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RESEARCH PAPER

Evolution of direct network effects: A perspective of market thickness of an online freight platform

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Abstract
The dynamics of network effects present challenges for platforms' management strategies across development stages, which have been overlooked in existing literature. Using data from a Chinese prominent freight exchange platform, this paper explores the evolution of direct network effects and offers an explanation for the inconsistent findings in existing literature. We find that direct network effects are positive initially but gradually lose significance and eventually turn negative as the market thickens. We consistently observe asymmetry in direct network effects, initially favoring carriers but shifting to shippers over time. Additionally, shippers experience earlier changes in direct network effects compared to carriers. We attribute the changes over time to the diverse perceptions of platform value resulting from an increased number of peers, as different forces dominate under different market thickness conditions. Our study contributes to the debate on direct network effects, providing insights into their variability based on market thickness.

Keywords Two-sided markets · Direct network effects · Market thickness · Online freight exchange platform

JEL Classification M15 · L96

Introduction

Platforms frequently adopt a "get big fast" (GBF) strategy (Halaburda & Felix, 2014; Sterman et al., 2007) in response to the "winner-take-all" dynamics observed in traditional markets (Anderson et al., 2014) after entry. This is due to the expectation of benefits of scale in the presence of network effects (Tsai et al., 2022). However, it is crucial to acknowledge that network effects can undergo substantial fluctuations over time (Zhu & Iansiti, 2019), which may lead to unintended consequences for platform policy. Pinduoduo, a Chinese e-commerce platform, achieved its rapid expansion at the early stages of its development through the attractiveness of other users' participation. In contrast, the sudden growth of an industry-leading P2P holiday rental platform in Australia resulted in a decline in user's engagement due to search friction (Li & Netessine, 2019). There exists substantial evidence demonstrating that network effects are not fixed, yet platforms often overlook their variability.

Network effects arise in a two-sided market when the perception of platform value is influenced not only by the value of service provided but also by the number of other users' participation (Rochet & Tirole, 2003). The effects of same-side users are called direct network effects (DNEs), while the effects of cross-side users are called indirect effects (CNEs) (Zhu & Iansiti, 2019). Existing literature on CNEs generally demonstrates a consensus regarding their outcomes. However, when it comes to DNEs, the evidence is more varied and inconclusive (Hinz et al., 2020; Li et al., 2018; Voigt & Hinz, 2015), which motivates us to investigate the factors that lead to this phenomenon. We postulate that the ongoing debate in the existing literature can be attributed to the limited

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consideration of the platform life cycle (Muzellec et al., 2015). We introduce the theory of market thickness to elucidate the shifts in the direction of DNEs at different stages of platform development. Market thickness refers to the effective number of participants within a market, which affects the probability of successful matches (McLaren, 2003). The market usually gets thicker with the accumulation of participants, and a thicker market indicates a higher availability of buyers for each seller and vice versa. Consequently, participants derive distinct perceptions of platform value from the same incremental quantity in the number of peers under different market thicknesses, leading to the dynamics of network effects. Besides, market thickness normally increases monotonously with platform development. Therefore, our study is aimed at examining the evolution of direct network effects over time, shedding light on the changes from a new perspective of market thickness, which is overlooked in current studies.

We obtain detailed data from a prominent online freight exchange platform in China, which serves as a marketplace for matching shippers and carriers in the truckload freight industry. The sample period spans from the inception of the platform on April 29, 2015, to April 30, 2021. We aggregate the data on a daily basis and employ time series models that incorporate a linear influence, drawing on existing literature (Hinz et al., 2020; Li et al., 2020; Voigt & Hinz, 2015). The availability of data from the initial stage of platform development provides a valuable opportunity to investigate the evolution of network effects. Instrumental variables are used to address potential endogeneity issues, and seemingly unrelated regression equations are used to jointly estimate models with simultaneous residuals. We also test the robustness of our results.

Our empirical analysis reveals that DNEs initially exert a positive influence on the participation of same-side users. However, as platform develops, the significance of these effects turns insignificant and then negative. DNEs are asymmetric when evolving. Specifically, carriers exerted stronger positive DNEs at the early stages, while shippers exerted stronger negative DNEs as the platform develops. The turning points for DNEs on shippers appear earlier in the platform's development compared to carriers. In our additional analysis, we find a difference from the literature regarding the significance of CNEs at the late stage of platform development. Our results indicate that CNEs become insignificant at this stage. Our findings highlight that the direction and magnitude of network effects are contingent upon the market thickness of the platform. This is because market thickness influences the matching probability and quality, ultimately affecting the perceptions of platform value that users derive from additional participants. As a result, different forces dominate over time, leading to changes in network effects.

Our findings contribute to the studies on platform operation management in two aspects. First, our study addresses the limitations of existing research by providing an explanation for the variation in direction of DNEs over time. By utilizing a new dataset from an emerging industry, we offer empirical evidence that DNEs change direction from positive to negative as the platform develops. This novel finding fills a gap in the literature and contributes to a deeper understanding of the dynamics and evolution of DNEs in platform operations. Second, our study introduces the theory of market thickness to explain the evolution of network effects in a new and comprehensive manner. By considering the varying matching probabilities under different levels of market thicknesses, we provide a nuanced and detailed understanding of the mixed results in existing literature. Our study provides an explanation for the changing degree of participants' preference for the scale of the platform over time.

The rest of this paper is organized as follows. "Literature review" reviews the related researches. "Hypothesis development" develops hypotheses. "Methods" presents data, variables, and models. "Empirical analysis" describes empirical results and robustness tests. "Discussions" concludes and discusses limitations and future researches.

Literature review

Network effects

In contrast to one-sided markets, the perceived value of the platform on participants is influenced not only by the platform itself but also by the number of other participants involved (Rochet & Tirole, 2003). This phenomenon, known as network externality or network effects (Li et al., 2010; Wang & Wang, 2017), carries substantial implications of platform operations.

Positive CNEs have been widely observed and agreed upon in various contexts (Ackerberg, 2006; Tucker & Zhang, 2010; Wallbach et al., 2019), but there are two contrasting views regarding the impact of DNEs. One perspective suggests that DNEs have a positive impact, which can be attributed to the word-of-mouth effect among buyers and learning effect among sellers in an online-to-offline platform (Li et al., 2018). Additionally, a positive DNE is also interpreted as the spillover of buyers' intertemporal demand influencing sellers on a video game platform (Haviv et al., 2020). On the other hand, the opposing view suggests that DNEs have a negative impact, often associated with competition effect observed in dating platform (Voigt & Hinz, 2015) and e-commerce platform (Hinz et al., 2020). Despite mixed empirical evidence, few studies have delved into the underlying factors that contribute to this phenomenon.

Theoretical studies have investigated various cases that involve different intensities of network effects (Chen & Xie, 2007; Niculescu et al., 2018; Sun et al., 2004), which shed light on the dynamics of network effects (Chu & Manchanda, 2016; Mullick et al., 2021). Empirical studies have provided evidence for the changes of CNEs, but there remains a lack of discussion on the changes of DNEs. According to Asvanund et al. (2004), it is evident that network effects exhibit variations based on the scale of the platform. Additionally, Li and Netessine (2019) suggest that the returns to scale are subject to alteration within the context of different market thickness. Given that market thickness normally increases monotonously with platform development, our research aims to examine the evolution of DNEs throughout the process of platform development. By drawing inspiration from the literature on market thickness, which will be reviewed in the next subsection, we intend to provide a comprehensive explanation for the contrasting findings related to DNEs.

