To Be or Not To Be on a Platform:

Offline Complementors' Decision to Join an Entrant Platform

Christine Choi

University of Michigan
701 Tappan Street
Ann Arbor, MI, 48109
e-mail: cyychoi@umich.edu

ABSTRACT

This paper examines how the characteristics of offline firms (potential complementors) influence the decision to join an entrant platform. Drawing on the value-based-view and the resource-based-view, I posit that firms are more likely to join the entrant platform when they can create more value through incurring lower adjustment costs to form a new partnership or benefit more from increasing their value appropriation abilities through inducing competition between platforms. Using data on restaurant partnerships with DoorDash after it entered Portland, Oregon, in 2018, I find that restaurants that had already partnered with at least one incumbent food delivery platform were more likely to join DoorDash. However, this relationship was weakened for restaurants that had tighter capacity constraints, multiple units, and greater access to offline customers.

Keywords: platforms; multihoming; value creation and appropriation; adjustment costs; interfirm relationships

INTRODUCTION

Recent advances in technology have enabled an increasing number of offline product and service providers to attract customers through online-to-offline (O2O) platforms (Chu & Wu, 2021; Li, Shen, & Bart, 2018; Zhu & Furr, 2016), such as TaskRabbit (for home-service providers), Grubhub (for restaurants), and Groupon (for local merchants). These O2O platforms provide wide networks and innovative technologies for partnered firms ("offline complementors") to reach a critical mass of consumers. Their rapid growth across many traditional industries has been referred to as a "trillion dollar opportunity" by industry experts (Rampell, 2010).

By collectively offering a wide variety of products and services, complementors attract users to the platform, resulting in an indirect network effect that attracts even more complementors and users to the platform (Evans, 2003; Rochet & Tirole, 2003). This effect enables a platform with the largest installed base of users and complementors to dominate the market, a winner-take-all (WTA) dynamic that has been noticed by many platform scholars (Katz & Shapiro, 1994; Schilling, 2002). Accordingly, prior studies on platform competition have predicted that early-entrant platforms will benefit from their network endowments and enjoy a first-mover advantage in recruiting complementors, whereas late entrants will have a competitive disadvantage (e.g., Park, 2004; Shapiro & Varian, 1999).

Despite the substantial network-endowment benefit and the WTA advantage of the early-entrant platform, some offline complementors have partnered with multiple platforms (or multihomed), including both early- and late-entrant platforms. For example, in the daily deals industry, many local merchants have partnered with both Groupon and LivingSocial (Li & Zhu, 2020), even though Groupon entered the industry later than LivingSocial. At the same time, some merchants have partnered with only one or none of the platforms, leading to variations in their multihoming decisions. The literature on multihoming has offered a few conditions that motivate complementors to join an entrant platform, such as its innovativeness (e.g., Venkatraman & Lee, 2004), installed base or convergence in architecture with competing platforms that lowers complementors' multihoming (i.e., porting) costs (e.g., Bresnahan, Orsini, & Yin, 2015; Corts & Lederman, 2009; Srinivasan & Venkatraman, 2020). While insightful, most existing studies do not examine the characteristics of complementors that would drive or hinder their decision to multihome. This provides an incomplete understanding of why offline complementors vary in their decisions to partner with an entrant platform, even when faced with the same market or entrant platform conditions.

Against this background, this paper examines how the characteristics of offline complementors influence their decision to partner with an entrant platform. To develop my argument, I take insights from the value-based view (Brandenburger & Stuart, 1996; Macdonald & Ryall, 2004) and the resource-based view (Penrose, 1959; Helfat & Eisenhardt, 2004). I argue that, in deciding whether to join a new partnership, firms will consider both the value that can be created from the partnership and any effects the new partnership may have on the value that can be appropriated from their existing partnerships. Specifically, the potential value to be created from the new partnership will be determined by the adjustment costs of transferring and transforming a firm's resources to fit those required by the new partnership (Madhok, Keyhani, & Bossink, 2015). Because adjustment costs decrease with relatedness between the new and the existing businesses (e.g., Dickler & Folta, 2020), firms that are already partnering with incumbent platforms will enjoy lower adjustment costs to transform their resources from an offline business model to an online business model; given these lower adjustment costs, they will expect a greater value creation from partnering with an entrant platform compared with firms that have no partnerships with incumbent platforms.

In addition to creating value, firms strive to appropriate the most value from their partnerships (Dyer, Singh, & Kale, 2008; Lavie, 2007). I argue that the concern for value appropriation is more salient in markets characterized by network effects, because the same (indirect) network effects and WTA dynamics that provide offline complementors a large pool of consumers also enable the leading platform to dominate the market, giving it substantial bargaining power over the complementors (Wang & Miller, 2019). Foreseeing the threat, firms already partnering with incumbent platforms will seek to reduce their reliance on these platforms by playing the incumbent platforms off against the entrant platform, thus restricting the market power of each platform. Combining these value creation and appropriation mechanisms, my baseline hypothesis suggests firms that are already partnered with incumbent platforms are more likely to partner with an entrant platform than firms that have no partnerships with an incumbent platform.

Given the baseline hypothesis, I then investigate how the concern for value creation and appropriation will vary across offline complementors. Offline complementors exhibit a wider range of heterogeneity across them than online complementors, or those who produce online products and services (e.g., software/game developers), due to three unique characteristics. First, unlike online complementors, which enjoy near-zero scaling costs once they incur the fixed costs for each version of their products (e.g., development cost) (Wang & Miller, 2019), offline complementors are more likely to face capacity constraints because they use non-scale free resources to perform physical activities, such as manufacturing, warehousing, and shipping (Tae, Luo, & Lin, 2020). Second, unlike online complementors, which face no geographic boundaries, most offline complementors are limited to serving local demand (Li et al., 2018). To overcome the location constraint, offline complementors have to establish multiple organizational units in different locations and coordinate resource sharing and joint activities across them. Third, unlike online complementors, which rely entirely on platforms to create and capture value (Zhu & Liu, 2018), most offline complementors have physical stores and offline customers as alternative means to create value.

Accounting for these unique features, I first argue that the baseline hypothesis will be negatively moderated if offline complementors expect greater marginal (i.e., between-platform) adjustment costs, and therefore a lower potential for value creation from joining an entrant platform. Specifically, offline complementors facing tighter capacity constraints will expect greater marginal adjustment costs to join an entrant platform because they may need to redeploy resources that are less relevant to the online business model or make further accommodations to improve the efficiency of their existing resources. Offline complementors from a multi-unit firm will also expect greater marginal adjustment costs because of a higher demand for the inter-unit coordination to adapt resources and routines from the existing partnerships to align with the new partnership. I also argue that the baseline hypothesis will be negatively moderated if offline complementors expect to benefit less from increasing their value appropriation by instigating competition between platforms. Specifically, those that enjoy greater alternative access to offline customers will rely less on platforms and are therefore in a stronger position to appropriate value from their existing platform partnerships. Given this stronger position, these complementors will be less concerned with value appropriation by their existing platform partners and will be less likely to join the entrant platform.

I test my hypotheses using data on restaurant partnerships with food delivery platforms in Portland, Oregon, from 2016 to 2018. Specifically, I examine the likelihood that a restaurant will partner with a food delivery platform, DoorDash, after the platform entered Portland in April 2018. The results support my predictions. Restaurants that had already partnered with at least one incumbent delivery platform were more likely to join DoorDash than those with no prior partnerships. However, this positive relationship was negatively moderated for restaurants that had (1) tighter capacity constraints, (2) multiple organizational units, and (3) greater access to offline customers.

This study contributes to the platform literature in several ways. First, it advances research on platform competition, particularly on how platform entrants can build a competitive advantage in markets characterized by network effects (e.g., Zhu & Iansiti, 2012). My findings suggest that entrant platforms may be able to expand their networks when entering a market where incumbents have already established larger complementor-installed bases. At the same time, entrant platforms may face difficulties in attracting potential partners that have tighter capacity constraints, more complex organizational structures, and better access to offline demand.

Second, this study joins the small set of papers (e.g., Cennamo, Ozalp, & Kretschmer, 2018; Huang, Ceccagnoli, Forman, & Wu, 2013) that explore complementor strategies. Although the literature has highlighted the importance of complementors for platform success, much of the attention has focused on the strategies platforms use to attract and control their complementors (e.g., Boudreau, 2010; Rietveld, Schilling, & Bellavitis, 2019). Given that there are a greater number and a more diverse group of complementors relative to platforms, understanding the heterogeneity across complementors and the mechanisms behind their platform-selection decision can further help platform owners devise effective strategies to attract complementors.

Third, this study extends the scope of existing platform studies that have primarily focused on online complementors to offline complementors by connecting their unique features with the value-based and resource-based views of strategy. My study suggests that adjustment costs associated with sharing and redeploying resources between business models and across partnerships can reduce the potential value created from a new partnership, thereby deterring firms from joining a new platform. In doing so, my study complements recent studies in arguing that pursuing new business models (e.g., Eklund & Kapoor, 2019) or partnerships (e.g., Madhok et al., 2015) is costly because of firms' resource constraints. Moreover, while prior studies have mainly considered the value-creation benefit of indirect network effects, my study highlights complementors' increasing concern for value appropriation under a WTA scenario, providing an alternative explanation for multihoming.

In addition to the platform literature, this study also contributes to the literature on interfirm relationships by showing that the decision of a firm to form a new partnership is influenced not only by a dyadic fit with the new partner (e.g., Rothaermel & Boeker, 2008) but also by the potential interdependencies among the firm's existing and new partnerships (Choi, 2020).

LITERATURE REVIEW

Two-sided platforms benefit from direct and indirect network effects. Direct network effects arise when users derive greater utility from participating on a platform with a larger number of other users (Farrell & Saloner, 1985; Katz & Shapiro, 1986; Tucker, 2008). For example, the value of telephone or online social media applications, such as Facebook, Instagram, and LinkedIn, increases with the number of people who are using the products and services. Indirect network effects arise when users derive greater utility from participating in a platform with a larger number of users from the other side of the network (Boudreau & Jeppesen, 2015; Hagiu, 2009; Rochet & Tirole, 2003). For instance, a larger installed base of buyers on a platform attracts more complementors to sell their products on that platform. At the same time, a wider variety of product offerings attracts more buyers to the platform. In tandem, these direct and indirect network effects can lead to the emergence of dominant platforms that maintain their competitive positions through WTA dynamics (Schilling, 2002).

Given the salience of network effects in platform-based markets, studies on platform competition have highlighted the importance of quickly building a large network or installed base for a platform to dominate the market. Specifically, by emphasizing the order-of-entry effect, they suggest that compared with an entrant, incumbents have an advantage in building a large installed base, and that a small lead on the initial network endowments will tip the market in their favor, even if the quality of their products and services is inferior to those of the entrant (e.g., Park, 2004; Schilling, 1999; Shapiro & Varian, 1999; Wade, 1995).

Despite the potential for WTA dynamics, some markets exhibit co-existence of both entrant and incumbent platforms, prompting several scholars to investigate conditions that allow multiple platforms to co-exist. They demonstrate that despite the lack of network endowments, an entrant platform can compete with incumbent platforms if it competes in markets characterized by low network intensity, which lowers users' switching costs (e.g., Chintakananda & McIntyre, 2014; Zhu & Iansiti, 2012). An entrant platform can also employ effective strategies, such as introducing innovative and high-quality products and services (e.g., Sheremata

2004; Tellis, Yin, & Niraj, 2009), targeting different customer segments to avoid direct competition with incumbent platforms (e.g., Cennamo & Santalo, 2013; Hanisch, 2020), or bundling its platform functionality from the existing market with that of the new market (i.e., envelopment) to leverage its existing user base (e.g., Eisenmann, Parker, & Van Alstyne, 2011).

