All dependent variables and pre-GRAMS moderators are log-transformed.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

and higher rates of mortality (Butelman et al. 2023). We then estimate Equation (2) for high-risk and low-risk drug transactions separately and report the estimation results in columns (1) and (2) of Table 7.[7] For high-risk drug transactions, we observe that leading vendors clearly demonstrate a more significant increase after the launch of search engines. In contrast, transactions involving low-risk drugs do not exhibit the same pattern of increase. Such heterogeneities empirically support our hypothesis that consumers' trustworthiness concern is one major mechanism driving the increase in market concentration.

The second measure we utilize is the legal status of the transaction, determined based on the regulation policies for a drug in its country of origin. Recognizing that shipping any controlled substances without authorization is inherently illegal, we leverage such differences in regulation policies across jurisdictions to classify drug transactions into varying levels of legal risk. For instances where vendors source a drug from multiple countries, we classify the transaction as high legal risk if the drug is banned in any of its countries of origin. Otherwise, when a drug is not regulated in the corresponding jurisdictions, we classify the drug transaction as low legal risk. Then, we conduct separate analyses for drugs classified as high legal risk and those as low legal risk, respectively, with the results reported in columns (3) and (4) of Table 7. The results consistently indicate that leading vendors experience a more pronounced increase in transactions involving high-legal-risk drugs compared with their counterparts, hence further supporting the trustworthiness-based mechanism we conjecture.

5.2. Scale-up Ability

Another potential mechanism that may explain the increased market concentration is the superior scaling capabilities of leading vendors. This scale-up capability can be reflected from two perspectives. On the one hand, leading vendors can leverage their economies-of-scale advantage to offer products at lower prices compared with their competitors (Goldmanis et al. 2010). In an environment where search engines intensify market competition by reducing search costs, leading vendors are better positioned to gain a competitive advantage by offering more significant price promotions, especially for popular products (Bar-Isaac et al. 2012). As a result, the implementation of search engines can drive greater consumer traffic toward leading vendors, who can be better positioned to capitalize on the increased visibility provided by the search engine.

On the other hand, leading vendors are more likely to possess the capacity to broaden their product range.

Table 7. Leading Vendors' Trustworthiness Advantage

	Health risk		Legal risk	
	(1) No. of transactions (high risk)	(2) No. of transactions (low risk)	(3) No. of transactions (high risk)	(4) No. of transactions (low risk)
Panel A: Pretreatment transaction volumes as leadership proxy				
After × Treat	0.18	0.20***	0.05	0.32***
	(0.12)	(0.06)	(0.11)	(0.09)
After × Treat × Leadership I	0.30***	0.02	0.30***	0.04
	(0.10)	(0.05)	(0.09)	(0.09)
Panel B: Pretreatment category number as leadership proxy				
After × Treat	0.13	0.12*	−0.04	0.26**
	(0.13)	(0.07)	(0.11)	(0.11)
After × Treat × Leadership II	0.96***	0.26	1.07***	0.25
	(0.35)	(0.20)	(0.29)	(0.34)
Panel C: Pretreatment active week numbers as leadership proxy				
After × Treat	−0.19	0.11	−0.30**	0.21
	(0.16)	(0.08)	(0.15)	(0.13)
After × Treat × Leadership III	0.47***	0.08	0.46***	0.10
	(0.14)	(0.07)	(0.13)	(0.11)
No. of observations	9,610	9,610	9,610	9,610
Website-specific time trend	Yes	Yes	Yes	Yes
Vendor fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes

Notes. For robustness, we also retest results in columns (3) and (4) using an "all-illegal" labeling strategy. That is, a transaction is labeled as illegal only if every exporting country deems the drug in question illegal. The analyses with this alternative labeling strategy yield results consistent with those in columns (3) and (4).

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

The decrease in search costs could prompt consumers to seek out a wider variety of products, potentially encouraging sellers to expand their assortment, particularly with popular products. By expanding product offerings, vendors can provide a convenient "one-stop shopping" experience for consumers, allowing them to meet a variety of needs in a single place (Rhodes and Zhou 2019). When a search engine makes it easier for consumers to discover one product from a specific vendor, it can lead to positive spillover effects, increasing sales of other products offered by the same vendor. This potential for increased sales across multiple products incentivizes vendors to expand their assortments, especially in popular product categories, following the introduction of a search engine (Bernstein and Guo 2023). However, adding new products to the portfolio requires substantial resources and effort (Mantrala et al. 2009), and newly introduced products often experience lower sales and carry higher financial risks (Cachon et al. 2008). Leading vendors, typically more resourceful and financially resilient, are likely to have an advantage in expanding their product offerings and hence gain more from search engine introduction (Hollenbeck and Giroldo 2022).

To empirically test the scale-up mechanism, we conduct three groups of analysis. In the first group, we aim to determine if leading vendors gain more advantages through increased sales in popular or niche products. To achieve this, we examine the vendor-level heterogeneity in the impact of GRAMS, focusing on weekly sales within popular and niche drug categories, respectively, for each vendor. The definitions of popular and niche categories remain consistent with those in Table 5. The results are reported in columns (1) and (2) of Table 8. The sales of popular products for the leading vendors increase more significantly after the search engine's entry (column (1)), whereas we do not observe a prevailing performance in niche drug sales of these vendors (column (2)).