Market thickness

Market thickness refers to the effective number of participants within a market, which encompasses the availability of buyers for each seller and vice versa (McLaren, 2003) or mutual distance between two-sided participants in a certain market (Gan et al., 2018). It is widely recognized that as the market scale expands, the availability of potential matches increases, and the mutual distance between two parties tends to decrease. As a result, many studies on market thickness employ market scale as a proxy for market thickness (Bimpikis et al., 2020; Li & Netessine, 2019). The focus of such studies often revolves around analyzing matching probabilities, rates, and the quality of matching outcomes. A thicker market increases the likelihood of finding suitable matches (McLaren, 2003) due to a larger choice set and a greater variety of transacting parties. This holds true even when the ratio of participants on both sides of the market remains unchanged (Gan & Li, 2016). While early studies demonstrate the positive effect of market thickness (Gan et al., 2018), a growing number of recent studies suggest that a sudden increase in scale can lead to a decline in the matching rate due to search friction and reduce the profit of platform when a market is already sufficiently thick (Li & Netessine, 2019). The existing literature shows varying matching probabilities across different levels of market thickness, providing an insightful explanation for the diverse effects from an identical increase in user's number throughout the platform development process. This finding inspires us to explore the evolution of network effects over time for two reasons.

First, in spite of the shared interest in returns to scale, research on market thickness primarily focuses on the effect of scale changes on matching quality and probability, whereas network effects focus on the direct effects of user base on the perceived value of products and services. However, it is often overlooked in existing literature that market thickness can influence the underlying mechanisms driving network effects. This is because perceived platform value by users from an incremental user base varies at different matching probabilities across levels of market thickness. Second, it is inevitable that scale will change during platform development, resulting in changes in network effects over time. In addition, the smooth and monotonous increase in market thickness with platform development over time creates an appropriate environment for exploring the dynamics of network effects. Therefore, it is essential to delve into the evolution of network effects over time from the perspective of market thickness.

This paper contributes to the existing literature in several aspects. First, while previous research has explored dynamic CNEs (Chu & Manchanda, 2016), there is a dearth of empirical evidence specifically addressing the mixed results in DNEs. Our study seeks to fill this gap by examining the evolving nature of DNEs over time and offering an insightful explanation for these changes from the perspective of market thickness. Second, our study offers an insightful explanation for the evolution from a new perspective of market thickness. The relationship between matching probability and market thickness (McLaren, 2003) gives rise to variations in the perceived value of an incremental user base, consequently impacting the dynamics of network effects over time. Despite the significant research conducted on network effects, the existing literature overlooks this crucial aspect. Third, the asymmetry in the magnitude of network effects for the two sides has been discussed extensively in the current body of research, but its variation over time has received limited attention. Our study expands upon the existing literature by not only examining the distinct performances of network effects on both sides but also placing greater emphasis on the diverse evolutionary processes.

Hypothesis development

Our study focuses on investigating the evolution of direct network effects (DNEs) on user influx within the context of an online freight platform that facilitates the matching of shippers and carriers in transportation services. We introduce the concept of market thickness to explain the observed variations. According to Fig. 1 in Gan and Li's (2016) work, matching probabilities increase rapidly at the early stages of market thickness development and soon slow down. The market becomes thicker as the platform accumulates its scale, resulting in heightened matching probabilities over time. Consequently, the perceived platform value from the same incremental same-side users varies over time as the matching probabilities increase along with market thickness, leading to the evolution of DNEs.

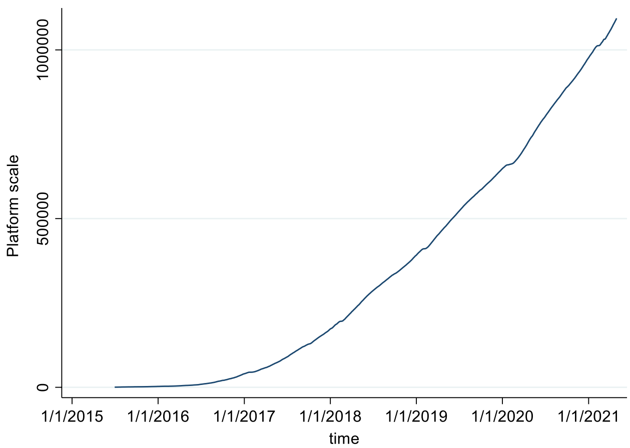


Fig. 1 Platform scale over time

Evolution of DNEs

The motivation of investigating the evolution of DNEs comes from the academic debates over the direction of DNEs. These debates primarily revolve around two distinct interpretations: learning effects associated with positive DNEs (Koh & Fichman, 2014) and competition effects associated with negative DNEs (Hinz et al., 2020). However, the existing literature overlooks the consideration of the growing market thickness in platform life cycle. We find that the market grows thicker monotonically as the platform develops over time, leading to an increase in matching probabilities (Gan & Li, 2016). Users perceive platform value differently from the number of same-side users when matching probabilities are different, which may lead to the phenomena that both forces coexist simultaneously but dominate at different stages of platform development. Consequently, this leads to changes in the direction of DNEs over time.

When the market is thin at the early stage of platform development, the likelihood of finding suitable matches is comparatively low (Gan & Li, 2016). In such instances, users may be incentivized to actively encourage the participation of more peers on the platform, as doing so can enhance their own experience (Li et al., 2018; Ward, 2022). The growing number of same-side users enhances users' perception by ensuring its credibility and building trust in the intermediary in a thin market. As a result, transaction costs are reduced (Li & Fang, 2022), and this, in turn, attracts a greater influx of users to join the platform. The existing literature predominantly characterizes the phenomenon as users' observational learning (Koh & Fichman, 2014). When market lacks sufficient thickness, users generally do not experience intense competition and congestion. In such cases, users are more inclined to engage in sharing and collaborative behavior, leading to the dominance of learning effects. Consequently, DNEs exhibit positive impact on both sides of the platform. Therefore, we propose the following hypothesis.

Hypothesis 1a: At the early stage of platform development, DNEs are positive significantly on the influx of both side users but become weaker as platform develops.

When the market becomes thicker with the development of the platform, we posit that the matching probability between users increases (Gan & Li, 2016), and the risk of using the platform decreases (Koh & Fichman, 2014). Consequently, users may perceive that there is reduced necessity to actively engage in efforts to attract more peers to the platform. The continuous increase in same-side users may no longer bring benefits to users and can even have negative effects, particularly when the matching rate reaches a significant level. At this point, adverse consequences may arise, such as delays in order pickups for shippers and increased difficulty in securing preferred orders for carriers. The other body of empirical evidence concerning DNEs supports the existence of competition effects among same-side users (Hinz et al., 2020; Voigt & Hinz, 2015) or congestion effects (Bernstein et al., 2020; Taylor, 2018). As the market becomes thicker, these effects gradually come into play and begin to dominate over the learning effects observed at the early stage. This transition results in a change in the direction of DNEs, shifting from positive to negative. Thus, we propose the following hypothesis.

Hypothesis 1b: With the development of platform, DNEs are no longer positive and exhibit a progressively negative trend over time for user influx on both sides of the platform.

Comparison between shippers and carriers

While the presence of asymmetry of DNEs has been confirmed in numerous studies (Hinz et al., 2020; Li et al., 2018), the dynamic perspective of asymmetrical DNEs and the potential changes in their direction over time have received limited attention in the existing literature. Our study aims to fill this research gap by conducting a comparative analysis of DNEs experienced by shippers and carriers throughout the evolutionary process. While the above hypotheses are likely to apply to more platforms, the following hypotheses are more specific to freight exchange platforms, as the comparison is influenced by the characteristics of the two groups of users. In particular, the behavior of small carriers and small and medium shippers differs, so does their asymmetric bargaining power in transactions (Miller et al., 2020). Carriers behave more like individuals who are more flexible but have less bargaining power and fewer viable means of obtaining freight information.