Platforms can also co-exist when complementors support multiple competing platforms, thereby limiting the market from tipping. Complementors multihome when the benefits of serving additional demand outweigh the costs associated with adopting a new platform. For example, studies suggest that complementors are likely to multihome when a competing platform provides a sufficient network size or non-overlapping user base, or when they face low porting costs to convert their products and services to be compatible with the competing platform's underlying technology (e.g., Bresnahan et al., 2015; Corts & Lederman, 2009; Landsman & Stremersch, 2011; Srinivasan & Venkatraman, 2020). In recent years, porting costs have been reduced in several industries as technological advancements have led many platforms to converge on their architectures, enhancing "the interoperability of their complements across multiple platforms" (Srinivasan & Venkatraman, 2020, p. 270). In particular, improvements in computer hardware and software operating systems, as well as the development of common standards and application-programming interfaces (APIs), have triggered platform convergence within and across industry boundaries (Corts & Lederman 2009; Srinivasan & Venkatraman, 2020). Since the architectural similarity between competing platforms decreases the need to customize complementors' products for each platform (Cennamo, et al., 2018; Tanriverdi & Chi-Hyon, 2008), many online complementors facing similar cross-platform architectures often multihome to cut operating costs through economies of scale or scope.

Overall, the studies on platform competition have highlighted the importance of complementors on the success of two-sided platforms, especially for an entrant platform. Nevertheless, they have largely focused on market conditions that increase complementors' incentive to multihome or on platform strategies to attract complementors, such as reducing platform-entry fees, subsidizing or supporting the development, production, marketing, and distribution activities of complementors (e.g., Li, Pisano, & Zhu, 2018; Rietveld, et al., 2019). With a few exceptions,[1] the effect of complementor attributes and their decisions to engage with a specific platform are largely understudied (McIntyre & Srinivasan, 2017). This void in the literature provides insufficient explanations for why complementors facing the same market condition or platform features differ in their platform-selection decisions. For example, even though many O2O platforms are transactional, serving as a market intermediary to facilitate efficient exchanges between buyers and sellers (Evans & Schmalensee, 2020; Teece, 2018), and therefore rely on indirect network effects, some offline complementors partner with both incumbent and entrant platforms (e.g., Li & Zhu, 2020). In addition, while offline complementors' product offerings are relatively independent of O2O platforms' technical architectures compared with online complementors, not all offline complementors mulithome. In

[1] Two notable exceptions are Venkataraman, Ceccagnoli, and Forman (2018) and Srinivasan and Venkatraman (2020). Specifically, Venkataraman et al. (2018) found that complementors are more likely to multihome by partnering with a competing platform when they have either engaged with the existing platform for a longer period or accumulated generalized human capital. Similarly, Srinivasan and Venkatraman (2020) demonstrated that complementors that have made greater existing platform-specific investments are less likely to join multiple platforms. While these studies shed light on complementor heterogeneity that influences their multihoming costs, the question of why certain complementors are more likely to be embedded with their existing platforms remains underexplored. Furthermore, they have primarily focused on the potential for value creation resulting from the reduced porting costs, whereas value appropriation is another important mechanism that influences complementors' decisions to collaborate with platforms (Huang et al., 2013). Finally, these studies are still limited to partnerships formed between online complementors and their innovation platforms, which provide the underlying technology for complementors to build their innovations (Teece, 2018).

light of these differences, it seems that additional factors, especially complementor-specific ones, may account for the heterogeneity in offline complementors' platform choice beyond market-based or platform-specific factors.

THEORY AND HYPOTHESES

Value Creation and Appropriation in Interfirm Collaborations

When determining whether to join a new partnership, firms may consider two factors: (1) the potential value that can be created from the new partnership, and (2) changes in value that can be appropriated from their existing partnerships following the formation of the new partnership.

Firms engage interfirm collaborations to create value by leveraging complementary resources between partners (e.g., Baum, Cowan, & Jonard, 2010; Katila et al., 2008; Rothaermel & Boeker, 2008). To create value through exploiting resource complementarity, however, firms may need to adjust and transform their own resources and routines to align with those of their partners (Madhok et al., 2015). At the same time, resource-constrained firms may need to withdraw and/or modify their resources from existing partnerships and redeploy them to a new partnership. During this process, firms will incur adjustment costs,[2] which influence the potential for value creation and consequently the formation of a new partnership.

[2] Adjustment costs arise when a firm redeploys its resources across businesses or modifies its resources to suit new activities (Helfat & Eisenhardt, 2004; Penrose, 1959; Sakhartov & Folta, 2014). These costs could be either direct or indirect (Helfat & Eisenhardt, 2004). Direct adjustment costs occur when the firm reallocates its resources across businesses, hires and trains employees, develops new technologies, or modifies organizational routines to better align with a new operation (Argyres, Mahoney, & Nickerson, 2019; Eklund & Kapoor, 2019; Rubin, 1973). Indirect adjustment costs occur when the process of transferring and modifying resources creates a disruption to the firm's existing business (Helfat &Eisenhardt, 2002), such as increased coordination challenges associated with resource sharing between businesses (Eklund & Kapoor, 2019; Zhou, 2011), compromised communication across organizational units (Henderson & Clark, 1990), or intensified conflicts and competition among organizational units (Ahuja & Novelli 2016; Christensen & Bower, 1996). While extant studies have identified adjustment costs that

In addition to creating value, firms need to appropriate value in order to benefit from a partnership (Adegbesan & Higgins, 2011; Dyer et al., 2008) and their ability to appropriate value is determined by the availability of alternative outside options (Hecker & Kretschmer, 2010; Macdonald & Ryall, 2004). Specifically, firms that have more outside options (e.g., those facing fewer competitors relative to their partners) will rely less on the focal partnership and hence can gain greater bargaining power vis-à-vis their partners (Gans & Ryall, 2017; Yan & Gray, 1994). While firms' concern about the value appropriation within a focal partnership has been a primary interest in the research on interfirm collaborations (e.g., Khanna, Gulati, & Nohria, 1998; Kumar, 2010), firms will also consider the potential effect of a new partnership on their existing partnerships when deciding whether to join the new partnership. In particular, if a newly added partnership intensifies competition among the focal firm's partners for its resources and attention, the firm can enhance its bargaining power vis-à-vis the partners (Choi, 2020; Lavie, 2007), further allowing it to appropriate more value from its existing partnerships. This increase in value appropriation ability can lead firms to engage in a new partnership.

In sum, a firm's likelihood of engaging in a new partnership will be shaped by the interdependencies between the new and existing partnerships. Specifically, a firm that can easily adjust and transfer resources across operations and partnerships can generate greater value from the new partnership, increasing the likelihood of joining it. In addition, a firm that can benefit more from increasing its future value appropriation capability against its existing partners by creating competition between partners will be more likely to join a new partnership.

---

arise when a firm diversifies into a new (or exits an existing) business or product category (e.g., Dickler & Folta, 2020; Hashai, 2015; Helfat & Eisenhardt, 2004; Lieberman, Lee, & Folta, 2017), adopts a new business model (e.g., Eklund & Kapoor, 2019), or changes its strategic position in response to environmental shocks (e.g., Argyres et al., 2019; Bigelow, Nickerson, & Park, 2019), the topic of adjustment costs arising from a new partnership has rarely been studied (Madhok et al., 2015 is an exception).

Value Creation and Appropriation in O2O Platform Partnerships

O2O platforms' partnerships with offline complementors (O2O partnerships for short) provide complementors the opportunity to create value through accessing the platform's technology and wide network, but the partnerships also require complementors to redeploy and modify their offline-oriented resources to align with the new online-business model, leading to both direct and indirect adjustment costs (e.g., Eklund & Kapoor, 2019; Helfat & Eisenhardt, 2004). For example, offline complementors may incur direct adjustment costs when they allocate employees from offline to online business, reconfigure production facilities and distribution channels to serve online customers, install and learn new technologies related to platform services, or modify routines to manage online orders. Offline complementors may also incur indirect adjustment costs when the adjustment process disrupts operational activities in their existing business (Helfat & Eisenhardt, 2004) by limiting the usage of current production facilities, creating coordination challenges to share resources between offline and online businesses, or intensifying internal conflicts between offline and online units to compete for the limited resources.

Offline complementors also face challenges in appropriating value from O2O partnerships because, in general, compared with complementors, platforms are in a more concentrated market (Cutolo & Kenney, 2020). The salience of network effects in O2O partnerships further heightens firms' concern for value appropriation (Hecker & Kretschmer, 2010). In the presence of network effects, the focal O2O partnership can exponentially enhance the efficiency or market power of the platform relative to its competitors by helping it attract more users, and hence more complementors (Wang & Miller, 2019). When this happens, the focal platform could dominate the market via WTA dynamics and gain substantial bargaining power over its complementors, allowing it to "squeeze" its complementors and appropriate most of the value created by the partnership. For example, given its panoptic view on all platform participants' activities, the dominant platform owner could subsequently change governance policies in its own favor (Cutolo & Kenney, 2020) or significantly increase the platform-participation fee.

Recognizing these challenges associated with value creation and appropriation, firms that already have existing relationships with incumbent platforms are more likely to benefit from joining an entrant platform than firms with no incumbent platform partnerships. This is because, first, as adjustment costs decrease with relatedness between the new and existing businesses (Dickler & Folta, 2020; Lieberman et al., 2017), firms that have collaborative experience with incumbent O2O platforms will incur lower costs of adopting a new platform (Li & Zhu 2020). Specifically, if a complementor has already reallocated or modified its existing resources, hired and trained its employees, procured necessary resources, and established efficient routines to manage online orders as a result of working with incumbent platforms, it can readily share or redeploy these resources to meet the demands of an entrant platform. These lower adjustment costs suggest the possibility of greater value creation from partnering with the entrant platform. Partnering with the entrant platform is also more attractive to firms that have partnered with incumbent platforms as those firms will be able to maintain or even improve their future abilities to appropriate value from the existing O2O partnerships by introducing competition between incumbent and entrant platforms. I therefore propose the following baseline hypothesis.

Baseline Hypothesis (BH). *Firms that have partnered with incumbent platforms are more likely to join an entrant platform than firms that have not partnered with any incumbent platforms.*

Capacity Constraints for Multihoming

The benefits associated with mulithoming (i.e., savings in adjustment costs and increase in value appropriation from the existing partnerships), however, will vary across complementors. In particular, the savings in adjustment costs in transforming an offline business to an online business through multihoming will be less acute for offline complementors that face tighter capacity constraints. Offline complementors are generally constrained in their production capacity because they use physical resources that are non-scale free (Tae et al., 2020) and are therefore subject to opportunity costs (Levinthal & Wu, 2010). For instance, Uber and Lyft drivers face a ceiling on the number of rides they can provide per day since they can only serve a limited number of passengers at any given time. Similarly, restaurants, dry cleaners, beauty salons, and pet service providers, which rely on physical spaces and/or machines, are constrained in scaling production capacity.

When offline complementors face tighter capacity constraints, or have fewer excess resources, they will incur greater marginal adjustment costs to join an entrant platform for two reasons. First, they may incur greater direct adjustment costs as they will need to reconfigure their existing resources and routines to improve operational efficiencies, redeploy resources from their offline business, or acquire new resources, which may require additional adjustment to be implemented to their existing activities. Second, offline complementors may incur greater indirect adjustment costs as withdrawing resources that are in greater use from their existing operations to a new partnership may create a greater void in the existing activities, sharing capacity constrained resources between platform partnerships may lead to greater coordination costs (e.g., Zhou, 2011) and competing for limited resources and managerial attention between platform partnerships may lead to greater internal conflict costs (e.g., Eklund & Kapoor, 2018).

These additional costs to redeploy and share capacity-constrained resources across partnerships will subsequently reduce the potential value to be created from the new O2O partnership, reducing the offline complementor's likelihood to join an entrant platform.

Hypothesis 1 (H1). *The positive relationship between partnerships with incumbent platforms and a firm's likelihood of joining an entrant platform will be weaker if the firm faces tighter capacity constraints.*

Inter-Unit Coordination Challenges for Multihoming

Offline complementors that are part of a multi-unit firm will also enjoy smaller savings in adjustment costs due to the need for additional coordination among units. To realize operational synergies, firms managing multiple units across geographic locations often standardize their routines and coordinate major activities in order to share resources (Chuang & Baum, 2003; Kalnins & Mayer, 2004). Exploiting synergies, however, entails coordination costs (Zhou, 2011), which can offset some multihoming benefits.