In the second and third groups of analyses, we further explore the paths that leading vendors take to increase the sales of popular drug categories: offering a price promotion or providing consumers with "one-stop" shopping convenience. To test vendors' price adjustment strategy, we repeat the analysis with the average unit price of all transactions[8] as the dependent variable and report the estimation results in columns (3) and (4) of Table 8. Contrary to existing experience (Goldmanis et al. 2010), we find that leading vendors' increased sales do not stem from the ability to provide a larger price promotion, given the fact that there is no significant difference in price change between leading and nonleading vendors for both popular (column (3)) and niche (column (4)) products.

Lastly, we investigate leading vendors' ability to expand their product offerings, especially in the

Table 8. Leading Vendors' Scale-up Ability: Overall Scale-up and Price Adjustment

	Scale-up effect		Price adjustment	
	(1) No. of transactions (popular)	(2) No. of transactions (niche)	(3) Average unit price (popular)	(4) Average unit price (niche)
Panel A: Pretreatment transaction volumes as leadership proxy				
After × Treat	0.22*	0.18***	0.28	0.21
	(0.12)	(0.06)	(0.21)	(0.13)
After × Treat × Leadership I	0.33***	0.00	−0.02	−0.03
	(0.10)	(0.05)	(0.18)	(0.13)
Panel B: Pretreatment category number as leadership proxy				
After × Treat	0.16	0.13**	0.05	0.01
	(0.13)	(0.06)	(0.30)	(0.18)
After × Treat × Leadership II	1.07***	0.14	0.46	0.36
	(0.36)	(0.15)	(0.75)	(0.51)
Panel C: Pretreatment active week numbers as leadership proxy				
After × Treat	−0.20	0.15**	0.35	0.15
	(0.16)	(0.07)	(0.35)	(0.23)
After × Treat × Leadership III	0.52***	0.02	−0.06	0.02
	(0.14)	(0.05)	(0.25)	(0.21)
No. of observations	9,610	9,610	7,984	2,050
Website-specific time trend	Yes	Yes	Yes	Yes
Vendor fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes

Notes. All dependent variables and moderators are log-transformed. For robustness, we also measure drug popularity via "the number of vendors who sold the drug in pre-GRAMS periods," and we get the same conclusion.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

popular drug categories. Following the definition of product diversity from existing literature, we first evaluate leading vendors' product expansion strategy in a generic way. Because of data limitations, we do not have access to vendors' offering information, so we calculate the numbers of unique products from popular versus niche categories that vendors sell in their weekly transactions as a proxy of vendors' overall assortment diversity (Hamilton and Richards 2009). The results using this variable as the dependent variable can be observed in columns (1) and (2) of Table 9. We find that leading vendors successfully transact more drugs from those popular categories in their portfolio when GRAMS makes it easier for consumers to identify these superstar items (column (1)). In contrast, these vendors do not expand more of their offerings to niche genres compared with nonleading vendors, probably due to these drugs' lower traffic and profit (column (2)). To further explore leading vendors' diversification strategy, we leverage assortment depth, the average number of different products offered within one popular/niche category, as the dependent variable and repeat the analysis. The corresponding results indicate that GRAMS' entry encourages leading vendors to enrich product choices (e.g., heroin with different purity or flavor) within popular categories (column (3)). However, such expansion is not observed for niche categories, as shown in column (4). These results further justify predominant vendors' greater capacity to offer a wider selection within each category, enhancing shopping convenience for customers.

To conclude, leading vendors gain more benefits from the introduction of search engines by providing a "one-stop" shopping experience rather than through superior price promotions. The price rigidity is probably because of the nature of the Darknet market. In illegal markets where trust is crucial, consumers are willing to pay a premium to compensate for the risks, and vendors lack incentives to provide discounts or promotional offers. Our study thus contributes to the search cost literature by revealing that, in trust-oriented markets like illicit markets, the introduction of search tools may not necessarily enhance consumer surplus. This finding contrasts with the prevailing view in previous literature, which emphasizes the potential for search tools to reduce product prices through increased competition, thereby benefiting consumers (Brynjolfsson et al. 2003, Wu et al. 2004, Bar-Isaac et al. 2012). Our findings highlight that the impact of introducing search engines on consumer welfare depends on the context of the markets.

6. Validity Checks and Robustness Tests

6.1. Validity of Control Websites

One potential issue of our empirical analyses is the validity of control websites. Considering the convenience offered by search engines, vendors may exit nonindexed markets to initiate their business in searchable

Table 9. Leading Vendors' Scale-up Ability: Product Diversity Advantage

	(1) No. of products (popular categories)	(2) No. of products (niche categories)	(3) No. of products per category (popular)	(4) No. of products per category (niche)
Panel A: Pretreatment transaction volumes as leadership proxy				
After × Treat	0.18***	0.09***	0.18***	0.09***
	(0.06)	(0.03)	(0.05)	(0.03)
After × Treat × Leadership I	0.13***	0.00	0.11***	0.00
	(0.05)	(0.02)	(0.03)	(0.02)
Panel B: Pretreatment category number as leadership proxy				
After × Treat	0.13*	0.07**	0.16***	0.06**
	(0.07)	(0.03)	(0.06)	(0.03)
After × Treat × Leadership II	0.49***	0.08	0.33**	0.08
	(0.18)	(0.07)	(0.13)	(0.07)
Panel C: Pretreatment active week numbers as leadership proxy				
After × Treat	−0.03	0.09**	−0.01	0.09**
	(0.08)	(0.04)	(0.07)	(0.04)
After × Treat × Leadership III	0.23***	0.01	0.20***	0.01
	(0.07)	(0.03)	(0.06)	(0.03)
No. of observations	9,610	9,610	9,610	9,610
Website-specific time trend	Yes	Yes	Yes	Yes
Vendor fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes

Notes. All dependent variables and moderators are log-transformed. For robustness, we also measure drug popularity via "the number of vendors who sold the drug in pre-GRAMS periods," and we get the same conclusion.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

markets following the launch of GRAMS. This switching between control and treated groups could compromise the integrity of control websites, potentially affecting the accuracy of our estimation. To clarify this, we conduct a website-level *t*-test to check the change in the weekly number of leaving vendors in nonindexed websites before and after the treatment. The *t*-test results show that there is no significant difference between the number of leaving vendors after the introduction of GRAMS (mean $= 0.77$, $N = 108$) and that in pre-GRAMS periods (mean $= 1.14$, $N = 58$), with a *t*-statistic of 0.76 and $p = 0.45$.[9] This provides evidence that the deployment of GRAMS did not incentivize more vendors to leave control websites. Moreover, we also test the shift in sales within control markets before and after the launch of GRAMS. Specifically, we conduct a Welch two-sample *t*-test to examine whether there is a significant change in the weekly transaction volumes of control websites before versus after GRAMS' introduction. The test results show that the average weekly sales from nonindexed websites during pre-GRAMS periods (mean $= 250.57$, $N = 58$) are not significantly different from those during post-GRAMS periods (mean $= 305.04$, $N = 108$), with a *t*-statistic of -0.55 and $p = 0.58$. Therefore, it's less likely that the launch of GRAMS attracts vendors to migrate from nonindexed to indexed websites on a large scale. Last but not least, we have addressed the multihoming issue in our analyses, and details can be found in Section 3.3 and Part IV of the Online Appendix.

6.2. Parallel Trend Test

According to Bertrand et al. (2004), one of the key assumptions for the validity of the DID estimation is that the trends of treated and control vendors should be the same had treatment not been given. To test this parallel trend assumption in our experiment, we add leads and lags in the DID model as follows:

$$\log(y_{ijt}) = \alpha + \theta_t + \sum_k \beta_k * Dummy_{jt}(k) + \delta_j t + \eta_i + \epsilon_{ijt}, \tag{3}$$

where the panel is aggregated by every three weeks to reduce fluctuations in weekly dependent variables and better clarify trends over time, y_{ijt} is the dependent variable of interest for each triweek aggregation, $Dummy_{jt}$ is a dummy on a triple-week basis indicating whether a vendor from website j is treated in time t, $\delta_j t$ represents website-specific time trends, η_i is the vendor fixed effect, θ_t is the time fixed effect on the triple-week basis, and ϵ_{ijt} represents the residual term. We include $Dummy_{jt}$ for all values of t except for $t-1$, which indicates the triple-week period immediately preceding the treatment, specifically from March 24 to April 15, 2014. This period is set to be the baseline. We exclude the first and the last triweek observations to make the data set aligned. The coefficient of interest, β_k, represents the treatment effect at each triple-week k relative to the baseline. If the parallel trend assumption holds, all the estimated β_k before treatment should not be statistically different from zero, and all those in the posttreatment periods will be significantly positive. To facilitate the understanding of the regression results, we plot the estimates in Figure 2. The y axis indicates the estimation of β_k, and the x axis represents triple-week k. The point $t = 0$ represents the period when GRAMS was introduced into the market. The period immediately before the introduction, denoted by $t - 1$, serves as the baseline for our coefficient estimation. Thus, each dot in the figure represents the difference in coefficients by comparing the estimate of a specific period to this baseline period. We observe that, before the treatment, the treated and the control vendors share a similar trend on transaction volumes and number of categories sold over time. Furthermore, we conduct the joint *F*-test for the coefficients of all pretreatment periods and find that estimates in all pretreatment periods are not significantly different from zero. We also report the *p*-values of the *F*-test for each dependent variable in Figure 2. Hence, the parallel trend assumption holds for our main analysis. The detailed numerical estimation for the coefficient of each period can be seen in Table A.5 of the Online Appendix.