Shippers behave more like small and medium enterprises with more bargaining power. Despite that carriers can refuse to provide service for shippers, which is an operational challenge for shippers (Scott et al., 2017), carriers are still more dependent on shippers with cargoes. This causes more asymmetries in the evolution of direct network effects.

As previously mentioned, the dominance of learning effects during the early stage of platform development leads to positive DNEs. To be more specific, we attribute these positive DNEs to the social influence (Chou et al., 2015) from observational learning of carriers through chat groups and shippers who are small and medium firms that observe and learn from each other, according to our interviews with the staff. We posit that the observational learning among carriers exerts a stronger impact compared to shippers. This is primarily because of the existence of more intensive communication channels, such as Internet-based chat group of carriers,[1] which facilitates a more direct and efficient way to learn from each other and encourages greater participation from peers. Furthermore, we contend that carriers with lower bargaining power in transactions (Miller et al., 2020) are more inclined to exert additional efforts to enhance the matching rate under a thin market. Thus, we propose hypothesis 2a.

Hypothesis 2a: At the early stage of platform development, positive DNEs on the influx of carriers are stronger than on shippers.

When the market gets thicker with the development of platform, the probability of finding a successful match increases. However, as previously discussed, participants experience diminishing benefits from the influx of additional peers. Instead, they may encounter heightened competition and congestion, leading to increased pressure and challenges in obtaining further advantages (Bernstein et al., 2020; Halaburda et al., 2018). Carriers with lower power in transactions and less access to information (Miller et al., 2020) invest more effort in finding suitable matches, even in the presence of competition. The platform removes information barriers by integrating resources of supply and demand in freight industry. More participants indicate more information sharing on the platform. Conversely, shippers who make less effort are more sensitive to competitive pressures. When shippers encounter increasing difficulties in achieving successful transactions, their enthusiasm for participation diminishes because they have little pressure to compete to hire carriers in the original transaction modes. Therefore, we propose that shippers experience stronger negative DNEs as the market becomes thicker. Thus, we propose hypothesis 2b.

Hypothesis 2b: At late stage of platform development, negative DNEs on the influx of shippers are stronger than on carriers.

As mentioned in hypotheses 1a and 1b, there are gradual changes in the attitudes towards the continued growth of same-side participants. Therefore, there are turning points where the attitudes change and one force gradually takes over the dominant position of the other for shippers and carriers, respectively. We believe that the turning points occur at different time for shippers and carriers. In the truckload freight industry, it is typically observed that shippers on the demand side possess greater power over compared to carriers (Miller et al., 2020). Carriers with lower power often take the initiative to actively seek suitable matches according to the transacting process on the platform. This proactive approach stems from their expectation of achieving a higher matching rate. Consequently, carriers exhibit a stronger preference for a thicker market compared to shippers. In that case, the turning points at which the positive DNEs become insignificant and subsequently turn negative tend to appear at a thinner market for shippers. Therefore, we propose the following hypothesis.

Hypothesis 3: Turning points for the direction of the evolution of DNEs appear earlier for shippers than for carriers.

Methods

Data

To empirically examine the evolution of network effects on user's participation, we collect platform's installed base and user's participation from the establishment of the platform. Therefore, we collect registration data from the first user registration on April 29, 2015, to April 30, 2021. During the sample period, we observe that 19,750 shippers and 1,073,718 carriers are registered on the platform. To control the potential influence from transactional characteristics, we also collect the corresponding transaction data and a total of 15,988,092 orders were listed during the sample period, out of which 15,347,504 orders were picked by carriers at the end of the sample period. We merge and aggregate these data on a daily base to observe changes over time, resulting in a time series of 2194 observations. In addition, we employ two more datasets to control other potential influence inside the platform and outside the platform. First, we attain the time of patent application as a proxy to infer platform

[1] A website about a new carrier looking for chat groups on the Internet: https://www.zhihu.com/question/323588154

Table 1 Daily new shippers and new carriers

		New shipper				New carrier			
Year	Obs	Mean	Std. dev	Sum	Cum	Mean	Std. dev	Sum	Cum
2015	184	1.49	2.33	275	458	10.29	9.81	1894	2203
2016	366	2.89	3.17	1057	1515	99.46	91.27	37,091	38,606
2017	365	6.32	4.22	2306	3821	356.15	142.85	164,780	168,601
2018	365	9.83	5.81	3587	7408	589.54	145.23	376,374	383,782
2019	365	12.34	7.44	4504	11,912	689.38	151.53	623,492	635,404
2020	366	16.01	10.01	5859	17,771	881.69	255.47	940,332	958,103
2021	120	16.49	10.52	1979	19,750	963.46	370.68	1,053,968	1,073,718

function update because the update data is not available and it is observed that the platform often files for patents for its exclusive updates. Second, we crawled the data containing the establishment time of 194 enterprises involved in online freight business, which may compete with the platform in our study.

To ensure data quality, we exclude early data with a large number of empty values in the principle of minimizing losses in sample size. Since July 2015 is the first month in which the proportion of zero daily registrations decreased significantly for both side users (90.3% in May, 46.7% in June, and 25.8% in July for shippers; 29% in May, 22.6% in June, and 16.1% in July for carriers), we exclude the data before July 2015 (2.87%).

As it is common in studies of market thickness to use market scale as a metric, we present the development of platform scale over time in Fig. 1. Figure 1 demonstrates a steady growth of market thickness without any abrupt spikes or declines as the platform develops.

We also provide a summary of the annual growth rates for both daily new shippers and daily new carriers in Table 1. From the table, it is evident that both the number of shippers and carriers experience gradual growth during the initial 2 years after the platform's establishment. Subsequently, both groups experience a phase of rapid growth. Notably, the influx of carriers surpasses that of shippers in terms of both magnitude and speed.

Variables

Dependent variable

We count the number of new registration of users on both sides on the platform separately and utilize them as our dependent variables. This measurement approach aligns with existing literature that captures the impact of network effects on user's perception of platform value by examining user's decision of whether to adopt a platform (Pontiggia & Virili, 2010; Song et al. 2018). Specifically, we aggregate user registration data on a daily basis, resulting in variables $news_t$ and $newc_t$, which represent the daily influx of shippers and carriers.

Independent variables

In line with the common approach to study network effects (Li et al., 2018, 2020), we utilize the cumulative sum of the number of registered users each day as installed base for both sides as our independent variables. Specifically, we sum up the daily growth for each day, resulting in variables $cums_t$ and $cumc_t$, which represent the installed bases of shippers and carriers. Figures 2 and 3 show the inflows and installed base on the daily basis.