For one unit of a multiunit offline complementor to join an entrant platform, it will need to exert additional effort to ensure an alignment between adjustments made to its existing resources and activities to fit the entrant platform and the other units' resources and activities that have been adapted to the incumbent platforms. For example, multiunit offline complementors often share the same point-of-sales and/or reservation systems across their units that are integrated with the existing platform partner's systems (e.g., Hawley, 2018; QSR, 2019). This integrated system, however, may either be less applicable to the new platform's system,[3] or

[3] Because multiunit complementors rely on a centralized system, standardized practices, and coordination across units, multi-unit complementors often develop platform-specific resources or routines that help them maintain standardization and compatibility across units. For example, multiunit complementors may integrate the platform's

require the complementor to adapt the new platform's system to the existing systems across all other units. This could be particularly relevant in the hospitality industry, where multiunit firms rely on the same reservation system and sales reporting lines to share information on real-time occupancy rates in order to coordinate local referrals across units (e.g., Woo, Cannella, & Mesquita, 2019). In addition, if a new partnership requires a complementor to modify its activities on incumbent platforms, such as redesigning promotions or product offerings to avoid cannibalization, a multiunit complementor will need to communicate across units to confirm that the changes will be collectively accepted and implemented by all units. This added layer of communication and coordination across multiple units, in addition to coordinating within units, will increase marginal adjustment costs to join an entrant platform, subsequently reducing the potential value created from the new O2O partnership. As a result, offline complementors with more units will be less likely to join the entrant platform.

Hypothesis 2 (H2). *The positive relationship between partnerships with incumbent platforms and a firm's likelihood of joining an entrant platform will be weaker if the firm has multiple organizational units.*

Alternative Access to Offline Customers and Multihoming

In addition to the potential for greater value creation (due to savings in adjustment costs) from the new platform partnership, offline complementors will also vary in the level of concern for value appropriation from their existing partnerships. Specifically, those that enjoy a stronger

---

technology with their existing system, design the platform specific guidelines and formal policies, install communication channels to directly reach the platform, or dedicate a team to facilitate interactions and information flow among multiple units and the platform (e.g., Hawley, 2018; QSR, 2019). When complementors develop resources that are specific to an existing platform, these resources may no longer be easily transferable to and deployable in other partnerships (Srinivasan & Venkatraman, 2020).

offline demand will be less concerned about value appropriation because they have more viable outside options to create value from their offline channels, further reducing their reliance on O2O partnerships (e.g., Macdonald & Ryall, 2004; Yan & Gray, 1994).[4] These alternative options increase the complementors' bargaining power relative to the platform partners, enabling the complementors to appropriate more value from the partnership (Wang & Miller, 2019). The availability of better outside options also reduces the complementors' concern about the potential dominance of any incumbent platforms. For example, when an incumbent platform partner takes over the online market and begins to expropriate excessive value from the partnership, complementors with greater offline demand can readily revert to their offline channels. Therefore, better access to offline customers will reduce offline complementors' concerns about value appropriation by incumbent platform partners, and subsequently their likelihood to join an entrant platform.

Hypothesis 3 (H3). *The positive relationship between partnerships with incumbent platforms and a firm's likelihood of joining an entrant platform will be weaker if the firm enjoys greater access to offline customers.*

[4] While it is feasible for better-recognized offline complementors to attract more customers on an entrant platform, thereby creating greater value, the proportion of those additional demands coming from the entrant platform to their existing offline demand may be minor when they are already enjoying high offline demand. Therefore, their marginal gains may be smaller than those of less-recognized offline complementors. Moreover, because platform partnerships often require complementors to split their revenue created from the platform (Cutolo & Kenney, 2020), offline complementors with sufficient offline demand will prefer transacting directly with their offline customers instead of expanding their online demand by joining an additional platform.

DATA AND METHODS

Empirical Setting: Restaurant Industry and Food Delivery Platforms

With the rise of the internet and digital technology, many online food-ordering and delivery platforms have emerged in the U.S. restaurant industry since the early 2000s. During the early years, platforms mainly focused on offering online food-ordering services via websites or phones. As the number of smartphone users and the popularity of the gig economy has grown, more platforms have emerged and expanded their businesses into O2O delivery services by establishing their own logistics networks and connecting restaurants with drivers and customers. For example, Grubhub, one of the largest food delivery platforms today, began its business in 2004 by creating a website providing information about neighborhood restaurants that had an in-house delivery service and allowing customers to place orders directly through its website. About ten years later, Grubhub expanded its business to offer a turnkey delivery service, which allowed restaurants without in-house delivery services to expand their business by "utilizing its on-the-ground network of delivery drivers" (Grubhub, 2016). Many other major players, such as Postmates (launched in 2011), DoorDash (launched in 2013), and Uber Eats (launched in 2014), also entered different local markets. The emergence of these turnkey delivery services attracted many restaurants that can generate additional profits by reaching a more geographically diverse and broader consumer base. The U.S. food delivery platforms have been consistently growing and reached annual revenue of $10.4 billion and a user base of 75 million in 2016 (Curry, 2021).

The restaurant industry is appropriate for testing my predictions for two reasons. First, the industry exhibits large variation in potential complementor attributes, including their existing partnerships with incumbent platforms, level of capacity constraints, organizational structures, and access to offline customers. For example, in 2016, about 15% of all delivery orders were placed through third-party delivery platform applications (Morgan Stanley, 2017), and the rest were placed either through a restaurant's website or by phone, implying a variation in restaurants' engagements with platforms. Restaurants also varied in their organizational structures across geographic locations (e.g., Kalnins & Mayer, 2004).

Second, restaurants' concern for value creation and appropriation plays a significant role in their decision to partner with delivery platforms. Between 2015 and 2019, food delivery platforms were still attracting six to nine million new users every year (Curry, 2021), and users rarely used multiple platforms (Hirschberg, Rajko, Schumacher, & Wrulich, 2016; Molla, 2019). This growth in non-overlapping user base provided an opportunity for restaurants to create additional value by joining multiple platforms.[5] Collaboration with delivery platforms, however, generates various types of adjustment costs for restaurants. For example, restaurants that join platforms first need to learn and integrate the new ordering and payment systems into their existing point-of-sale system. They also need to alter their physical space to set up a delivery area, where completed orders could be packaged and picked up by delivery drivers, and reallocate their employees to either in-house or delivery orders in order to minimize operational friction (Marston, 2018). Furthermore, as food quality becomes relatively more salient in the delivery market than other factors, such as ambiance or customer service (He, Han, Cheng, Fan, & Dong, 2019), restaurants have to develop new cooking methods and/or delivery packaging in order to maintain the taste, appearance, temperature, and overall quality of their food.

In addition to adjustment costs, many restaurants affiliated with delivery platforms are concerned with value appropriation from the O2O partnerships, as restaurants generally far

[5] Because customers rarely used multiple platforms during the sample period, restaurants rarely switched between platforms, or terminated their existing platform partnerships to join a new platform.

outnumber platforms, providing the latter significant bargaining power. For example, platforms often charge high commission rates, ranging from 15% to 30% of the partners' online delivery revenues (Littman, 2019). In addition, platforms have asymmetric access to and control of their user information, engendering some platforms to redirect user traffic by influencing the search results on the platform's website and smartphone application (Saddle Back BBQ, n.d.). Many platforms also monopolize user information without sharing the data with their partnered restaurants in order to optimally design their own marketing and promotional activities at the expense of their partnered restaurants (Bagley, 2019).

Data

I focus on restaurants in Portland Oregon where I was able to access comprehensive restaurant information in the city. I combined multiple data sources to construct a restaurant unit-level data set. First, information about restaurants in Portland between 2016 and 2017 was drawn from Reference USA offered by Infogroup. The publication provides information on firms at the unit level, such as annual sales, number of employees, and industry code. I included firms in North American Industry Classification System (NAICS) codes 7224-7225 (i.e., 722410 "drinking places", 722511 "full-service restaurants", 722513 "limited-service restaurants", 722514 "cafeterias, grill buffets, and buffets", 722515 "snack and nonalcoholic beverage bars"). I excluded any duplicate observations that had the same restaurant name and address information but different unique business codes. This led to a total of 2,915 unique restaurants. I then manually collected their price and menu information from Google and Yelp.

Second, I merged the restaurant dataset with a proprietary dataset with information scraped from four major food delivery platforms (i.e., Postmates, Grubhub, UberEats, and

DoorDash) to identify O2O partnerships formed between each restaurant and platform. The data sets were matched by restaurant name and address; ambiguous matches were further verified manually via web searches. A limitation of the food delivery platform data is that it has been scraped with irregular time intervals. The dates when each platform was scraped are indicated by the black cells in Figure 1. As a result, the data does not provide the exact date when a restaurant first joined a particular platform. If a restaurant was not observed in the data scraped at time t but was observed in the data scraped at time $t+n$, I assumed that the restaurant had joined the platform between t and $t+n$. In addition to the restaurant data, I searched Factiva and the official press releases by the four major delivery platforms, Grubhub, UberEats, DoorDash, and Postmates, for their entry dates into Portland, which are indicated by the grey cells in Figure 1. Postmates entered the city first in March 2015, followed by Grubhub in February 2016, UberEats in November 2016, and DoorDash in April 2018. Based on the entry order and the availability of data, I focused on the last entrant DoorDash and treated the other three as incumbent platforms when DoorDash entered the city.

Insert Figure 1 about here

Third, to obtain information on restaurants' access to offline customers, I matched the restaurant and food delivery platform data to Yelp's open data set[6] based on restaurant name and address. A total of 2,245 (77%) restaurants were matched. Launched in 2004, Yelp serves as the largest restaurant user-generated review website that provides information about restaurants' qualities to potential offline customers (Parikh, Behnke, Vorvoreanu, Almanza, & Nelson, 2014). Accordingly, prior studies have found that an increase in a restaurant's Yelp review rating has an

[6] https://www.yelp.com/dataset

economically significant impact on improving its offline revenues (e.g., Luca, 2016). Thus, a restaurant that has a better Yelp review rating is considered to have better access to its offline customers.

Given the availability of data, my final sample period is from October 2016 to September 2018. I dropped observations with missing values, and my final sample includes 2,024 restaurants.

In addition to quantitative data, I am in the process of collecting qualitative data through semi-structured interviews with restaurant owners/employees and platform representatives. As of this writing, I have conducted eleven interviews with restaurant owners or employees and two interviews with platform representatives. An average interview lasted about 45 minutes, and the interviews offered insights that are consistent with my arguments.

Variables

The unit of analysis is each restaurant. The dependent variable, $Join_{it}$, is a binary variable equal to 1 if restaurant *i* joined DoorDash between May 2018 (one month from DoorDash's entry date) and September 2018 (when DoorDash was last scraped in 2018), and 0 otherwise.

$Existing\ relationships\ with\ incumbent\ platforms_{it-1}$, the main independent variable, is a binary variable equal to 1 if restaurant *i* was observed on any incumbent platform any time between the beginning of the sample period to one month before DoorDash's entry. A restaurant's $Capacity\ constraint_{it-1}$ is measured using the ratio between its estimated sales and the number of employees before DoorDash's entry,[7] log transformed. Because each employee can serve only a limited number of orders, a higher ratio indicates that the restaurant was facing tighter capacity constraints. A restaurant's inter-unit coordination challenges, $Chain_{it-1}$, is indicated as 1 if restaurant *i* is part of a chain restaurant (i.e., a restaurant that manages at least two units), or 0 if it is an independent restaurant. Finally, a restaurant's access to offline customers is measured using $Average\ review\ star_{it-1}$, the restaurant's average Yelp review star before DoorDash's entry.