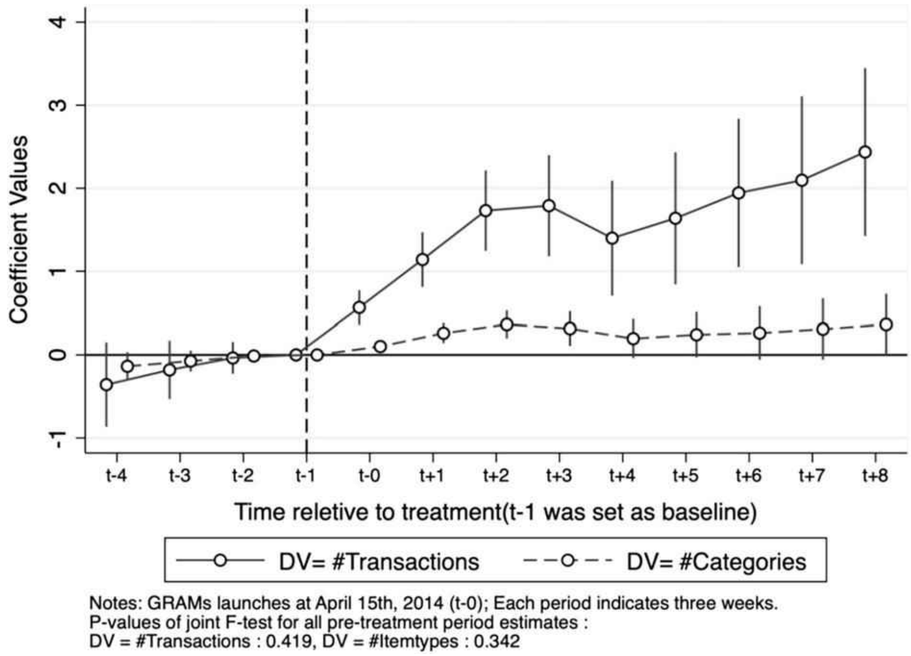
6.3. Placebo Test

Another issue that the estimation of the DID model may suffer from is a false-positive result, meaning the observed treatment effects might arise by chance. To exclude this possibility, we randomly assign the treatment status to the vendor (category) panel while maintaining the ratio of treated vendors (categories) to control vendors identical to that of the original sample. Using the new panel, we re-estimate β_1 in Equation (1) at the vendor (category) level and repeat the process 10,000 times. Table 10 summarizes the results. We observe that the average treatment effects generated by this placebo treatment are not significantly different from zero for all the dependent variables, indicating that our original estimates do not happen by chance.

6.4. Effect of GRAMS on All Types of Transactions

In our main analysis, we focus on drug transactions because drug products constitute the predominant share of Darknet markets. In this section, we conduct a robustness check by considering transactions involving all available items in Darknet markets. With the same model specification as Equation (1), we repeat the DID estimations with full sample and report the

Figure 2. (Color online) Parallel Trend Test for Treated and Control Vendors



results in Table 11. The results provide consistent evidence that the introduction of GRAMS can significantly boost the transaction numbers of all illicit items on Darknet markets. We also repeat estimation in Equation (2) and show the results in Table 12, which continue to observe a significantly increased market concentration when including nondrug transactions in the analysis.

6.5. Effect of GRAMS on All-Vendor Samples

In the main analysis, we adopt the approach PSM on vendors to improve the sample balance. We now include the entire sample to retain data from all vendors during our study period and repeat the overall and heterogeneous estimations. As shown in Tables 13 and 14, our main conclusions still hold.

6.6. Effect of GRAMS Using Generalized Synthetic Control Estimation

One caveat of the current estimated effect of GRAMS arises from the small sample size because we matched 166 GRAMS-indexed vendors with 92 nonindexed vendors. To mitigate the potential concerns on the generalizability of our conclusions, we employ Generalized Synthetic Control (GSC). This approach generates counterfactual estimates for the treated units by reweighing the control units (Xu 2017). Given the relatively smaller number of control units, we adopt a reverse strategy, creating counterfactual estimates for the nonindexed vendors by reweighing all indexed vendors. Figure 3 shows that, before the search engine's entry, counterfactual control units (dashed line) are very close to the actual control units (solid line) for both the number of transactions and the number of drug categories. After the launch of GRAMS, on the other hand, we observed that the market performance values of the counterfactual control units are significantly higher than those of the actual control units. This indicates that the treated vendors have a greater number of transactions and drug categories compared with the control vendors, which is consistent with our main analyses.

Because the primary focus of our study is to assess the impact of search engines on market structure, we

Table 10. Placebo Test

	Vendor level		Drug category level	
	(1) No. of transactions	(2) No. of categories	(3) No. of transactions	(4) No. of vendors
Mean	−0.0012	−0.0002	−0.0003	−0.0003
Standard deviation	0.0799	0.0283	0.1216	0.0822
Statistic (*H0*: Mean = 0)	−1.5133	−0.8178	−0.2205	−0.3072
p-value	0.1302	0.4135	0.8255	0.7587

Table 11. Average Treatment Effect of GRAMS on All-Type Transactions

	Vendor level		Category level	
	(1) No. of transactions	(2) No. of categories	(3) No. of transactions	(4) No. of vendors
After × Treat	0.62***	0.20***	0.56***	0.37***
	(0.13)	(0.04)	(0.19)	(0.09)
No. of observations	9,637	9,637	4,071	4,071
Website-specific time trend	Yes	Yes	Yes	Yes
Vendor fixed effect	Yes	Yes		
Drug category fixed effect			Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes

Note. All dependent variables are log-transformed.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 12. Vendor-Level Heterogeneous Effects of GRAMS on All-Type Transactions

	(1) Moderator = *Leadership I*	(2) Moderator = *Leadership II*	(3) Moderator = *Leadership III*
After × Treat	0.36***	0.31**	0.03
	(0.13)	(0.14)	(0.17)
After × Treat × Moderator	0.23**	0.78**	0.39***
	(0.11)	(0.38)	(0.14)
No. of obsevations	9,637	9,637	9,637
Vendor fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Website-specific time trend	Yes	Yes	Yes

Notes. Dependent variable is weekly sales. Dependent variables and moderators are log-transformed.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 13. Average Treatment Effect of GRAMS on Vendors Using All-Vendor Samples

	(1) No. of transactions	(2) No. of categories
After × Treat	0.82***	0.22***
	(0.09)	(0.03)
No. of observations	72,288	72,288
Website-specific time trend	Yes	Yes
Vendor fixed effect	Yes	Yes
Time fixed effect	Yes	Yes