$$cums_t = cums_{t-1} + news_t = \sum_{i=1}^{t} news_t$$

$$cumc_t = cumc_{t-1} + newc_t = \sum_{i=1}^{t} newc_t$$

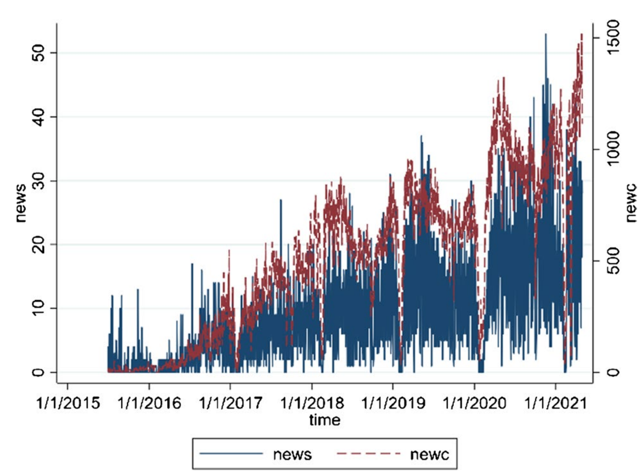


Fig. 2 Influx of both sides over time

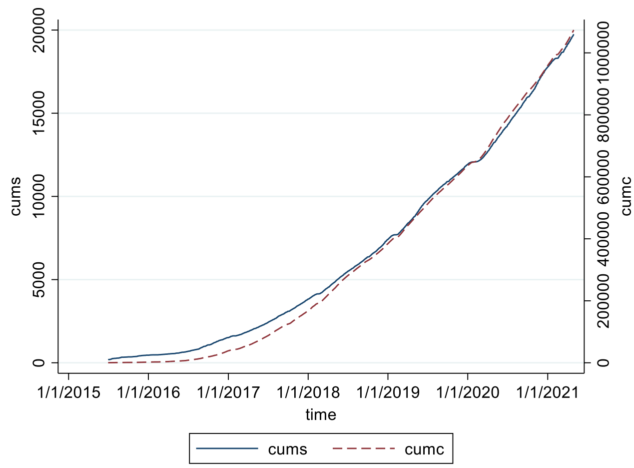


Fig. 3 Installed base of both sides over time

and carriers, respectively. Fourth, to control for platform version updates or function innovation (Hinz et al., 2020), we construct a binary variable $ifpatent_t$, indicating whether a patent has been filed at time t. Due to the unavailability of data on platform function updates, we consider platform function updates to be platform innovations (Chen et al., 2023) and use patent applications as a proxy, referring to studies in the field of innovation. According to our interviews with platform staff, the platform files patents for most updates, and there should be a strong correlation between the timing of patent filings and platform function updates. Therefore, it is also reasonable to use this method from the practical perspective.

At the industrial level, we construct a binary variable $opponent_t$ to account for the presence of outside competition in the industry. $opponent_t$ takes 1 if there is a new company entering the online freight exchange business at time t and 0 otherwise. At market level, we incorporate linear and quadratic time trends as control variables to capture advertising activities (Chu & Manchanda, 2016), common variation over time, and unobserved factors related to time. These time trends allow us to control for any systematic changes in the market conditions that may affect our dependent variables. In addition, we construct binary variables to represent each individual statutory holidays and a binary festival variable $festival_t$ to indicate the occurrence of any statutory holiday collectively. If there are any statutory holidays at time t, $festival_t$ is set to 1, otherwise, 0.

Table 2 Summary statistics

	Variable	Meanings	Mean	Std. dev	Min	Max
Dependent variables	cums	Cumulative sum of registered shippers at month t	6717.86	5802.20	187	19,750
	cumc	Cumulative sum of registered carriers at month t	344,709.10	328,187.10	316	1,073,718
Independent variables	news	Number of daily registration of shippers at month t	9.18	8.36	0	53
	newc	Number of daily registration of carriers at month t	503.71	357.46	0	1517
Control variables at platform level	trrate	Ratio of cumulative pick-up orders and issued orders at month t	80.38	15.60	48.65	96.00
	avgp	Average unit freight price of all orders at month t	0.31	0.05	0.15	0.69
	qs	Ratio of the number of issued orders and installed base of shippers at month t	94.52	51.03	0	273.05
	qc	Ratio of the number of pick-up orders and installed base of carriers at month t	2.06	0.89	0	5.03
	ifpatent	Equal 1 if a patent is applied, 0 otherwise	0.01	0.08	0	1
Control variables at industrial level	opponent	Equal 1 if a competitor enters, 0 otherwise	0.06	0.23	0	1

$N = 2131$. Control variables at market level, such as holidays and time trends, are not included in Table 2 because they are common knowledge

Control variables

We construct control variables at three levels. At platform level, we include the following control variables: first, we construct the order pickup rate $trrate_t$, which is calculated as the ratio of the number of picked-up orders to the total number of listed orders at time t. We use it to capture the perception of internal competition within the platform. Second, we construct average unit freight price $avgp_t$, which is calculated as the average price per weight of cargoes and per distance of routes of all the orders at time t. We use it to capture the price index of transportation services on the platform. Third, following findings of existing literature that highlight user quality influences user matching (Chu & Manchanda, 2016), we construct user quality qs_t and qc_t for each side. These two variables are calculated as the ratio of the number of picked-up orders and installed bases of shippers

Table 2 provides the definitions and summary of the variables used in our analysis. Notably, the installed base and influx of carriers are substantially larger than those of shippers, which reflects the industry's conditions and suggests that shippers hold more influence over carriers in the matching process. Moreover, carriers display a greater focus on matching probabilities compared to shippers. Additionally, the average ratio of cumulative pick-up orders to issued orders is found to be 80.38%, indicating that the majority of orders issued on the platform are successfully fulfilled. Furthermore, the average unit freight price per weight and per distance is approximately 0.31, which is consistent with the information gathered from interviews conducted with platform staff. It is important to note that market-level control variables are presented in the table to prevent unnecessary repetition of information because they are derived from common knowledge.

Model specification

We adopt a commonly used approach in existing empirical research by assuming a linear relationship between the installed base of users on both sides of the platform and their respective participation (Voigt & Hinz, 2015). We establish time series models for shippers and carriers respectively to estimate the evolution of DNEs. Building upon the approach suggested by Chu and Manchanda (2016), we incorporate interaction terms of dummy variables representing year and month, as well as installed base of each side. This allows us to capture the time-varying DNEs and examine the dynamics and changes over time. The following regression models (1) and (2).

$$\begin{aligned} news_t = {} & \alpha_1 + \beta_{1\bar{t}}\text{year}_t * \text{month}_t * cums_{t-1} + \beta_2 cumc_{t-1} \\ & + \gamma_1 qc_t + \delta_1 C_t + \eta_1 F_t + \upsilon_1 t + \upsilon_2 t^2 + \varepsilon_{t1} \end{aligned} \tag{1}$$

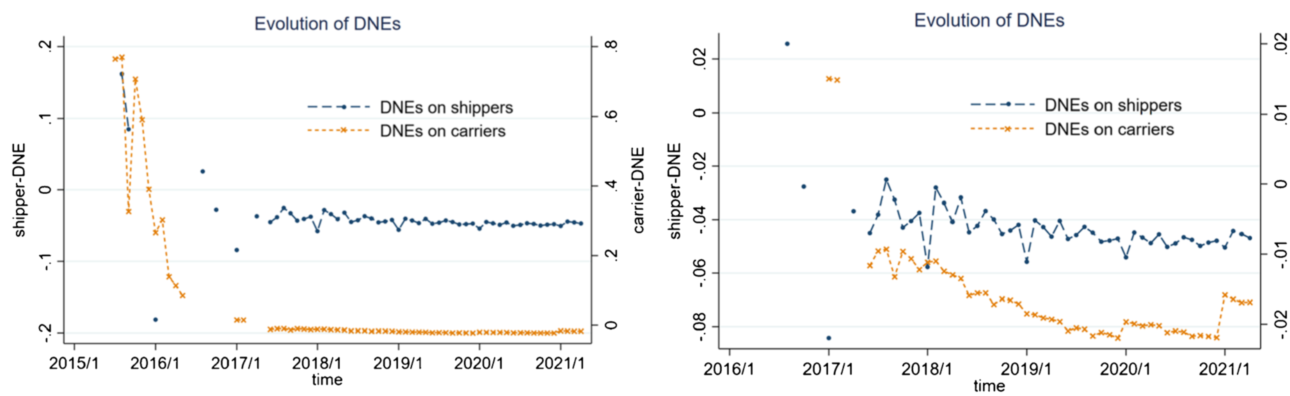
$$\begin{aligned} newc_t = {} & \alpha_2 + \beta_3 cums_{t-1} + \beta_{4\bar{t}}\text{year}_t * \text{month}_t * cumc_{t-1} \\ & + \gamma_2 qs_t + \delta_2 C_t + \eta_2 F_t + \upsilon_3 t + \upsilon_4 t^2 + \varepsilon_{t2} \end{aligned} \tag{2}$$

where $news_t$ and $newc_t$ represent the daily registration count of shippers and carriers, and $cums_t$ and $cumc_t$ are installed bases of shippers and carriers at time t. The dummy variables $year_t$ and $month_t$ represent the year and month, respectively, in which time t falls (Chu & Manchanda, 2016). If it is the year or month, the dummy variable is set to 1; otherwise, it is 0.