Several restaurant-level control variables are included. First, I controlled for a restaurant's average food $Price_i$– ranging from 1 ($) to 4 ($$$$). A restaurant's price can have a mixed effect on its likelihood of joining an O2O platform. In particular, a recent study by Li and Wang (2021) found that, although higher-priced restaurants on food delivery platforms face lower online demand (i.e., takeout orders) as customers are more likely to order from lower-priced restaurants, higher-price restaurants face a larger increase in their offline demand (i.e., dine-in). Second, I control for a $Store\ size_i$, estimated by Reference USA. Restaurants with larger store sizes may be less likely to join the delivery platform since they have already incurred higher sunk costs to serve offline customers (e.g., more spaces for dining tables), leading to greater opportunity costs to serve delivery orders. Third, to account for local competition that may influence a restaurant's incentive to join O2O platforms (e.g., Li et al., 2018), I included the $Number\ of\ competitors\ within\ 1km_{it-1}$, which is the total number of other restaurants within a 1km distance from the focal restaurant before DoorDash's entry. Fourth, because a restaurant's platform adoption choice depends on its awareness of O2O platforms, which increases with the

[7] Since Reference USA only provides annual information for the estimated sales and employees, these variables were used as of the December 2017 data.

restaurant platform adoption rate in its neighborhood (Cheyre & Acquisti, 2018), I controlled for the $\%\ of\ nearby\ restaurants\ on\ incumbent\ platforms_{it-1}$, measured using the percentage of restaurants within a 1km distance that had partnered with at least one incumbent platform before DoorDash's entry. Last, I included *Industry* (NAICS) fixed effects and *Zip-code* fixed effects to account for unobservable time-invariant industry and regional factors.

Descriptive statistics are presented in Table 1. On average, about 30% of restaurants had existing relationships with incumbent platforms before DoorDash entered the city. The average capacity-constraint level was 4.01. Supplementary information shows that an average restaurant had an annual sale of $689,120 and employed 12.6 employees, resulting in roughly $4,557 monthly sales per employee. In addition, on average, 38% of the restaurants were chain restaurants, and an average restaurant received 3.61 review stars on Yelp before DoorDash's entry.

Insert Table 1 about here

Table 2 provides the correlation matrix. The correlations among the main independent variables are generally low.

Insert Table 2 about here

Model Specification

My main regression estimated the likelihood of a partnership being formed between a restaurant and DoorDash:

$$\begin{aligned} Join_{it} = {} & \beta_0 + \beta_1 Existing\ relationships\ with\ incumbent\ platforms_{it-1} \\ & + \beta_2\ Existing\ relationships\ with\ incumbent\ platforms_{it-1} * \ Capacity\ constraint_{it-1} \\ & + \beta_3\ \ Existing\ relationships\ with\ incumbent\ platforms_{it-1} * Chain_{it-1} \end{aligned}$$

$$+ \beta_4 \, Existing\ relationships\ with\ incumbent\ platforms_{it-1} * Average\ review\ star_{it-1} + X_{it-1} + \varepsilon_{it-1},$$

where $X_{it-1}$is a vector of control variables, and $\varepsilon_{it-1}$is an error term.

Following recent studies that have used linear models to examine dichotomous outcomes (e.g., Giustiziero, 2020; Theeke & Lee, 2017), I adopted an ordinary least squares (OLS) model, which provides estimations that are consistent with logistic regression (Angrist & Pischke, 2009) but offers a more intuitive interpretation of the marginal effects. My results are robust to nonlinear logistic models, presented in the robustness section. In all models, standard errors are clustered by restaurants' Zip-codes. BH predicts β_1>0, H1 predicts β_2<0, H2 predicts β_3<0, and H3 predicts β_4<0.

RESULTS

Table 3 reports my main results. Model 1 is the baseline model with control variables. The results show that higher-priced restaurants are more likely to join DoorDash, but restaurants with larger physical stores are less likely to join the platform. A restaurant's local competition, and other restaurants' platform adoption rates in its neighborhood have no significant impact.

Insert Table 3 about here

Model 2 introduces *Existing relationships with incumbent platforms*. The coefficient is positive and significant (p-value<0. 01), supporting Baseline Hypothesis. Specifically, changing the value of the *Existing relationships with incumbent platforms* from zero to one (i.e., from having no relationships with incumbent platforms to having at least one relationship before DoorDash's entry) increased a restaurant's likelihood of partnering with DoorDash by 24.1%.

Model 3 adds the main effects of the three moderators. With the inclusion of the main effects of the moderating variables, the *Existing relationships with incumbent platforms* remains consistent with a positive significant effect (*p*-value<0.01). The main effects of *Capacity constraint*, *Chain* and *Average review star* are negative but insignificant (*p*-value=0.38, *p*-value=0.48 and *p*-value=0.13 respectively).

Model 4 introduces *Capacity constraint* and its interaction with *Existing relationships with incumbent platforms*. The coefficient to the interaction term is significantly negative (*p*-value = 0.06), supporting Hypothesis 1.

Model 5 introduces *Chain* and its interaction with *Existing relationships with incumbent platforms*. The interaction effect is negative (*p*-value= 0.04), supporting Hypothesis 2.

Model 6 introduces *Average review star* and its interaction with *Existing relationships with incumbent platforms.* The coefficient to the interaction term is significantly negative (*p*-value = 0.02), supporting Hypothesis 3.

Model 7 introduces the full model with coefficients consistent with those in Models 1-6. Figure 2 graphs the marginal effects as reported in Model 7. The three panels plot the effect of the three moderators, valued at their mean, as well as mean plus or minus one standard deviation, respectively on the link between *Existing relationships with incumbent platforms* and the focal restaurant's likelihood of joining DoorDash. Values of all other variables are fixed at their means. As the graphs illustrate, the positive impact of *Existing relationships with incumbent platforms* on a restaurant's likelihood of joining DoorDash was negatively moderated by a restaurant's *Capacity constraint*, *Chain* and *Average review star*.

Robustness Checks

I also tested the robustness of my results to alternative measures, additional controls, and alternative specifications. Table 4 to 6 report the results.

Insert Table 4 about here

To ensure the main results are robust to the different periods of when the dependent variable was captured, Model 1 in Table 4 introduces an alternative measure of *Join*, which is coded as 1 if a restaurant was first observed on DoorDash in May 2018 (i.e., one month from DoorDash's entry date) and 0 if a restaurant was first (or never) observed on the platform from July to September 2018. The results remain consistent with the main regression results.

Model 2 in Table 4 controls for a restaurant's food type, which has been coded into 25 broad food categories (i.e., Asian, bakery, pizza, steak) based on raw information collected from Yelp and Google. Because some food (e.g., pizza, sandwiches) may travel better than others (e.g., seafood, steak), food type could influence a restaurant's likelihood of joining a platform. The results obtained from including food-type fixed effects remain consistent with the main results.

Model 3 in Table 4 reruns the main specification using a nonlinear logistic regression to check if the results are affected by different econometric specifications. As noted earlier, the results remain significant.

Insert Table 5 about here

Table 5 explores whether a restaurant's decision to join DoorDash depends on the specific incumbent platforms that it has partnered with. The incumbent platforms may vary in their specific internal operational systems (e.g., user interfaces, payment methods), making some more compatible with DoorDash than others. To investigate this effect, I replaced *Existing relationships with incumbent platforms* with three separate binary variables: *Existing relationships with Postmates*, *Existing relationships with Grubhub* and *Existing relationships with UberEats*. Each variable equals to 1 if a restaurant was observed on the respective incumbent platform before DoorDash's entry. Model 1 introduces the main effects for these three variables. The coefficients for all three variables are positive and significant, suggesting that the effect in BH is consistent across all three incumbent platforms. Models 2 to 4 introduce interaction effects between each moderator and each binary variable for the respective incumbent platform. The coefficients to the interaction terms for all three hypotheses are negative across different incumbent platforms, remaining qualitatively similar to my main result. In a supplementary analysis, I further replaced the binary variable *Existing relationships with incumbent platforms* with a continuous variable, the total number of incumbent platforms that a restaurant partnered with before DoorDash's entry. The results are consistent with the main regression results.

Insert Table 6 about here

Table 6 investigates alternative measures. Model 1 introduces an alternative measure for *Capacity constraint*, which is grouped into quantiles. Because many restaurants are private businesses, Reference USA employs an internally developed estimation model to approximate restaurants' sales and employee information based on multiple sources (e.g., U.S. Department of Commerce, Bureau of Economic Analysis). Estimation based on the same model, however, reduced the variances in sales and employee information across restaurants, thereby the variance in *Capacity constraint*. Thus, I ran robustness checks by grouping the variables into five quantiles, and the results remain consistent.

Model 2 further measures *Capacity constraint* using the ratio between the number of employees and *Store size*. The measure was log transformed to reduce skewness and can be interpreted similarly to the original measure. That is, the higher the ratio, the tighter the capacity constraint. The results remain qualitatively similar to the main result.

Models 3 and 4 introduce alternative measures for *Chain.* Because larger chain restaurants may have different characteristics than smaller chain restaurants, I replaced the dummy variable of *Chain* with a category variable that indicates whether a restaurant is a stand-alone restaurant, a *Local chain* restaurant (with all or most of its units in Portland), or a restaurant that belongs to a *National chain* (e.g., McDonalds). Results presented in Model 3 are similar to the main findings. In Model 4, I measured *Chain* as a continuous variable, *Unit*, using the number of units that a restaurant operated within the city before DoorDash's entry. The coefficient to the interaction term between *Unit* and *Existing relationships with incumbent platforms* remains negative and significant.[8]

Model 5 introduces an alternative measure of *Average review star*. While most Yelp reviews were written by offline customers, a few reviews were written by those who used online delivery services. It is thus possible that a restaurant's engagements with O2O platforms may have influenced its overall Yelp review rating. In order to obtain a more robust measure for a

[8] The main effect of *Unit* is positive and significant (p-value<0.01), suggesting that, on average, restaurants with more units within the city are more likely to join the entrant platform. This could correspond to efficiencies in scale that multiunit firms enjoy from sharing successful routines and coordinating on major activities across units (e,g., Chuang & Baum, 2003) when adopting a new platform partnership. For example, because multiunit restaurants perform similar operational activities, they can share the best practices associated with O2O partnerships developed from one unit to others, develop an integrative technology that could be implemented across units or spread the negotiation and contracting costs associated with a new partnership across units, achieving economies of scale in total adjustment costs. While the efficiencies in scale may decrease the average unit-level adjustment costs as the number of unit increases, they may increase the unit-level marginal adjustment costs to adapt the unit's existing platform partnerships to a new platform partnership, as suggested in H2. However, further investigation is needed since Unit does not capture all the restaurants' units in other geographic markets, which could be an important factor that influences the restaurant's platform partnership decision, especially for national chain restaurants.

restaurant's access to offline customers, I measured a restaurant's *Average review star* on Yelp before the first incumbent platform's (i.e., Postmates) entry into the city.[9] The results remain consistent with the main regression results.

Model 6 also introduces an alternative measure of *Average review star.* Since a restaurant's access to offline customers may also depend on the total number of Yelp reviews, in addition to its average Yelp review star, I replaced *Average review star* with *Total number of Yelp reviews*, measured using the total number of Yelp reviews before DoorDash's entry. The coefficient to the interaction term between *Total number of Yelp reviews* and *Existing relationships with incumbent platforms* remains negative and significant.

Alternative Mechanisms

I performed a few additional tests to ensure that my main results are robust to alternative mechanisms. Table 7 presents these results.

Insert Table 7 about here

Uncertainty Mitigation

First, it could be possible that a restaurant's motivation to multihome is driven by its intention to mitigate the uncertainty related to which platforms will win in the future (Venkataraman et al., 2018) rather than its concern of value creation and appropriation. To address this alternative mechanism, I reran my specifications by excluding two sets of restaurants that are the most likely to be concerned with the uncertainty mechanism. First, in Model 1, I dropped Pizza and Chinese fast-food restaurants, which have been traditionally more focused on

[9] For supplementary analyses, I am in the process of removing these Yelp reviews that were written by online customers using machine learning techniques.

serving take-out and delivery orders and therefore may be more sensitive to network effects that can be brought about by a successful platform. The results remain consistent with the main findings. Second, since restaurants in markets that does not have a clear dominant incumbent platform may be more inclined to reduce uncertainty by joining multiple platforms, I excluded restaurants from those markets in Model 2. Specifically, I calculated each incumbent platform's market share by using the ratio between the number of restaurants that are affiliated with each platform within the same Zip-code before DoorDash's entry and the total number of restaurants within the same Zip-code. The average market share for the top three platforms in each Zip code was 15%, with a standard deviation of 0.45. In Model 2, I dropped restaurants in Zip codes where not a single incumbent platform had more than 15% of the market, and the results remain consistent with the main findings.