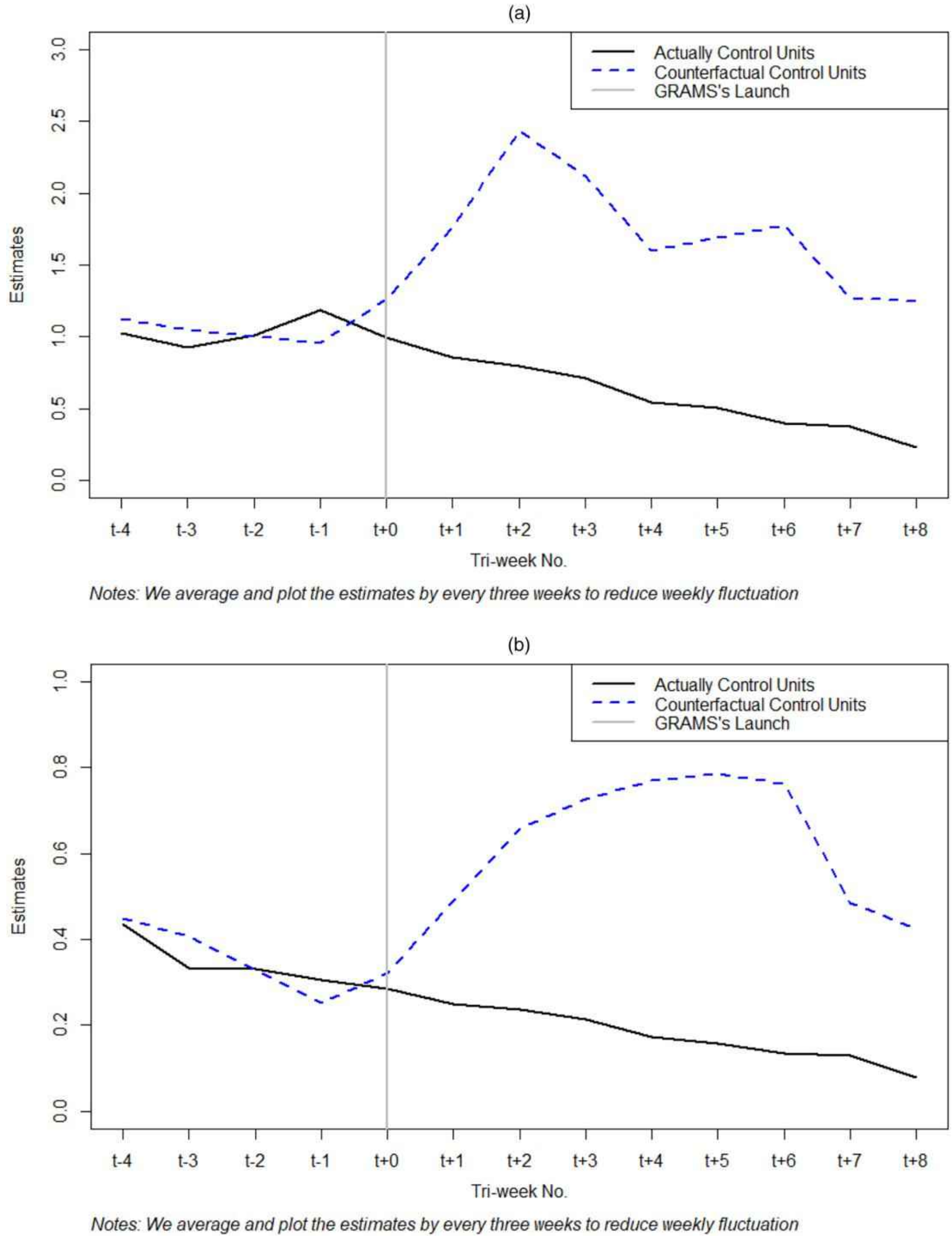
Note. All dependent variables are log-transformed.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 14. Vendor-Level Heterogeneous Effect of GRAMS on All-Vendor Samples

	(1) Moderator = *Leadership I*	(2) Moderator = *Leadership II*	(3) Moderator = *Leadership III*
After × Treat	0.59***	0.44***	−0.06
	(0.09)	(0.10)	(0.13)
After × Treat × Moderator	0.16**	0.80***	0.52***
	(0.07)	(0.26)	(0.10)
No. of observations	72,288	72,288	72,288
Vendor fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Website-specific time trend	Yes	Yes	Yes

Notes. Dependent variable is weekly sales. Dependent variables and moderators are log-transformed.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