qs_t and qc_t represent user qualities of the shipper and the carrier, respectively. Matrix C_t contains the same set of control variables for both shippers and carriers across the two models, including the lagged one-period order pickup rate $trrate_t$, the average unit price $avgp_t$, an indicator for patent application $ifpatent_t$, an indicator for competitor $oppnent_t$ and dummy variables representing whether the day falls within statutory holidays. Matrix F_t includes year fixed effects, month fixed effects, and weekday fixed effects. Moreover, linear time trend t and quadratic time trend t^2 are included in all the models to capture the common variation in market over time. Following the established approach in existing literature (Hinz et al., 2020; Li et al., 2018), we consider a lag of one period for the independent variables. This approach aligns with the practical consideration that our studied platform typically requires a certain time span, which is generally within one day, to review the qualifications of registered users. We focus on examining the evolution of DNEs on shippers, represented by $\beta_{1\bar{t}}$, and on carriers, represented by $\beta_{4\bar{t}}$.

To address potential endogenous bias, we add variables in three levels of platforms, industry, and markets to capture as many omitted factors as possible and incorporate one-period lag of focal independent variables in the model. Additionally, we employ a two-stage linear squares (2SLS) approach with instrumental variables using the following methodology: (1) the two-period lagged terms of focal independent variables (Li et al., 2020), (2) national level consumer confidence index and consumer satisfaction index, and (3) the entrepreneur confidence index and entrepreneur prosperity index. These monthly indices are collected from the State Statistics Bureau of China and are also have also been employed in Chu and Manchanda's (2016) research. Since we analyze DNEs at a daily level, we treat each day within the same month as having the same value of each index. These three types of instrumental variables are selected from the existing literature on network effects in the context of two-sided platforms (Chu & Manchanda, 2016; Li et al., 2020). In our analysis, the selection of instruments for each endogenous variable depends on the specific model under consideration. In model (1) of shippers, we employ methods (1) and (3) as instruments for related installed base of both sides. In model (2) of carriers, we employ methods (1) and (2) as instruments for related installed base of both sides. The selection is made from both economic and statistical perspectives. From an economic perspective, the installed base of carriers is influenced by consumer-related indices, as carriers are individuals who are strongly influenced by the consumer market, while the installed base of shippers is influenced by entrepreneur-related indices, as shippers are mostly small and medium enterprises. Furthermore, we think that the two-period lagged terms and one-period lagged market-related indices are relevant to the one-period lagged installed base, which satisfies the requirement of relevancy. Additionally, they do not directly influence the current influx of users, which satisfies the requirement of exclusivity. From a statistical perspective, we conduct a series of tests on instrumental variables, and the results are reported in Table A1 of Appendix A. Our results show that there are no concerns regarding weak identification or overidentification of the instrumental variables utilized in our study.

In addition to addressing endogeneity, there is still concern regarding simultaneity. The registration of shippers



(a)Evolution of DNEs from July 2015 (b) Evolution of DNEs from July 2016

Fig. 4 Evolution of DNEs

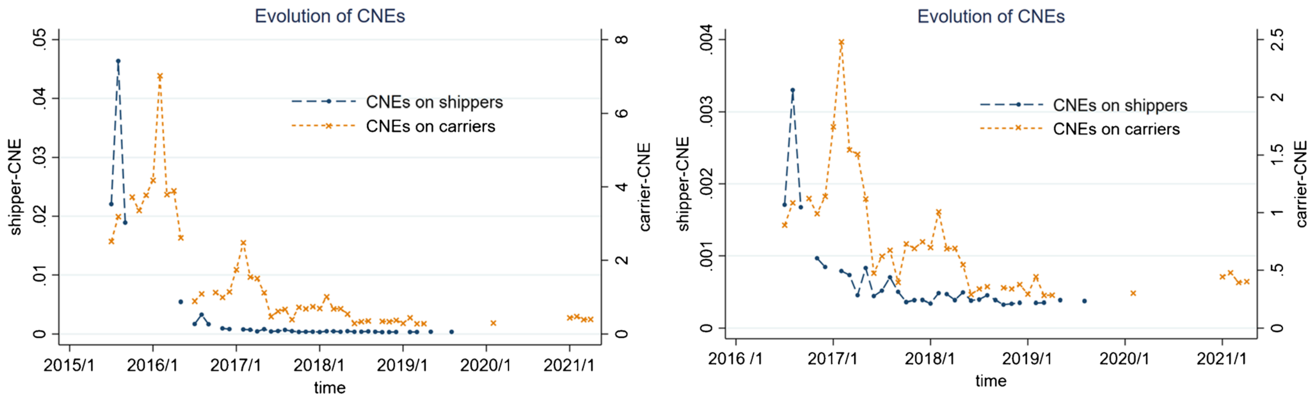
and carriers into the platform can occur simultaneously, and the inflow of each side can be influenced by the other. This introduces the potential for contemporaneous cross-equation error correlation, which means that the error terms of models (1) and (2) on observation i are correlated. $E\left(\varepsilon_{is}\varepsilon_{ic}|X_i\right) = \sigma_{sc} \neq 0$, where s and c represent model (1) for shippers and model (2) for carriers, respectively. To address the concern of simultaneity, we adopt an approach from existing literature by employing seemingly unrelated regression equations (SURE). SURE is first proposed by Zellner (1962) to improve the efficiency of estimation for multiple equations with some relation. This method allows for the consideration of correlated residuals of the two equations and enables us to obtain the final estimated coefficients and is lately used in some studies on network effects to obtain consistent estimation (Hinz et al., 2020; Voigt & Hinz, 2015). We implement SURE approach to re-estimate the coefficients of equations $\widehat{\beta}_{\mathrm{SUR}} = \widehat{\beta}_{\mathrm{GLS}}(\widehat{\Omega})$, using the estimated covariance matrix $\widehat{\Omega} = \frac{1}{n}\widehat{\varepsilon}_{2\mathrm{SLS}}\widehat{\varepsilon}_{2\mathrm{SLS}}{}' \otimes I_n$ of our first-step 2SLS.

Empirical analysis

Estimation results of DNEs

Due to the length of estimated results of the regressions, we present them in Table A1 of Appendix A. Notably, each regression yields 70 coefficients through the interaction terms. To facilitate a more intuitive understanding about the evolving nature of DNEs, we illustrate the estimation results of all the significant coefficients from the 70 results in Fig. 4a. We exclude insignificant results from the illustration to focus on the meaningful findings. To facilitate a clearer observation of the evolution of the late stage of platform development, we also truncate the results starting from July 2016 in Fig. 4a and present it in Fig. 4b.