Ghost Postings

The second alternative mechanism is associated with "ghost postings" by a platform, or the listing of restaurants on a platform without their consent. To address the concern of ghost postings, Model 3 reruns the main analysis by including only restaurants that were still observed on DoorDash after May 2019 (one year after DoorDash's entry into the city). Although I was not able to observe whether each restaurant signed a formal contract with each respective platform, I was able to observe the last date that the data vendor re-scraped a restaurant's information on each platform. From this, I assumed that if a restaurant was "ghost posted" by DoorDash, then it would have removed itself from the platform between its first observed period and May 2019 and therefore would have not been recaptured by the data vendor. About 20% of the sample was dropped, and the results remained consistent with the main result.

Exclusive Contracts

Finally, because it is possible that chain restaurants may have formed exclusive contracts with incumbent platforms that prevent them from joining an entrant platform, I manually collected press releases from each platform to verify the presence of exclusive contracts. In particular, I collected announcements related to any partnerships formed between a platform and a restaurant from the platform's first press release date until the end of 2018. I augmented this data by obtaining partnership announcements from SDC Platinum. This resulted in a total of 80 announcements (19 from Postmates, 28 from UberEats, 12 from Grubhub, 21 from DoorDash). Of the 80 announcements, only 10 mentioned exclusivity.[10] This low number indicates that restaurants rarely formed exclusive contracts with delivery platforms, a finding echoed by several interviews conducted with restaurant owners and delivery platform representatives. Thus, the alternative mechanism for exclusive contracts was not a serious concern in this setting.

Mechanism Testing: Complementors' Value Appropriation Concern

Insert Table 8 about here

Table 8 tests one of the proposed mechanisms behind the main results, that is, complementors that are more concerned about value appropriation from their existing partnerships are more likely to join an entrant platform. To further investigate this, I constructed a Herfindahl-Hirschman concentration index to estimate incumbent platforms' market

[10] Examples:

- https://postmates.com/blog/sugarfish-and-kazunori-exclusively-on-postmates
- https://www.uber.com/newsroom/halalguys/

concentration rate in each geographic area or industry. *HHI* is measured as the sum of each platform's squared market share, proxied as the ratio between the number of restaurants that were on each platform and the total number of restaurants that were on any platform by each Zip-code or NAICS code before DoorDash's entry. Then, I estimated the effect of *HHI* on a restaurant's likelihood of joining DoorDash using a subsample of data that includes only restaurants having at least one existing relationship with the incumbent platform. Model 1 presents the results for *HHI* calculated based on Zip-code, and Model 2 presents the results for *HHI* calculated based on NAICS code. Positive coefficients from both models (*p*-value=0.19 in Model 1 and *p*-value=0.04 in Model 2) suggest that partnered restaurants from more platform-consolidated markets are more likely to join DoorDash.

Sensitivity Analysis

Insert Table 9 about here

While the additional analyses validate my findings, it is possible that omitted variable bias could generate statistically significant results for my main independent variable even if it does not have any true effect on the dependent variable. To estimate how much bias would need to exist in order to remove my main result for BH (i.e., $\beta_1 = 0$), I conducted a sensitivity analysis, developed by Oster (2019), on the estimated relationship between existing relationships with incumbent platforms and a restaurant's likelihood of joining DoorDash reported in Model 3 from Table 3. Although this analysis does not remove the sources of unobservable omitted variable bias, it estimates a parameter $\delta \geq 0$ that represents the relative amount of variation these unobserved variables will need to explain in order to remove the estimated relationship. A value of $\delta = 1$ means that the unobserved variables are at least as important as the observed variables (i.e., control variables included in the model) in explaining the variation. To estimate δ, one needs to specify a value of R_{max}, which is the R-squared from a hypothetical regression including both observed and unobserved variables. In many cases, since the outcome of interest cannot be fully explained even with the inclusion of a full set of control variables (e.g., due to measurement error), the method suggests a value for R_{max} to be $R_{max} = 1.3 * R_M$, where R_M is the R-squared for my estimated model. Following the suggestion, I calculated δ for $R_{max} = 0.11$ (1.3*0.085) and found $\delta = 5.3$. This means that the bias from the selection on unobservable variables would need to be 5.3 times greater than the selection on observable variables in order to erase the main effect. These results are presented in Table 9.

Qualitative Evidence

To better understand my empirical setting and underlying mechanisms of complementors' decision to join an entrant platform, I conducted semi-structured interviews with restaurant owners and delivery platform representatives as well as collected relevant news articles that provide further insights. This qualitative evidence supplements my quantitative findings.

When joining food delivery platforms, restaurant owners incurred both direct and indirect adjustment costs as they learned new technology, adjusted their existing operational activities, and made mistakes resulting from imperfect adaptation. For example, one of the restaurant-affiliated interviewees noted:

> *There were a few operational hurdles. One, having people to monitor that new order system. Basically, the order would come in through the tablet, and then you type it into*

> *the point of sale so then it floats into our sales tool. Another piece was since a lot of the orders are coming in evening hours, where we historically weren't as busy, we had to change our labor model a little bit to be able to support those new sales that that weren't there before. And then the third thing was like, okay, now you have DoorDash drivers coming into the store to pick up the order, and in the busy lunch rushes, [DoorDash] created a quite a bit of complexity. You are trying to manage the whole line and the in-store customers and then now, the manager has to go and give time to the DoorDash driver to get the order and see if it was ready and that sort of thing, and even through the process of the line, like when that DoorDash order comes in, where did it go and what place between the customers in the store to make its way down the line, having it ready not too early where it's going to get cold, but not too late where the customer is going to be upset because its late…So overtime, we went to like a pickup shelf as well, so we can leave the bag there for DoorDash there. It didn't have to be this thing of like coming in and talking to the manager, having them [manager] go and get it, and bring it to you.*

Similarly, another restaurant owner stated:

> *Third-party apps provide you with some sort of a tablet that their app is installed in. Order comes in on a tablet and you need to find a way to somehow transfer that order information to your own point of service system, which ideally should print to the kitchen printer. So our staff is now trained to look at one tablet, and then transfer the guest's and order information manually by going into our own point of service system. And then we enter in and put it through and then our point of service system communicates with the kitchen printer, so it prints to the kitchen…So it did change the job expectations for the front of the house. They are not servers at the table site anymore, they have to be able to*

feel comfortable working with many screens and some basic level technology, more so than before.

Despite the offline-to-online adjustment costs, restaurants often enjoyed savings in between-platform adjustment costs through multihoming since the operational activities were similar across platforms, which is consistent with my arguments for BH. While an interviewee did not explicitly mention the terms of adjustment cost savings, the restaurant owner stated “The back-end office stuffs, different companies [delivery platforms] have different ways, but it doesn't happen often enough. And when you break it down, they are pretty much the same actually.”

In addition to value creation, restaurant owners were concerned about value appropriation from O2O partnerships. One restaurant owner noted, “The platform commission fee is about 23-25% of our revenue, which is very high given the restaurant’s already thin margins. There wasn’t much negotiation because we pretty much didn’t have any leverage for bargaining.”

Interviewees further suggest that capacity-constrained restaurants were reluctant to join an entrant platform, as suggested by H1. For example, a platform sales representative stated, “One of the major reasons why restaurants decline to join our platform is, when they are operationally constrained. When they are maxed out to their capacity, we can’t bring them in. From the local restaurant perspective, it’s easier for them to stay with whatever platforms they are already partnered with. It really depends on their capacity to take more orders.” An interview with a restaurant owner also implied that improving operational efficiency requires additional costs. The owner noted, “I think the bigger company like Grubhub has relationships with major point of service programs where they integrate, so the server does not have to manually enter every single item but that also costs money... Because our volume [from the delivery platforms] is small, we just enter it [delivery orders] into our system."

Consistent with the arguments for H2, interviewees report that chain restaurants often developed resources that are specific to their incumbent platforms, which may be harder to be deployed in a new platform partnership. For example, an interview by DoorDash chief operating officer from SkiftTable noted that "A company like [The Cheesecake Factory] wants to know that you're delivering across their entire system at the level they want. They want a point of sale integration, they want consistent training across their staff so they know how to do it and if something goes wrong they want you to systemically make it right" (Hawley, 2018). From my interview, a franchisee owner mentioned:

> *Sometimes, different platforms apply different rules. For example, some platforms might not allow you to increase food prices or sell items that are also offered on competing platforms…To change something major, the headquarters needs to authorize the change, because they need to make sure that all stores are also selling the same items at the same price.*

This helps substantiate my arguments for H2 that multi-unit complementors may face additional inter-unit coordination challenges when joining an entrant platform.

Finally, restaurants with greater access to offline customers were often less concerned about value appropriation from their incumbent platforms as they were able to negotiate for greater value appropriation from their existing partnerships. One restaurant owner said:

> *Well before the pandemic our bread-and-butter was dining-in business and we didn't really push that hard for takeout, like there was no like a huge incentive, so to speak, to do a lot of third-party delivery accounts…I believe they [Grubhub] initially wanted about*

> *30% and we were able to talk it down to about 27%. We just straight up said, like these numbers are not going to work for us now…it's maybe one or two percent, but that's still significant for a small business.*

Another owner mentioned, "We are not joining another platform because we have so many customers at the moment. The average wait line for our food is over 30 minutes. We don't need more delivery customers." This evidence suggests that restaurants that had greater access to offline customers are less reliant on O2O partnerships, and therefore faced less need to improve their value appropriation abilities by instigating competition between incumbent and entrant platforms.

DISCUSSION AND CONCLUSION

This study examines the role of the organizational attributes of offline firms (potential offline complementors) in shaping their decision to partner with an entrant platform. My results, based on partnerships formed between restaurants and DoorDash in Portland from 2016 to 2018, show that restaurants already having at least one existing partnership with an incumbent platform were more likely to join the entrant platform (DoorDash). However, this positive relationship was weaker for restaurants that faced tighter capacity constraints, operated multiple organizational units, and had greater access to offline customers. These results confirm that complementors' concern about potential value creation from a new partnership and changes in value appropriation from their existing partnerships plays an important role in determining their decision to partner with an entrant platform.

This study makes a number of contributions. First, it enriches the platform competition literature that studies how entrant platforms can build competitive advantages in markets characterized by network effects (e.g., Cennamo & Santalo, 2013; Zhu & Iansiti, 2012). Unlike traditional firms in established markets that mainly rely on their internal resources and capabilities to compete, firms in network-based markets need to partner with external participants, such as complementors or users. Given the need for such partnerships, studies on platform competition have emphasized the salience of first-mover advantage (e.g., Chintakananda & McIntyre, 2014; Schilling, 1999; Wade, 1995) and disadvantages that entrant platforms face when attracting users and complementors. Contrary to the expectation, my findings suggest that complementors' concern for value creation and appropriation may enable an entrant platform to expand its network more readily by entering markets where incumbent platforms have already built larger installed bases. Nevertheless, an entrant platform may be at a disadvantage in recruiting offline complementors that have less excess capacity, complex organizational structures, and a strong access to offline customers.

Second, by identifying the sources of complementors' heterogeneity and the impact on their decision to partner with an entrant platform, this study extends the scope of the platform literature that has mainly focused on platform strategies (e.g., Boudreau, 2010; Rietveld, et al., 2019). While the literature has highlighted the role of complementors on establishing and sustaining a platform's competitive advantage, surprisingly little attention has paid to why complementors engage with a particular platform (McIntyre & Srinivasan, 2017). In particular, the literature provides limited insights into why complementors facing the same market conditions or platform features vary in their decisions to partner with a particular platform. By shifting the attention from market conditions or platform features to complementor strategies, my study advances the existing literature by highlighting the importance of understanding the heterogeneity among complementors, which can serve as a better basis for platform owners to devise strategies to establish and maintain their relationships with complementors.