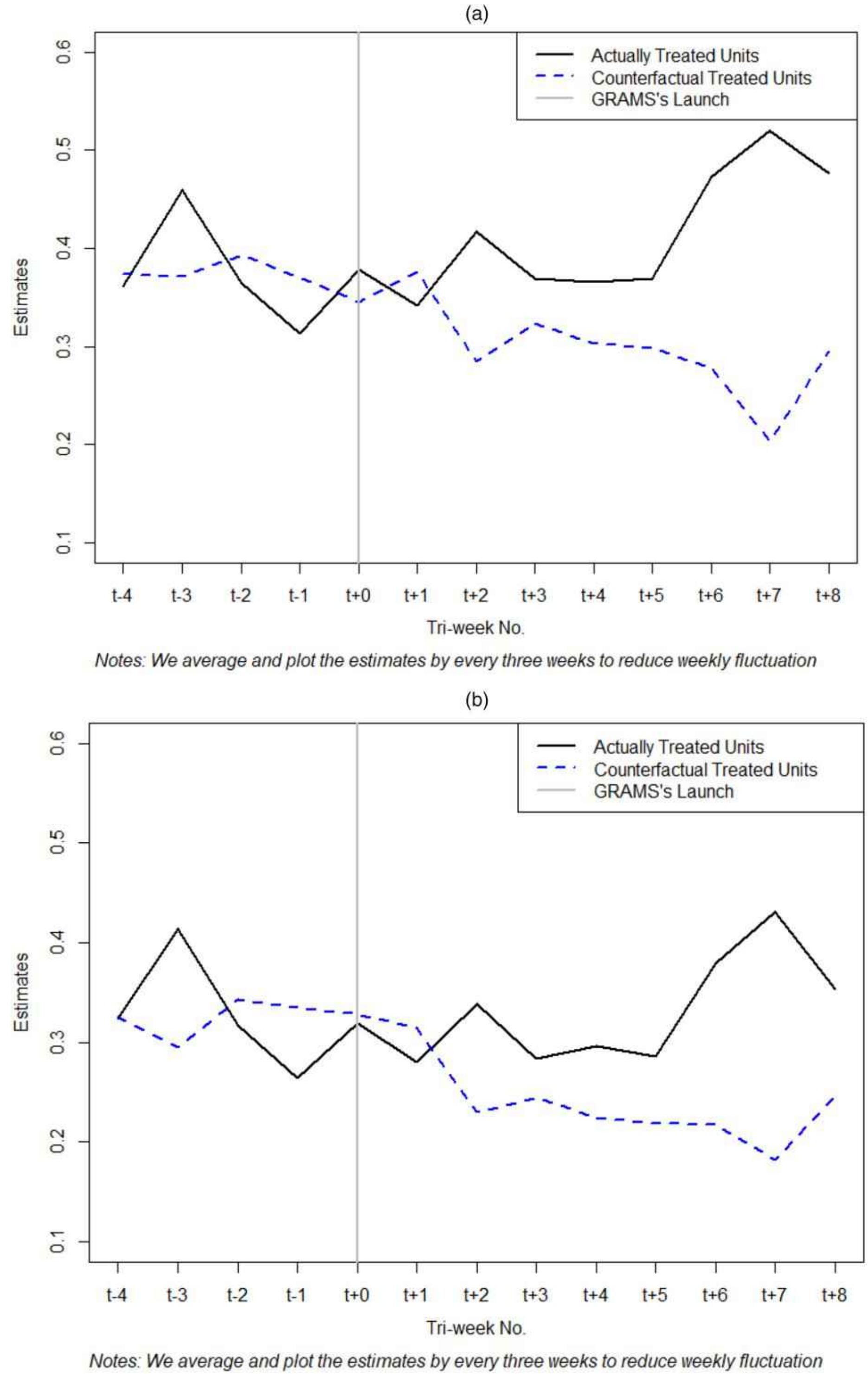
Figure 3. (Color online) GSC Estimation of GRAMS' Effect on Vendors' Overall Performance



Notes. (a) Dependent variable: # *Transactions.* (b) Dependent variable: # *Drug categories.*

therefore use GSC to further verify the intensified market concentration observed in both vendor and drug category sales on GRAMS-indexed websites, as reported in Figure 4. Because the number of indexed websites and nonindexed websites is similar, we generate counterfactual estimates for the Gini index of GRAMS-indexed websites by reweighing that of all nonindexed websites. Figure 4 shows that before the search engine's entry, counterfactual treated units (dashed line) show a roughly similar trend to the actual treated units (solid line) for Gini values at both vendor and category levels. After the launch of GRAMS, on the other hand, we observed that the vendor- and category-level Gini values of the actual treated units are significantly larger than that in the counterfactual treated units, indicating that GRAMS-indexed websites

Figure 4. (Color online) GSC Estimation on GRAMS' Effect on Market Structure



Notes. (a) Dependent variable: *Vendor-level Gini.* (b) Dependent variable: *Category-level Gini.*

show a significantly more concentrated sales distribution among vendors and categories compared with websites that were never indexed by the search engine. This is consistent with our conclusion in the main analysis.

6.7. Selection Bias Issue

Despite our rigorous analysis, one crucial factor that could impact the accuracy of our estimation is how vendors (or websites) are selected to be indexed by the search engine, in other words, the potential selection bias. According to the creator of GRAMS, websites are mainly indexed into this search engine via two ways. The first channel is through manual crawling, where the GRAMS administrator scrapes vendors' information from a website for indexing on the search engine. The second way is through API connection, where websites provide access for GRAMS to index their vendor information. The decision to index a website in GRAMS is hence mainly determined by the availability of data collection techniques. In the GRAMS announcement, we find no indication that the administrator followed a specific standard to index marketplaces.[10] As shown in Table A.1 of the Online Appendix, some indexed websites were even of a smaller scale during the pretreatment periods. Therefore, market size is less likely to be a consideration when the administrator made indexing decisions. In addition, to account for potential growth disparities among websites, we incorporate a website-time trend as a control variable in our empirical analysis to mitigate the concern of indexing uncertainty. Moreover, it is important to note that the GRAMS' indexing decision is determined at the website level and not at the vendor level. Because our main empirical analysis and mechanism explanations are at the vendor level, we hence believe that the website level selection, if any but less likely, does not substantially impact the accuracy of our estimations. Lastly, we adopt PSM to balance pre-GRAMS features of vendors from both indexed and nonindexed groups. We believe that all these processes and evidence effectively minimize potential impact of selection bias issue in our analysis.