From the observations of Fig. 4a, it is evident that as the platform further develops, DNEs transition from being statistically significant to becoming insignificant, and eventually negative. This shift in the direction of DNEs can be attributed to the increasing influence of competition and congestion on the platform, which gradually comes to dominate in driving DNEs and ultimately leads to negative outcomes. As the market becomes thicker and more crowded with same-side users, users may experience reduced benefits and increased challenges in transactions due to heightened competition and congestion (Bernstein et al., 2020; Voigt & Hinz, 2015). This leads to a diminishing perception of platform value through incremental same-side users. The negative DNEs become even stronger as the market becomes thicker according to Fig. 4b. These findings support hypothesis 1b. Furthermore, Fig. 4 shows a relatively stable state at the late stage, indicating a trend of stationary negative DNEs along with the ever-increasing market thickness. In addition to analyzing the evolving nature for both shippers and carriers on the platform, our study also compares the differences in their respective evolutions. According to Fig. 4a, it is evident that there are more points representing positive DNEs on carriers compared to shippers during the early stages of platform development. Furthermore, the positive DNEs are stronger on carriers than those on shippers at early stage of platform development. These findings support hypothesis 2a. This indicates that carriers may exhibit higher sensitivity to changes in matching probabilities and place a greater emphasis on the establishment of platform reputation, particularly at the early stages of platform development when the market is relatively thin. As a result, carriers tend to perceive a greater value in the platform, leading to stronger positive DNEs compared to shippers at early stage. Conversely, as the market becomes thicker, negative DNEs on



(a)Evolution of CNEs from July 2015

(b) Evolution of CNEs from July 2016

Fig. 5 Evolution of CNEs

carriers are weaker compared shippers according to Fig. 4b. These findings support hypothesis 2b, indicating that the influx of shippers is hindered more significantly by competition compared to carriers as platform develops.

Furthermore, the similar but different growth patterns shown in Fig. 3 indicate a potential difference in the evolution of DNEs between shippers and carriers. The accumulation rate of shippers is faster than that of carriers at the early stage, which may lead to earlier aversion to competition and cause an earlier turning point. The results of the evolution of shippers and carriers shown in Fig. 4a provide further empirical evidence. The turning points of shippers where DNEs transition from statistically significant to insignificant and transition from insignificant to negative appear both earlier compared to carriers. This observation suggests that the market thickness required for carriers to experience competition or congestion from additional same-side users is larger than that for shippers. Therefore, hypothesis 3 is supported.

Additional analysis on CNEs

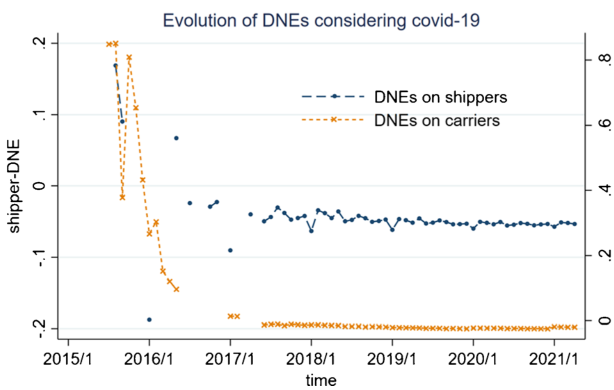
The other type of network effects that exist on a two-sided platform besides DNEs is CNEs. DNEs reflect the influence of the number of same-side users, while CNEs reflect the influence of the number of cross-side users. Unlike DNEs, which are concluded as positive learning or negative competition in the existing literature, CNEs reach an almost consistent conclusion on the matching platform and also are also the focus of study from the timing of their proposal. Empirical studies, as well as in theoretical studies, generally support the presence of positive CNEs (Chakravarty et al., 2006; Chao & Derdenger, 2013; Fuentelsaz et al., 2012; Wu & Chamnisampan, 2021). These positive CNEs arise from more choices for successful matching on the platform. From a dynamic perspective, Chu and Manchanda (2016) conduct an investigation in the context of a retailing platform and find evidence suggesting a decrease in the magnitude of asymmetric CNEs over time.

Following the results of existing literature, we incorporate the hypotheses of asymmetric CNEs between shippers and carriers, as well as their decreasing trend over time. To estimate the evolution of CNEs, we employ models (3) and (4), similar to the estimation approach used for the evolution of DNEs. Our focus is on the coefficient $\beta_{6\bar{t}}$ for shippers and $\beta_{8\bar{t}}$ for carriers.

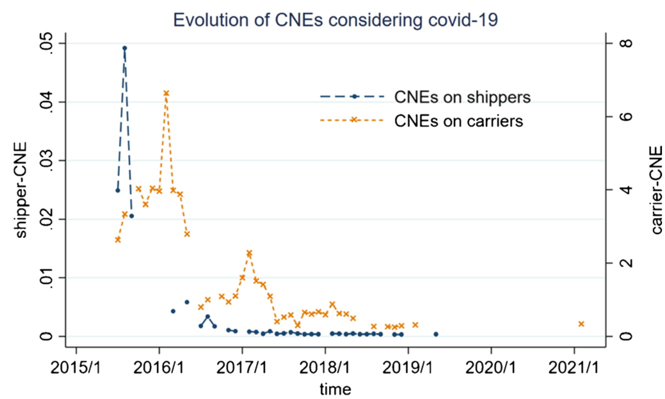
$$
\begin{aligned}
news_t = {} & \alpha_3 + \beta_5 cums_{t-1} + \beta_{6\bar{t}}\text{year}_t * \text{month}_t * cumc_{t-1} \\
& + \gamma_3 qc_t + \delta_3 C_t + \eta_3 F_t + \upsilon_5 t + \upsilon_6 t^2 + \varepsilon_{t3}
\end{aligned}
\tag{3}
$$

$$
\begin{aligned}
newc_t = {} & \alpha_4 + \beta_{7\bar{t}}\text{year}_t * \text{month}_t * cums_{t-1} + \beta_8 cumc_{t-1} \\
& + \gamma_4 qs_t + \delta_4 C_t + \eta_4 F_t + \upsilon_7 t + \upsilon_8 t^2 + \varepsilon_{t4}
\end{aligned}
\tag{4}
$$

The estimation results for CNEs are also reported in Table A1 of Appendix A. To provide a concise representation, we focus on the significant coefficients of CNEs and present them in Fig. 5. Figure 5a, b displays the results of CNEs starting from July 2015 and July 2016, respectively. First, we verify asymmetric CNEs on a matching platform by comparing the evolutionary processes of carriers and shippers in Fig. 5. Second, we also find a decreasing trend in the magnitude of CNEs over time. From Fig. 5a, we can observe that there is an initial increase of CNEs on carriers at the early stage, followed by a subsequent decrease with fluctuation when market becomes thicker. In contrast, CNEs on shippers decrease all the time. When the market is thin with limited matching probabilities, users perceive a substantial increase in the likelihood of finding suitable matches



(a)Evolution of DNEs



(b) Evolution of CNEs

Fig. 6 Evolution of network effects considering COVID-19

with each additional participant, which is accompanied by a higher perception of platform value. The benefits diminish as the market gets thick. This is because the matching probability is high enough in a thick market, making it challenging for users to perceive additional value of platform from an incremental quantity in the number of cross-side users on the platform.