Third, this study contributes to the multihoming literature, which has been primarily interested in understanding online complementor behaviors (e.g., Srinivasan & Venkatraman, 2020; Venkataraman et al., 2018) than those of offline complementors. Specifically, it complements existing studies by delineating key differences between online and offline complementors and connecting the literature with the value-based and resource-based views of strategy. In doing so, it sheds light on unique challenges that offline firms face when adjusting their existing businesses to adopt innovation provided by digital platforms and their growing concern for value appropriation under WTA dynamics, providing alternative explanations for multihoming. Furthermore, my study indicates that offline complementors' incentive to multihome may vary from that of online complementors. Specifically, while prior studies found that better-positioned online complementors are more likely to multihome (e.g., Bresnahan et al., 2015), my results show that better-positioned offline complementors are less likely to multihome.

Finally, this study contributes to the literature on interfirm relationships by suggesting that a firm's decision to form a new partnership is influenced by the potential interdependencies between its existing and new partnerships, in addition to a dyadic fit between two focal partners, as suggested in many studies (e.g., Katila et al., 2008; Rothaermel & Boeker, 2008). Recent studies on alliance portfolio have begun to shed light on interdependencies across multiple alliances by investigating the effect of portfolio configuration on firm performance (e.g., Aggarwal, 2020; Jiang, Tao, & Santoro, 2010; Lavie, 2007; Wassmer & Dussauge, 2011). Nevertheless, they have paid little attention to why firms vary in their portfolio configuration in the first place. My findings provide insights into this by indicating that firms that have already developed fungible resources or those that lack bargaining power vis-à-vis their existing partners are more likely to expand their collaborative portfolio by forming a new partnership. However, this tendency is weaker when firms lack the capacity to establish the new partnership, face greater inter-unit coordination challenges, or have more alternative value-creating opportunities.

In addition to theoretical contributions, this study has managerial and policy implications. In the past decade, platforms have flourished in many industries by gaining considerable market power, heightening regulators' concerns about antitrust policy. My study suggests that one potential way to prevent a single platform from dominating the market is to level the playing field for platforms by providing a better infrastructure for offline firms to reduce their adjustment costs that are required to join O2O platforms. Once the market experiences substantial demand for O2O platforms, more new platforms will enter the market, stimulating market competition. Unlike the expectations of a WTA dynamic, my study suggests that market competition can be sustained because of offline complementors' concerns about value creation and appropriation. My findings also suggest that for an entrant platform to successfully enter new markets, it could subsidize offline complementors that face tighter capacity constraints or inter-unit coordination challenges for managing multiple units. Entrant platforms could also devise promotional or marketing activities that primarily target those with greater access to offline customers.

This study has some limitations that suggest opportunities for future research. First, this study theoretically and empirically focuses on platform partnerships that exhibit low differentiation (e.g., low differences in core technology and in business model or platform quality) across competing platforms. Therefore, the arguments and findings are most relevant for complementors that face relatively low marginal adjustment costs (e.g., porting costs) to join an additional platform. Furthermore, since complementors (restaurants) in my context rarely switched between platforms, my arguments may be less relevant to offline complementors that have strong incentives to withdraw from their existing platforms to join a new one. Future studies could examine the generalizability of my findings to other O2O platform settings.

Second, because of the limited availability of data, this study has examined only one city and one entrant-platform setting. To partially address the generalizability issue, I have estimated the main analyses for BH, H1, and H2[11] using samples collected for Las Vegas in 2016 and Detroit in 2018. In Las Vegas, DoorDash was the last entrant, as in Portland, but in Detroit, where DoorDash, Grubhub, and UberEats had already been operating, Postmates was the last. The results for these other markets are consistent with my main findings. Nevertheless, a natural extension of this paper could be to investigate whether these results are consistent across different periods, platforms, and cities.

Third, this study is subject to potential concerns associated with selection based on unobserved variables. Including restaurant or platform fixed effects might rule out unobservable but time-invariant firm heterogeneity, but unfortunately my data do not allow for panel analyses. Future studies could address this empirical challenge by finding more detailed data with an exogenous source of variation in forming offline firms' initial partnerships.

Finally, due to limitations in the data, my sample period was short. Future studies can collect longitudinal data and investigate whether the relationships between restaurants and platforms change over time. For example, while not salient during my sample period, competition between food delivery platforms has prompted some major platforms to consolidate through mergers and acquisitions (e.g., UberEats and Postmates). Future research may analyze

[11] I am in the process of collecting additional Yelp review data for these cities.

how offline complementors react to platform consolidations, such as whether they will join even more competing platforms or terminate their relationships with the consolidated platforms in order to limit the single platform's market power.

In sum, this paper focuses on heterogeneity across offline firms and studies how their unique organizational characteristics influence their decision to partner with an entrant platform. Importantly, offline firms are more likely to join the entrant platform when they can create greater value from the new partnership due to lower adjustment costs or when they can benefit more from enhancing their value appropriation abilities by stimulating competition among platforms. Notwithstanding the limitations, I hope this work will motivate future research to exploit the rich source of heterogeneity among offline complementors, thereby advancing the literature that has primarily focused on platform strategies.

Reference

Adegbesan, J. A., & Higgins, M. J. (2011). The intra-alliance division of value created through collaboration. *Strategic Management Journal*, *32*(2), 187–211. https://doi.org/10.1002/SMJ.872

Aggarwal, V. A. (2020). Resource congestion in alliance networks: How a firm's partners' partners influence the benefits of collaboration. *Strategic Management Journal, 41*(4), 627–655. https://doi.org/10.1002/smj.3109

Ahuja, G., & Novelli, E. (2016). Incumbent Responses to an Entrant with a New Business Model: Resource Co-Deployment and Resource Re-Deployment Strategies. *Advances in Strategic Management, 35*, 125–153. https://doi.org/10.1108/S0742-332220160000035006

Angrist JD, Pischke JS. 2009. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press: Princeton, NJ.

Argyres, N., Mahoney, J. T., & Nickerson, J. (2019). Strategic responses to shocks: Comparative adjustment costs, transaction costs, and opportunity costs. *Strategic Management Journal*, *40*(3), 357–376. https://doi.org/10.1002/smj.2984

Bagley, K. (2019). Why Restaurant Delivery Companies Don't Share Their Data. Retrieved August 24, 2021, from https://medium.com/@kb_77275/why-restaurant-delivery-companies-dont-share-their-data-267b97e587eb

Baum, J. A. C., Cowan, R., & Jonard, N. (2010). Network-Independent Partner Selection and the Evolution of Innovation Networks. *Http://Dx.Doi.Org/10.1287/Mnsc.1100.1229*, *56*(11), 2094–2110. https://doi.org/10.1287/MNSC.1100.1229

Bigelow, L., Nickerson, J. A., & Park, W.-Y. (2019). When and how to shift gears: Dynamic trade-offs among adjustment, opportunity, and transaction costs in response to an innovation shock. *Strategic Management Journal*, *40*(3), 377–407. https://doi.org/10.1002/smj.2996

Boudreau, K. (2010). Open platform strategies and innovation: Granting access vs. devolving control. *Management Science*, *56*(10), 1849–1872. https://doi.org/10.1287/mnsc.1100.1215

Boudreau, K. J., & Jeppesen, L. B. (2015). Unpaid crowd complementors: The platform network effect mirage. *Strategic Management Journal*, *36*(12), 1761–1777. https://doi.org/10.1002/smj.2324

Brandenburger, A. M., & Stuart, H. W. (1996). Value-based Business Strategy. *Journal of Economics & Management Strategy*, *5*(1), 5–24. https://doi.org/10.1111/j.1430-9134.1996.00005.x

Bresnahan, T., Orsini, J., & Yin, P.-L. (2015). Demand heterogeneity, inframarginal multihoming, and platform market stability: Mobile apps. *Proceedings of the 9th IDEI-TSE-IAST Conference on The Economics of Intellectual Property, Software and the Internet*. Retrieved from http://idei.fr/sites/default/files/IDEI/documents/conf/Internet_2016/Articles/yin.pdf

Cennamo, C., Ozalp, H., & Kretschmer, T. (2018). Platform architecture and quality trade-offs of multihoming complements. *Information Systems Research*, *29*(2), 461–478. https://doi.org/10.1287/isre.2018.0779

Cennamo, C., & Santalo, J. (2013). Platform competition: Strategic trade-offs in platform markets. *Strategic Management Journal*, *34*(11), 1331–1350. https://doi.org/10.1002/smj.2066

Cheyre, C., & Acquisti, A. (2018). Online Intermediaries, Prices, and Survival: A Study of OpenTable and New York City Restaurants, 38.

Chintakananda, A., & McIntyre, D. P. (2014). Market Entry in the Presence of Network Effects: A Real Options Perspective. *Journal of Management*, *40*(6), 1535–1557. https://doi.org/10.1177/0149206311429861

Choi, C. (2020) Joining the Shark Tank: How Does Competition for External Knowledge Influence Corporate Venture Capital Investments? Working Paper

Christensen, C. M., & Bower, J. L. (1996). Customer power, strategic investment, and the failure of leading firms. *Strategic Management Journal*, *17*(3), 197–218. https://doi.org/10.1002/(sici)1097-0266(199603)17:3<197::aid-smj804>3.0.co;2-u

Chu, L. Y., & Wu, B. (2021). Designing Online Platforms for Customized Goods and Services: A Market-Frictions Based Perspective. *Academy of Management Review*, amr.2020.0247.

https://doi.org/10.5465/amr.2020.0247
Chuang, Y. T., & Baum, J. A. C. (2003). It's all in the name: Failure-induced learning by multiunit chains. *Administrative Science Quarterly*. Johnson School at Cornell University. https://doi.org/10.2307/3556618
Corts, K. S., & Lederman, M. (2009). Software exclusivity and the scope of indirect network effects in the U.S. home video game market. *International Journal of Industrial Organization*, *27*(2), 121–136. https://doi.org/10.1016/j.ijindorg.2008.08.002
Curry, D. (2021). Food Delivery App Revenue and Usage Statistics. Retrieved August 24, 2021, from https://www.businessofapps.com/data/food-delivery-app-market/
Cutolo, D., & Kenney, M. (2020). Platform-Dependent Entrepreneurs: Power Asymmetries, Risks, and Strategies in the Platform Economy. *Academy of Management Perspectives*. https://doi.org/10.5465/amp.2019.0103
Dickler, T. A., & Folta, T. B. (2020). Identifying internal markets for resource redeployment. *Strategic Management Journal*, *41*(13), 2341–2371. https://doi.org/10.1002/smj.3205
Dyer, J. H., Singh, H., & Kale, P. (2008). Splitting the pie: rent distribution in alliances and networks. *Managerial and Decision Economics*, *29*(2–3), 137–148. https://doi.org/10.1002/MDE.1391
Eisenmann, T., Parker, G., & Van Alstyne, M. (2011). Platform envelopment. *Strategic Management Journal*, *32*(12), 1270–1285. https://doi.org/10.1002/smj.935
Eklund, J., & Kapoor, R. (2019). Pursuing the New While Sustaining the Current: Incumbent Strategies and Firm Value During the Nascent Period of Industry Change. *Organization Science*, *30*(2), 383–404. https://doi.org/10.1287/orsc.2018.1229
Evans, D. S. (2003). Some Empirical Aspects of Multi-sided Platform Industries. *Review of Network Economics*, *2*(3). https://doi.org/10.2202/1446-9022.1026
Evans, D. S., & Schmalensee, R. (2020). Markets with Two-Sided Platforms. *Routledge*, (April).
Farrell, J., & Saloner, G. (1985). Standardization, Compatibility, and Innovation. *The RAND Journal of Economics*, *16*(1), 70. https://doi.org/10.2307/2555589
Gans, J., & Ryall, M. D. (2017). Value capture theory: A strategic management review. In *Strategic Management Journal* (Vol. 38, pp. 17–41). https://doi.org/10.1002/smj.2592
Hagiu, A. (2009). Merchant or Two-Sided Platform? *Review of Network Economics*, *6*(2), 115–133. https://doi.org/10.2202/1446-9022.1113
Hanisch, M. (2020). Digital Platform Strategies : Strategic Trade-Offs in Multi-Sided Markets tin. *Academy of Management Proceedings*, (1).
Hashai, N. (2015). Within-industry diversification and firm performance- an S-shaped hypothesis. *Strategic Management Journal*, *36*, 1378–1400. https://doi.org/10.1002/smj
Hawley, K. (2018, August 1). The Cheesecake Factory Will Partner Exclusively With DoorDash for Delivery. Retrieved September 5, 2021, from https://table.skift.com/2018/07/31/the-cheesecake-factory-will-partner-exclusively-with-doordash-for-delivery/
He, Z., Han, G., Cheng, T. C. E., Fan, B., & Dong, J. (2019). Evolutionary food quality and location strategies for restaurants in competitive online-to-offline food ordering and delivery markets: An agent-based approach. *International Journal of Production Economics*, *215*(March 2017), 61–72. https://doi.org/10.1016/j.ijpe.2018.05.008
Hecker, A., & Kretschmer, T. (2010). Outsourcing decisions: The effect of scale economies and market structure. *Strategic Organization*, *8*(2), 155–175. https://doi.org/10.1177/1476127010365021
Helfat, C. E., & Eisenhardt, K. M. (2004). Inter-temporal economies of scope, organizational modularity, and the dynamics of diversification. *Strategic Management Journal*, *25*(13), 1217–1232. https://doi.org/10.1002/smj.427
Henderson, R. M., & Clark, K. B. (1990). Architectural Innovation : The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. *Administrative Science Quarterly*, *35*(1), 9–30. Retrieved from http://www.jstor.org/stable/2393549
Hirschberg, C., Rajko, A., Schumacher, T., & Wrulich, M. (2016). The changing market for food

delivery. https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/the-changing-market-for-food-delivery