6.8. Other Robustness Checks

In this section, we briefly summarize other robustness checks we conducted. One major concern about the reliability of our empirical conclusions might come from the law enforcements occurred on these Darknet markets, as prior studies have shown that law arrests can significantly affect Darknet market transactions (Chan et al. 2023). To alleviate this concern, we collect information of the arrest events occurring through our study window[11] and rerun our estimations by accounting for the influence of such arrest events. Specifically, we introduce a series of dummy variables θ_{jt} to indicate whether there are arrests or not for each website j in week t. By including these control items into Equation (1) and Equation (2), our estimations remain robust (see Tables A.6, A.7, and A.8 in the Online Appendix). Therefore, the conclusions reported in our main analyses are free from the potential impacts of arrests. A second concern is that some vendors, aiming to avoid law enforcement, remain dormant for extended periods and are rarely active. To address this, a robustness check excluding these inactive vendors, and a reassessment of the treatment effect is conducted. We compute the activeness ratio by dividing vendors' number of active weeks by the total length of the vendors' career before GRAMS. We then select those vendors whose ratio exceeds the average. The robustness check results, shown in Table A.9 of the Online Appendix, indicate that the market concentration effect remains significant when focusing solely on active vendors. Another concern is the potential impact of vendors' locations on their trading behavior, as vendors in proximate areas are more likely to face similar law enforcement policies. To account for this, we incorporate proxies of vendors' geographical information into the matching procedure. This information is determined by the source countries of vendors' transactions prior to GRAMS.[12] Using this refined sample, we find that the vendor-level heterogenous effect is still pronounced with high significance. The results can be found in Table A.10 of the Online Appendix. Lastly, our conclusion could be affected if some treated vendors engage in transactions of drugs that were never sold by control vendors before GRAMS. We therefore restrict our analysis to transactions involving drug categories commonly traded by vendors from both treated and control websites. Using the filtered transactions, we redo PSM with original PSM matching variables introduced in Section 3.3 and retest the vendor-level heterogeneity. The results of this subsample analysis remain robust. We show the statistics of drug sales by category during the pre-GRAMS periods in Table A.11 and the re-estimated vendor-level heterogeneity in Table A.12 of the Online Appendix.

7. Conclusion

This study presents causal evidence regarding the impact of a cross-website search engine on online illegal market structure dynamics and the underlying mechanisms. Utilizing a difference-in-differences framework, we discover that the introduction of a search engine on the Darknet leads to a more concentrated distribution of sales, at both vendor and drug category levels. Further analyses reveal that leading vendors disproportionally benefit more from the introduction of the search engine, a phenomenon attributed to their superior trustworthiness and ability to scale-up. Specifically, consumers prefer leading vendors when transacting high-risk drugs, likely due to their priority on trustworthiness to avoid potential legal prosecutions. Moreover, leading vendors manage to gain disproportional benefits by expanding their product assortments with more popular products, providing the convenience of one-stop shopping. These mechanisms collectively explain the increased concentration toward leading vendors following search engines' entry in online illegal markets.

This work contributes to the literature on search engine impact and Darknet market in several ways. Firstly, this study is the first empirical analysis to reveal the effect of search engines on the structural dynamics of a multivendor online economy. Although existing studies have discussed the impact of search cost reduction on market performance, most of them are mainly through analytical modeling and lack an empirical understanding. Some relevant empirical efforts are discussions about the impact of recommender systems, which also help reduce search cost in ecommerce. However, consumers' distinct behaviors during the searching process using search engines warrants a separate investigation. Through detailed empirical analysis, we initially unveil the market concentration effect that search engines impose on real-world online markets, which is contradictory to the long-tail effect at product level observed in existing empirical studies which focus on single-vendor scenarios. The current study unveils the dynamics of sales distribution in a multiple-vendor e-commerce market, which better reflects real-world situations compared with conclusions drawn from single-vendor settings in the previous papers.

Secondly, we propose and verify two mechanisms to explain the concentration effect of search engines on market structure. Specifically, the first mechanism highlights the importance of vendor trustworthiness in these Darknet settings, whereas the second mechanism underscores the pivotal role of vendor scalability. Surprisingly, leading vendors do not achieve scale by lowering prices, as commonly documented by prior studies that focus on regular markets, but rather by expanding their selection of popular products. Therefore, the characteristics of market environments play a significant role in the market structure dynamics when examining the impact of new technologies like search engines.

Thirdly, our study significantly deepens the understanding of Darknet market operations, particularly regarding the influence of technological advancements. By exploring the impact of search engines on Darknet market dynamics, we uncover key operational characteristics such as price stickiness and strong consumer loyalty to leading vendors, even when search technologies facilitate the exploration of alternative options. This is because consumers in these illegal settings prioritize minimizing enforcement risk over economic considerations. The introduction of search engines increases the exposure of these leading vendors, and the leading vendors, in turn, leverage the chance of search technology entry to scale up their operations. As a result, this leads to a disproportionate concentration of sales toward leading vendors on Darknet markets following the entry of search engines. These findings will fill a critical gap in the literature related to Darknet markets, complementing previous literature that sought to unravel the operating characteristics of Darknet markets. We believe that our study provides valuable insights that can inform more effective law enforcement strategies in combating crimes on the Darknet. It is also important to note that, although our study uses the Darknet as the empirical context, the implications of our findings extend beyond this specific market and can be generalized to other market environments, particularly those where trustworthiness plays a pivotal role or when customer interests are poorly protected by law systems.