Despite the shared positive outcomes and overall decreasing trend observed, the evolving nature of users in our study exhibits slight variations when compared to Chu and Manchanda's (2016) study. Specifically, we find insignificant CNEs on both sides during the late stages, as illustrated in Fig. 5b. We attribute this disparity to the different variety of participant demands in our study. Chu and Manchanda (2016) investigate an e-commerce platform characterized by a wide range of participant demands, which could be further stimulated by an increasing variety of products. In such a context, it is expected that an increase in the number of cross-side users would consistently lead to a higher perception of platform value of users even in the presence of a thick market. Conversely, both carriers and shippers exhibit a certain level of preference and inertia towards transportation routes on our studied platform. As a result, the variety of participant demands is limited in our context. Given the limited variety of demand, a continuous increase in cross-side users may fail to increase platform value due to the high matching probability in a thick market. Moreover, this increase could potentially introduce challenges such as choice overload (Halaburda et al., 2018) or search friction (Li & Netessine, 2019). In such a context, any further increase in cross-side users does not yield extra benefits as the market becomes excessively thick, indicating a trend of insignificant CNEs along with the ever-increasing market thickness. Consequently, this leads to a different outcome characterized by insignificant CNEs during the late stage.

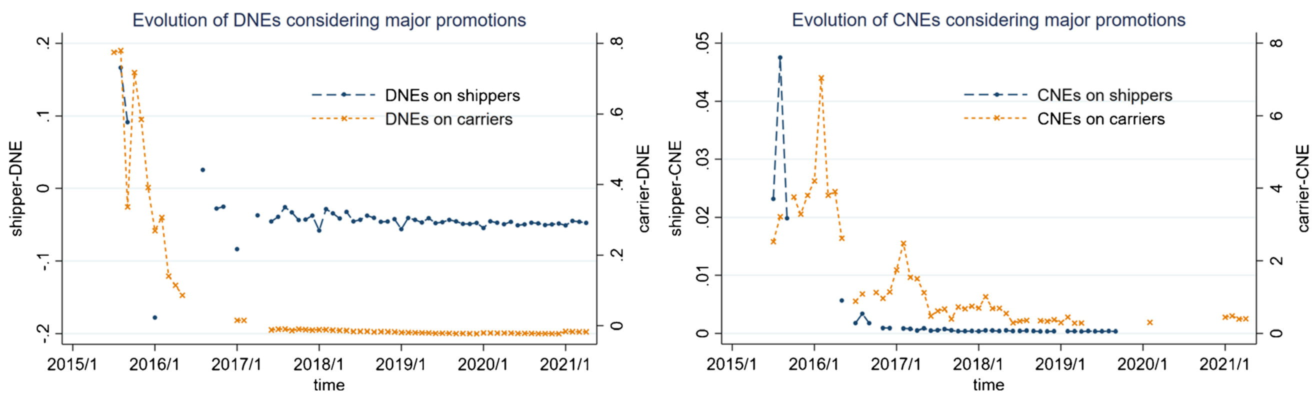
Robustness check

The influence of the breakout of COVID-19

To address concerns on the potential influence of the COVID-19 outbreak, we introduce two dummy variables in our models to control for the epidemic's impact. The first dummy variable spans from the initial outbreak to the end of Wuhan's lockdown. The second dummy variable covers the entire duration of the outbreak until the end of our sample, capturing the persistent impact of the epidemic on physical transport. The platform undertakes truckload transportation mostly for basic commodities such as grain and coal, which was less affected by the outbreak of COVID-19 than parcel delivery, so the platform did not take any measures to combat its influence, according to our interviews with the staff. Therefore, the control for the outbreak should be sufficient. By examining the estimation coefficients, as depicted in Fig. 6, we observe that the evolution law remains unchanged despite the presence of the epidemic. Full estimation results are presented in Table B1 in Appendix B.

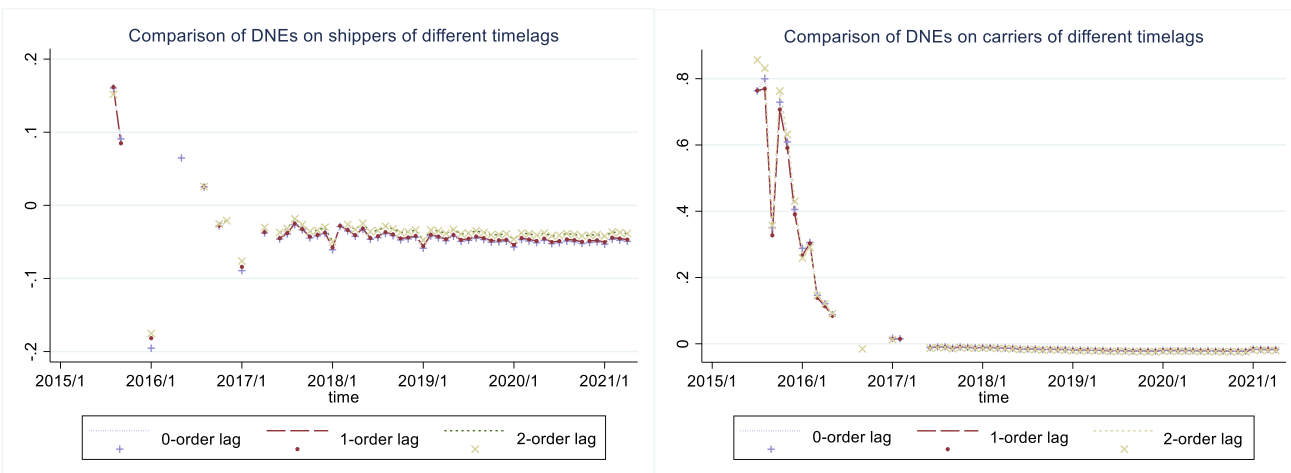
The influence of major promotions of e-commerce

Given that our studied platform provides logistics services, it is plausible that the registration process may be affected by the retail marketing activities commonly associated with e-commerce platforms. To address concerns regarding the potential influence of marketing promotion, we have included controls for major marketing campaigns such as Double 11, Double 12, and 618 middle-year promotions in our models. The estimation results, as shown in Fig. 7, indicate that these variables are neither statistically significant nor altering our main findings. Full estimation results are presented in Table B2 in Appendix B.