Huang, P., Ceccagnoli, M., Forman, C., & Wu, D. J. (2013). Appropriability mechanisms and the platform partnership decision: Evidence from enterprise software. *Management Science*, *59*(1), 102–121. https://doi.org/10.1287/mnsc.1120.1618

Jiang, R. J., Tao, Q. T., & Santoro, M. D. (2010). Alliance portfolio diversity and firm performance. *Strategic Management Journal*, *31*(10), 1136–1144. https://doi.org/10.1002/smj.869

Kalnins, A., & Mayer, K. J. (2004). Franchising, ownership, and experience: A study of pizza restaurant survival. *Management Science*, *50*(12), 1716–1728. https://doi.org/10.1287/mnsc.1040.0220

Katila, R., Rosenberger, J. D., & Eisenhardt, K. M. (2008). Swimming with Sharks : Technology Ventures. *Administrative Science Quarterly*, *53*(2), 295–332. https://doi.org/10.2189/asqu.53.2.295

Katz, M. L., & Shapiro, C. (1986). Technology Adoption in the Presence of Network Externalities. *Journal of Political Economy*, *94*(4), 822–841. https://doi.org/10.1086/261409

Katz, M. L., & Shapiro, C. (1994). Systems Competition and Network Effects. *Journal of Economic Perspectives*, *8*(2), 93–115. https://doi.org/10.1257/jep.8.2.93

Khanna, T., Gulati, R., & Nohria, N. (1998). The dynamics of learning alliances: competition, cooperation, and relative scope. *Strategic Management Journal*, *19*(3), 193–210. https://doi.org/10.1002/(SICI)1097-0266(199803)19:3<193::AID-SMJ949>3.0.CO;2-C

Kumar, M. V. S. (2010). Differential Gains Between Partners in Joint Ventures: Role of Resource Appropriation and Private Benefits. *Organization Science*, *21*(1), 232–248. https://doi.org/10.1287/orsc.1080.0393

Landsman, V., & Stremersch, S. (2011). Multihoming in Two-Sided Markets: An Empirical Inquiry in the Video Game Console Industry. *Journal of Marketing*, *75*(6), 39–54. https://doi.org/10.1509/jm.09.0199

Lavie, D. (2007). Alliance portfolios and firm performance: A study of value creation and appropriation in the U.S. software industry. *Strategic Management Journal*, *28*(12), 1187–1212. https://doi.org/10.1002/smj.637

Levinthal, D. A., & Wu, B. (2010). Opportunity Costs and Non-Scale Free Capabilities: Profit Maximization, Corporate Scope, and Profit Margins. *Strategic Management Journal*, *31*(7), 780–801. https://doi.org/10.1002/smj.845

Li, H., Shen, Q., & Bart, Y. (2018). Local market characteristics and online-to-offline commerce: An empirical analysis of Groupon. *Management Science*, *64*(4), 1860–1878. https://doi.org/10.1287/mnsc.2016.2666

Li, H., & Zhu, F. (2020). Information Transparency, Multihoming, and Platform Competition: A Natural Experiment in the Daily Deals Market. *Management Science*, (October). https://doi.org/10.1287/mnsc.2020.3718

Li, J., Pisano, G., & Zhu, F. (2018). Marketplace Scalability and Strategic Use of Platform Investment. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3310484

Li, Z., & Wang, G. (2021). The Role of On-Demand Delivery Platforms in Restaurants. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3813891

Lieberman, M. B., Lee, G. K., & Folta, T. B. (2017). Entry, exit, and the potential for resource redeployment. *Strategic Management Journal*, *38*(3), 526–544. https://doi.org/10.1002/SMJ.2501

Littman, J. (2019). Delivery by the numbers: How top third-party platforms compare. Retrieved August 24, 2021, from https://www.restaurantdive.com/news/delivery-by-the-numbers-how-top-third-party-platforms-compare/564279/

Luca, M. (2016). Reviews, Reputation, and Revenue: The Case of Yelp.Com. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.1928601

Macdonald, G., & Ryall, M. D. (2004). How Do Value Creation and Competition Determine Whether a Firm Appropriates Value? *Management Science*, *50*(10), 1319–1333. https://doi.org/10.1287/mnsc.1030.0152

Madhok, A., Keyhani, M., & Bossink, B. (2015). Understanding alliance evolution and termination: Adjustment costs and the economics of resource value. *Strategic Organization*, *13*(2), 91–116. https://doi.org/10.1177/1476127015580309

Marston, J. (2018). Delivery Is Making These Restaurants Literally Redesign the Way They Do Business. Retrieved August 15, 2021, from https://thespoon.tech/delivery-is-making-these-restaurants-literally-redesign-the-way-they-do-business/

McIntyre, D. P., & Srinivasan, A. (2017). Networks, platforms, and strategy: Emerging views and next steps. *Strategic Management Journal*, *38*(1), 141–160. https://doi.org/10.1002/smj.2596

Molla, R. (2019). Uber Eats is facing a price war — just like Uber - Vox. Retrieved August 31, 2021, from https://www.vox.com/recode/2019/5/17/18624623/ubers-eats-food-delivery-loyalty-grubhub-doordash

Morgan Stanley (2017). Alexa, What's for Dinner Tonight? https://www.morganstanley.com/ideas/online-food-delivery-market-expands

Oster, E. (2019). Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics* 37(2):187-204.

Parikh, A., Behnke, C., Vorvoreanu, M., Almanza, B., & Nelson, D. (2014). Motives for reading and articulating user-generated restaurant reviews on Yelp.com. *Journal of Hospitality and Tourism Technology*, *5*(2), 160–176. https://doi.org/10.1108/JHTT-04-2013-0011

Park, S. (2004, November 13). Quantitative analysis of network externalities in competing technologies: The VCR case. *Review of Economics and Statistics*. https://doi.org/10.1162/0034653043125275

Penrose, E. (1959). Theory of the Growth of the Firm. White Plains, NY: M. E. Sharpe, Inc. (originally published in 1959).

QSR. (2019). Jersey Mike's Streamlines Uber Eats Delivery with POS Integration. Retrieved from https://www.qsrmagazine.com/news/jersey-mike-s-streamlines-uber-eats-delivery-pos-integration

Rampell, A. (2010). Why Online2Offline Commerce Is A Trillion Dollar Opportunity. Retrieved July 8, 2021, from https://techcrunch.com/2010/08/07/why-online2offline-commerce-is-a-trillion-dollar-opportunity/

Rietveld, J., Schilling, M. A., & Bellavitis, C. (2019). Platform Strategy: Managing Ecosystem Value Through Selective Promotion of Complements. *Organization Science*, *30*(6), 1232–1251. https://doi.org/10.1287/orsc.2019.1290

Rochet, J.-C., & Tirole, J. (2003). Platform Competition in Two-Sided Markets. *Journal of the European Economic Association*, *1*(4), 990–1029. https://doi.org/10.1162/154247603322493212

Rothaermel, F. T., & Boeker, W. (2008). Old technology meets new technology: complementarities, similarities, and alliance formation. *Strategic Management Journal*, *29*(1), 47–77. https://doi.org/10.1002/SMJ.634

Rubin, P. H. (1973). The Expansion of Firms. *Journal of Political Economy*, *81*(4), 936–949. https://doi.org/10.1086/260089

Saddle Back BBQ. (n.d.). How Google, Doordash, & Grubhub conspire to screw local restaurants. Retrieved August 22, 2021, from https://www.saddlebackbbq.com/how-google-doordash-grubhub-conspire-screw-local-restaurants

Sakhartov, A. V., & Folta, T. B. (2014). Resource relatedness, redeployability, and firm value. *Strategic Management Journal*, *35*(12), 1781–1797. https://doi.org/10.1002/smj.2182

Schilling, M. (1999). Winning the standards race: Building installed base and the availability of complementary goods. *European Management Journal*, *17*(3), 265–274. https://doi.org/10.1016/S0263-2373(99)00005-5

Schilling, M. A. (2002). Technology Success and Failure in Winner-Take-All Markets : The Impact of Learning Orientation , Timing , and Network Externalities. *Academy of Management Journal*, *45*(2), 387–398.

Shapiro, C., & Varian, H. R. (1999). The art of standards wars. *California Management Review*, *41*(2), 8–32. https://doi.org/10.2307/41165984

Sheremata, W. A. (2004). Competing through innovation in network markets: Strategies for challengers. *Academy of Management Review*, *29*(3), 359–377. https://doi.org/10.5465/AMR.2004.13670986

Srinivasan, A., & Venkatraman, V. N. (2020). Architectural Convergence and Platform Evolution: Empirical Test of Complementor Moves in Videogames. *IEEE Transactions on Engineering Management*, *67*(2), 266–282. https://doi.org/10.1109/TEM.2018.2881560

Stein, J. C. (1997). Internal Capital Markets and the Competition for Corporate Resources. *The Journal of Finance*, *52*(1), 111–133. https://doi.org/10.1111/j.1540-6261.1997.tb03810.x

Tae, C. J., Luo, X., & Lin, Z. (2020). Capacity-constrained entrepreneurs and their product portfolio size: The response to a platform design change on a Chinese sharing economy platform. *Strategic Entrepreneurship Journal*, *14*(3), 302–328. https://doi.org/10.1002/sej.1360

Tanriverdi, H., & Chi-Hyon, L. (2008). Within-industry diversification and firm performance in the presence of network externalities: Evidence from the software industry. *Academy of Management Journal*, *51*(2), 381–397. https://doi.org/10.5465/AMJ.2008.31767300

Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Research Policy*, *47*(8), 1367–1387. https://doi.org/10.1016/j.respol.2017.01.015

Tellis, G. J., Yin, E., & Niraj, R. (2009). Does quality win? Network effects versus quality in high-tech markets. *Journal of Marketing Research*, *46*(2), 135–149. https://doi.org/10.1509/jmkr.46.2.135

Tucker, C. (2008). Identifying formal and informal influence in technology adoption with network externalities. *Management Science*, *54*(12), 2024–2038. https://doi.org/10.1287/mnsc.1080.0897

Venkataraman, V., Ceccagnoli, M., & Forman, C. (2018). Multihoming within Platform Ecosystems: The Strategic Role of Human Capital. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3134846

Wade, J. (1995). Dynamics of organizational communities and technological bandwagons: An empirical investigation of community evolution in the microprocessor market. *Strategic Management Journal*, *16*(1 S), 111–133. https://doi.org/10.1002/smj.4250160920

Wang, R. D., & Miller, C. D. (2019). Complementors' engagement in an ecosystem: A study of publishers' e-book offerings on Amazon Kindle. *Strategic Management Journal*, *41*(1), 3–26. https://doi.org/10.1002/smj.3076

Wassmer, U., & Dussauge, P. (2011). Value creation in alliance portfolios: The benefits and costs of network resource interdependencies. *European Management Review*, *8*(1), 47–64. https://doi.org/10.1111/j.1740-4762.2011.01003.x

Woo, H. S., Cannella, A., & Mesquita, L. (2019). How intra- and interfirm agglomeration affect new-unit geographic distance decisions of multiunit firms. *Strategic Management Journal*, *40*(11), 1757–1790. https://doi.org/10.1002/smj.3070

Yan, A., & Gray, B. (1994). Bargaining Power, Management Control, and Performance in United States-China Joint Ventures: A Comparative Case Study. *The Academy of Management Journal*, *37*(6), 1478–1517.