Our study also offers insightful practical insights into anti-cybercrime interventions for Darknet markets. First, this study alerts law enforcement agents of the importance of monitoring and regulating technological updates within the Darknet, because such technologies could more severely foment criminal transaction activities on these Darknet markets by facilitating transactions among participants. By promptly detecting and suppressing updates in these search engine–like technologies in the Darknet, police can curb criminal activity in Darknet markets more effectively and on a larger scale. Second, our findings provide insights into more effective resource allocation in combating Darknet crimes. For example, enforcement efforts should be concentrated and targeted toward leading vendors, which are predominantly favored by consumers and boosted by search technologies. Attempts to stigmatize leading vendors can be employed to destroy buyers' trust, negatively affecting vendors, and disrupting transactions. As leading vendors leverage one-stop shopping convenience, it is essential to investigate their drug supply channels to further trace key suppliers of illicit products. Our findings also offer additional insights into identifying these leading vendors by examining factors such as transaction volumes, active tenure, and product diversity.

In addition to regulations of underground economies, our conclusions provide valuable guidance for the practical management of general commercial markets. Firstly, policymakers and regulators should consider the implications of search engines on market competition. Without such consideration, the concentration of market sales among dominant vendors, as observed in this study, raises concerns about market monopolies. When necessary, some regulations can be developed to intervene in the implementation of new technologies, preventing them from harming smaller vendors and ensuring market fairness. Secondly, our study provides insights into the development of search-cost-reduction technology. Designers of search engines should consider the specific market features where technologies are deployed. Our results suggest that, although search engines are generally seen as tools to boost diversity, trust-oriented markets may show more concentrated outcomes following the deployment.

Design modifications that promote greater visibility for smaller vendors could be beneficial.

However, our study faces several limitations warranting further investigation. Firstly, although our findings from online illegal markets may apply to other trust-oriented markets like second-hand platforms, more explorations can be done to validate it when data becomes accessible in the future. Secondly, our analysis concentrates on drug transactions, which dominate Darknet markets, highlighting the need to ascertain if our results would differ across other product domains. Data on transactions on nondrug items such as weapons, if available in the future, can also help extend the findings. Furthermore, the absence of consumer identifiers in feedback challenges a detailed analysis of demand-switching behavior. Future research incorporating more comprehensive identity information could provide deeper insights into consumer-vendor dynamics. Lastly, relying solely on consumer-side data (i.e., transactions) to assess market structure changes limits our study. Future access to detailed supply-side data (e.g., product offerings or supply chain relations) could further enrich our understanding of leading vendors' diversification strategy at a more fine-grained level.

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Endnotes

[1] GRAMS uses Pretty Good Privacy (PGP) encryption keys to identify vendors who operate in multiple marketplaces. Details can be found in Reddit posts by "gramsadmin" who announced the launch of GRAMS.

[2] At the period of our study, GRAMS's functionalities were primarily designed to index and aggregate information to facilitate consumer search. This ensures that any impact we observe is specifically due to the search engine's role in reducing search costs, without contamination from additional features like advertising or recommendations commonly associated with search engines like Yahoo! or Google.

[3] We adopt this reversed matching procedure due to the relatively smaller number of control vendors.

[4] A detailed discussion for the PGP-based identification can be found in Part IV of the Online Appendix.

[5] Because the dependent variables are log transformed, the coefficient can be interpreted as the percentage increase, as calculated by $e^{coefficent} - 1$.

[6] The DEA has categorized drugs into five risk levels according to users' physical and psychological dependency, with Schedule I considered as most dangerous. We define the drugs within Schedule I and II as the higher-risk genres and the remaining levels as lower-risk genres. The detailed categorization of drugs in our study can be found in Table A.3 in the Online Appendix.

[7] To provide more granular insights, we conduct a subgroup analysis across each of the five DEA risk schedules rather than grouping them into high-health-risk and low-health-risk categories. The results reveal a concentration of sales toward leading vendors for transactions involving Schedule I and Schedule II drugs, whereas no such patterns are observed for the remaining three lower-risk schedules. Detailed results are available in Table A.4 in the Online Appendix.

[8] The unit price of each transaction is calculated dividing transaction price (in USD) by quantity (in grams). For timestamps when transaction price information is missing, we use average of price values before and after to pad. If the price in all the following (previous) timestamps is missing, we directly apply the price in the nearest previous (following) time to fill in. We leave the price as missing value when both previous and following price labels are not available in the archive. The price missing issue leads to a smaller number of observations in columns (3) and (4) of Table 8.

[9] Leaving vendors are defined by their last feedback record. In other words, we consider vendors leaving the website from week t if we do not find any relevant feedback for them from week $t+1$ afterward until the end of our study period.

[10] The administrator of GRAMS, known as "gramsadmin" on Reddit.com, released all official announcements about new markets joining GRAMS and the technical updates of GRAMS. We retrieve these posts from the text archives of Reddit.

[11] We collect the arrest events through the archive provided by Branwen et al. (2015): https://gwern.net/dnm-arrest. We only include arrest events that are against websites covered by our study and occurred during our study period. We use "public known dates" as the arrest event dates and retain multiple dates for the same targeted vendor because consequent media reports may cast additional impact on Darknet market business.

[12] Technically, we create four continental dummy variables, *is_asia*, *is_europe*, *is_oceania*, and *is_americas* to indicate a vendor's geographic location based on the origin country of this vendor's pre-GRAMS transactions. Combining these location variables with all other PSM matching variables introduced in Section 3.3, we redo PSM and generate a new panel-weekly panel for robustness check.

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