(a)Evolution of DNEs (b) Evolution of CNEs

Fig. 7 Evolution of network effects considering major promotions



(a) Comparison of DNEs on shippers (b) Comparison of DNEs on carriers

Fig. 8 Comparison of DNEs of different time lags

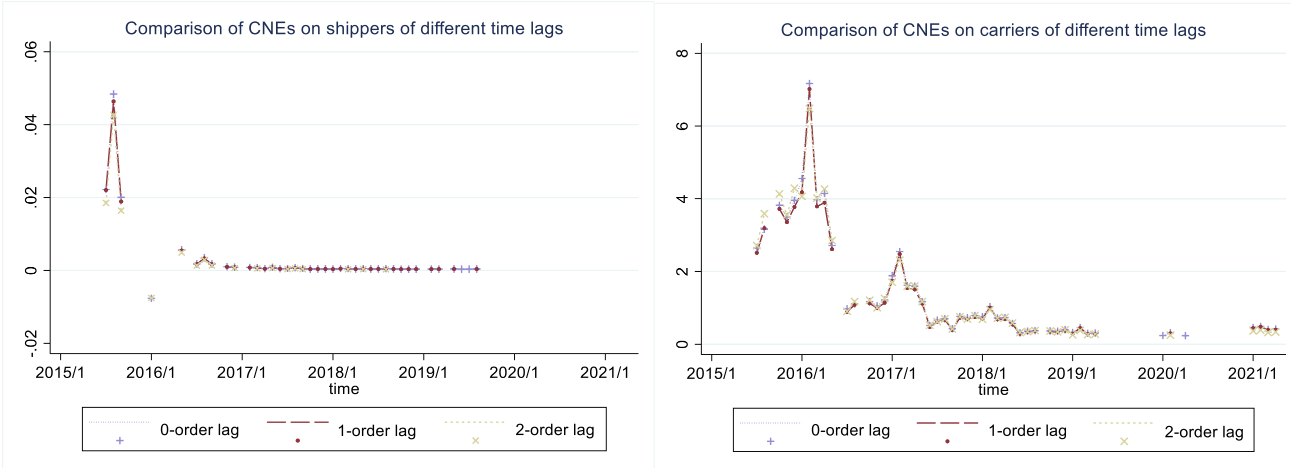
The selection of time lags

To address concerns on the selected time lags in our models, we conduct tests using zero-period lagged terms and two-period lagged terms. For independent variables with a zero-order lag, we employ instrumental variables of two-period lagged terms. For independent variables with a second-order lag, we employ instrumental variables with an additional lag following the main models. The estimation results of these are presented in Figs. 8 and 9, confirming the robustness of our main findings. Full estimation results are presented in Table B3 for independent variables with 0-order lag and Table B4 for independent variables with 2-order lag in Appendix B.

Discussions

Conclusions

The integration of freight resources and the removal of information barriers through online freight exchange platforms have successfully attracted a substantial number of shippers and carriers (Miller et al., 2020). Studies on network effects have consistently highlighted the significance of the installed base of two-sided users in determining the value of platforms (Rochet & Tirole, 2003). However, it is important to note that rapid expansion does not always guarantee favorable outcomes (Zhu & Iansiti, 2019). While early expansion can contribute to building reputation and increasing user



(a) Comparison of CNEs on shippers

(b) Comparison of CNEs on carriers

Fig. 9 Comparison of CNEs of different time lags

adoption, continuous expansion beyond a certain level of market thickness may yield diminishing returns due to competition and congestion. Despite the recognized importance of network effects, the dynamic nature of these effects has received limited attention in current studies.

This paper examines the evolution of network effects using data from the establishment phase of a prominent online freight platform. We adopt an approach that allows for time-varying coefficients to capture changes over time. Through our analysis, we provide evidence on the evolution of direct network effects and demonstrate that the forces governing the direction of DNEs vary depending on the thickness of the market. As our empirical evidence shows, DNEs on both sides are positive at the early stage of platform development but gradually lose significance as platform develops and even become negative at the late stage. We attribute the observed phenomena to the increase of market thickness along with platform development. At the early stages, when the market is relatively thin and matching probabilities are low, users can benefit from additional same-side users because of the mutual learning and reputation establishment, resulting in positive perceptions of platform value. As the market becomes thicker and matching probabilities increase, competition dominates instead, resulting in negative perceptions of platform value from an additional increase in same-side users. These negative effects become stronger as the number of same-side users continues to increase. In our additional analysis, we confirm the presence of asymmetric positive CNEs over time, consistent with previous literature. However, contrary to existing findings, we observe that these effects become insignificant as the market reaches a certain level of thickness. When the market becomes sufficiently thick, the continued increase in cross-side users loses its appeal for users, particularly in cases where there is limited variety of demand. Additionally, our results show a relatively stable state at the late stages for both network effects, suggesting a stationary state along with the ever-increasing market thickness after a certain level. As for the differences in the evolution of network effects on both sides, our analysis reveals that carriers experience stronger positive DNEs, while shippers face stronger negative DNEs. Additionally, we observe that the turning points, where DNEs become insignificant and negative, and CNEs start to decrease and become insignificant, occur earlier for shippers compared to carriers.

Our research makes a significant contribution to the field of network effects by incorporating the concept of market thickness as a novel mechanism to explain the evolution of these effects over time. To the best of our knowledge, we are the first to empirically demonstrate the changing direction of DNEs over time. While scholars have made notable contributions to the study of network effects, there is still a gap in understanding the conflicting conclusions regarding DNEs. Our study offers an explanation for the mixed results found in previous studies on DNEs from the perspective of market thickness. Additionally, our research findings about the trend of insignificant CNEs demonstrate the diminishing benefits associated with increasing cross-side users as the market thickness increases. They complement existing research by highlighting that network effects perform differently in different types of platforms. This novel finding opens up another avenue of investigation and extends the existing research on CNEs. Furthermore, our findings on the distinct evolution patterns observed for shippers and carriers contribute to the discussion on asymmetric network effects. We emphasize that there is not only asymmetry in the magnitude of network effects but also in the timing of their transition of attitude towards increasing number of participants.

Implications

The rapid growth of online freight platforms facilitated by the Internet has created significant opportunities. However, it is important to recognize that expansion does not always lead to proportional benefits for the platform due to changing network effects across different levels of market thickness. Our work empirically examines evolutionary network effects over time and reveals that platform could not benefit from the expansion of scale all the time. Based on our findings, we propose several recommendations for platform management. First, we find that DNEs transfer from positive to negative with the accumulation of same-side users. Therefore, the platform should adopt differentiated policies for different levels of market thickness. For example, when the market is thin, the platform could emphasize that there are many other shippers or carriers participating in this platform to elevate users' perceived value and attract more participation. However, when it becomes difficult for the platform to reap benefits from the increased scale as the market grows too thick, the platform should take measures to weaken the perception of competition coming from too many same-side users. These measures could include a suitable recommendation to reduce the difficulty of finding a match, a reward for completing a transaction to increase the value of continued use, and so on. Second, we find that the shippers have more power over carriers so they care less about more potential matching and are more sensitive to competition. This is reflected in the lower positive DNEs at early stages, stronger negative DNEs at late stages, lower positive CNEs all the time, and earlier turning points for the attitude towards increasing number of participants for shipper side. Therefore, we emphasize the importance of providing additional business values to shippers beyond the basic value of matching. For example, the platform can rate the credit of carriers to reduce the selecting costs for shippers, manage the transportation process, and guarantee their cargo value to reduce operations costs and avoid the risk of loss.

In summary, different from existing literature that focuses on the asymmetric resource allocation policies for different sides of users, our study further emphasizes the differentiated policies over time and also the asymmetric timing to adopt these policies for different sides of users.

Limitations

There are some limitations of this paper. First, the online freight exchange platform industry is still in its rapid growth phase, and so is the platform. According to S-shaped curve in studies on business life cycles (Lu & Beamish, 2004), our analysis is based on a sample interval that does not include the stable growth phase. This limited time frame may not capture the full extent of the evolution of network effects over the long term, despite our results show a trend towards a stationary stage. Future research with a longer time horizon, especially extending to a stable growth phase of the business, could provide a more comprehensive understanding of the dynamics at play. Second, our findings are primarily applicable to matching platforms that provide professional services, such as truckload transportation services. The characteristics and dynamics of network effects may differ in other types of platforms, and caution should be exercised when generalizing our results to other industries or platform types. Third, an important aspect that we do not consider in our study is user churn. Besides, there is no specific way for users to log out of the platform by now. Once a user registers, he can always trade on it. While our studied platform is working on developing methods to measure churn, we lack this data. We are suggested to use a 1-month period as a standard to determine user disengagement by the staff, but we observe instances where user transaction patterns do not conform to this standard. Moreover, the use of survival analysis, a more sophisticated approach, was challenging due to the large volume of transaction data. The complexity and size of the transaction data can pose computational difficulties, making it impractical to employ certain analytical methods. Future studies that incorporate churn data could provide further insights into the relationship between network effects and user behavior.

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Declarations

Competing interests The authors declare no competing interests.

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