Zhou, Y. M. (2011). Synergy, coordination costs, and diversification choices. *Strategic Management Journal*, *32*(6), 624–639. https://doi.org/10.1002/smj.889

Zhu, F., & Furr, N. (2016). Products to platforms: Making the leap. *Harvard Business Review*, *2016*(April), 2012–2014.

Zhu, F., & Iansiti, M. (2012). Entry into platform-based markets. *Strategic Management Journal*, *33*(1), 88–106. https://doi.org/10.1002/smj.941

Zhu, F., & Liu, Q. (2018). Competing with complementors: An empirical look at Amazon.com. *Strategic Management Journal*, *39*(10), 2618–2642. https://doi.org/10.1002/smj.2932

TABLES AND FIGURES

TABLE 1 Summary statistics (N=2,024)

Variable	Mean	Std. Dev.	Min	Max
Join	0.44	0.50	0.00	1.00
Existing relationships with incumbent platforms (1,0)	0.30	0.46	0.00	1.00
Capacity constraint	4.01	0.08	2.93	5.48
Chain (1,0)	0.38	0.48	0.00	1.00
Average review star	3.61	0.67	1.00	5.00
Price	1.52	0.57	1.00	4.00
Store size	4566.70	10362.86	750.00	100000.00
Number of competitors within 1km	186.10	240.47	1.00	855.00
% of nearby restaurants on incumbent platforms	0.25	0.06	0.00	0.67

TABLE 2 Correlation matrix (N=2,024)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Join	1							
(2)	Existing relationships with incumbent platforms (1,0)	0.23***	1						
(3)	Capacity constraint	-0.09***	-0.10***	1					
(4)	Chain (1,0)	0.03	0.20***	-0.17***	1				
(5)	Average review star	-0.03	-0.04	0.02	-0.37***	1			
(6)	Price	0.04	0.04	-0.04	-0.12***	0.18***	1		
(7)	Store size	-0.05*	0.04	-0.04	0.10***	-0.01	0.22***	1	
(8)	Number of competitors within 1km	-0.01	-0.01	0.04	-0.07***	0.07**	0.04	0.01	1
(9)	% of nearby restaurants on incumbent platforms	0.00	-0.01	0.00	0.00	0.01	-0.02	-0.04	0.03

*** p<0.01, ** p<0.05, * p<0.1

TABLE 3 Main results of OLS models

DV=Join (DD)	(1)	(2)	(3)
Existing relationships with incumbent platforms (1,0) (BH)		0.241***	0.245***
		(0.024)	(0.025)
Capacity constraint			-0.166
			(0.186)
Chain (1,0)			-0.019
			(0.026)
Average review star			-0.031
			(0.020)
Price	0.040*	0.030	0.032
	(0.022)	(0.022)	(0.022)
Store size	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Number of competitors within 1km	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
% of nearby restaurants on incumbent platforms	-0.053	0.007	0.009
	(0.178)	(0.179)	(0.181)
Industry FE	YES	YES	YES
Zip-code FE	YES	YES	YES
Constant	0.404***	0.334***	1.116
	(0.057)	(0.054)	(0.778)
Observations	2,024	2,024	2,024
R-squared	0.037	0.084	0.085

Robust standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

TABLE 3 (continued) Main results of OLS models

DV=Join (DD)	(4)	(5)	(6)	(7)
Existing relationships with incumbent platforms (1,0) (BH)	4.546**	0.288***	0.546***	5.517**
	(2.171)	(0.030)	(0.132)	(2.113)
Existing relationships with incumbent platforms * Capacity constraint (H1)	-1.077*			-1.184**
	(0.545)			(0.536)
Existing relationships with incumbent platforms * Chain (H2)		-0.095**		-0.172***
		(0.043)		(0.048)
Existing relationships with incumbent platforms * Average review star (H3)			-0.084**	-0.129***
			(0.035)	(0.036)
Capacity constraint	-0.092	-0.156	-0.168	-0.069
	(0.192)	(0.185)	(0.186)	(0.192)
Chain (1,0)	-0.019	0.011	-0.017	0.039
	(0.026)	(0.028)	(0.026)	(0.027)
Average review star	-0.030	-0.031	-0.007	0.007
	(0.020)	(0.019)	(0.020)	(0.019)
Price	0.032	0.031	0.032	0.031
	(0.022)	(0.022)	(0.022)	(0.022)
Store size	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of competitors within 1km	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
% of nearby restaurants on incumbent platforms	-0.005	0.011	0.013	0.003
	(0.183)	(0.181)	(0.180)	(0.181)
Industry FE	YES	YES	YES	YES
Zip-code FE	YES	YES	YES	YES
Constant	0.818	1.068	1.028	0.566
	(0.796)	(0.772)	(0.776)	(0.786)
Observations	2,024	2,024	2,024	2,024
R-squared	0.088	0.087	0.088	0.095

Robust standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

TABLE 4 Robustness Checks

DV=Join (DD)	Alternative measure for DV (1)	Food type FE (2)	Logit model (3)
Existing relationships with incumbent platforms (1,0) (BH)	4.508**	5.568**	25.808**
	(1.869)	(2.244)	(11.761)
Existing relationships with incumbent platforms * Capacity constraint (H1)	-0.983**	-1.221**	-5.594*
	(0.478)	(0.572)	(2.960)
Existing relationships with incumbent platforms * Chain (H2)	-0.203***	-0.169***	-0.758***
	(0.046)	(0.045)	(0.220)
Existing relationships with incumbent platforms * Average review star (H3)	-0.076**	-0.107***	-0.576***
	(0.034)	(0.035)	(0.171)
Capacity constraint	-0.044	0.006	-0.335
	(0.202)	(0.184)	(0.898)
Chain (1,0)	0.019	0.032	0.170
	(0.026)	(0.029)	(0.118)
Average review star	0.048**	-0.004	0.030
	(0.020)	(0.020)	(0.083)
Price	0.055***	0.031	0.140
	(0.019)	(0.020)	(0.099)
Store size	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)
Number of competitors within 1km	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)
% of nearby restaurants on incumbent platforms	0.077	0.045	-0.008
	(0.166)	(0.178)	(0.800)
Industry FE	YES	YES	YES
Zip-code FE	YES	YES	YES
Food type FE	NO	YES	NO
Constant	0.211	0.304	-0.680
	(0.815)	(0.740)	(3.783)
Observations	2,024	2,021	2,024
R-squared	0.095	0.128	0.072

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 5 Robustness checks for BH

DV=Join (DD)	Alternative measures for BH			
	(1)	(2)	(3)	(4)
Existing relationships with Postmates (1,0) (BH)	0.209***	5.469*	0.204***	0.208***
	(0.031)	(2.837)	(0.032)	(0.032)
Existing relationships with Grubhub (1,0) (BH)	0.097***	0.101***	5.351	0.092***
	(0.033)	(0.035)	(4.199)	(0.033)
Existing relationships with UberEats (1,0) (BH)	0.163***	0.161***	0.153***	4.032**
	(0.041)	(0.039)	(0.040)	(1.706)
Existing relationships with Postmates * Capacity constraint (H1)		-1.184		
		(0.709)		
Existing relationships with Postmates * Chain (H2)		-0.056		
		(0.054)		
Existing relationships with Postmates * Average review star (H3)		-0.140***		
		(0.037)		
Existing relationships with Grubhub * Capacity constraint (H1)			-1.272	
			(1.073)	
Existing relationships with Grubhub * Chain (H2)			-0.259***	
			(0.089)	
Existing relationships with Grubhub * Average review star (H3)			-0.015	
			(0.057)	
Existing relationships with UberEats * Capacity constraint (H1)				-0.901**
				(0.425)
Existing relationships with UberEats * Chain (H2)				-0.237***
				(0.070)
Existing relationships with UberEats * Average review star (H3)				-0.049
				(0.050)
Capacity constraint	-0.173	-0.118	-0.145	-0.132
	(0.192)	(0.192)	(0.195)	(0.189)
Chain (1,0)	-0.013	0.002	0.015	0.006
	(0.026)	(0.024)	(0.027)	(0.027)
Average review star	-0.031	-0.002	-0.028	-0.025
	(0.019)	(0.018)	(0.018)	(0.018)
Price	0.032	0.032	0.031	0.030
	(0.021)	(0.022)	(0.021)	(0.021)
Store size	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of competitors within 1km	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
% of nearby restaurants on incumbent platforms	-0.004	0.010	0.010	-0.009
	(0.182)	(0.186)	(0.187)	(0.184)
Industry FE	YES	YES	YES	YES
Zip-code FE	YES	YES	YES	YES
Constant	1.143	0.809	1.020	0.956
	(0.800)	(0.794)	(0.813)	(0.779)
Observations	2,024	2,024	2,024	2,024
R-squared	0.085	0.092	0.091	0.089

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 6 Robustness checks for H1-H3

DV=Join (DD)	Alternative measures for:			
	H1	H1	H2	H2
	(1)	(2)	(3)	(4)
Existing relationships with incumbent platforms (1,0) (BH)	0.878***	0.687***	5.518**	5.028**
	(0.149)	(0.225)	(2.103)	(2.220)
Existing relationships with incumbent platforms * Capacity constraint (H1)	-0.035*	-0.019	-1.184**	-1.113*
	(0.018)	(0.034)	(0.537)	(0.564)
Existing relationships with incumbent platforms * Chain (H2)	-0.172***	-0.158***		
	(0.050)	(0.051)		
Existing relationships with incumbent platforms * Local Chain (H2)			-0.168**	
			(0.068)	
Existing relationships with incumbent platforms* National Chain (H2)			-0.174***	
			(0.053)	
Existing relationships with incumbent platforms * Unit (H2)				-0.003***
				(0.001)
Existing relationships with incumbent platforms * Average review star (H3)	-0.130***	-0.132***	-0.129***	-0.093**
	(0.037)	(0.038)	(0.036)	(0.034)
Capacity constraint	0.012	0.014	-0.068	-0.141
	(0.011)	(0.020)	(0.193)	(0.180)
Chain (1,0)	0.040	0.033		
	(0.026)	(0.028)		
Local Chain (1,0)			0.033	
			(0.040)	
National Chain (1,0)			0.049	
			(0.042)	
Unit				0.005***
				(0.001)
Average review star	0.009	0.009	0.009	0.020
	(0.019)	(0.020)	(0.022)	(0.019)
Price	0.032	0.030	0.030	0.011
	(0.021)	(0.022)	(0.023)	(0.022)
Store size	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of competitors within 1km	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
% of nearby restaurants on incumbent platforms	0.012	0.024	0.005	0.044
	(0.181)	(0.178)	(0.184)	(0.166)
Industry FE	YES	YES	YES	YES
Zip-code FE	YES	YES	YES	YES
Constant	0.247***	0.364***	0.558	0.802
	(0.084)	(0.113)	(0.796)	(0.741)
Observations	2,024	2,024	2,024	2,024
R-squared	0.094	0.092	0.095	0.114

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 6 (continued) Robustness checks for H1-H3

DV=Join (DD)	Alternative measures for H3	
	(5)	(6)
Existing relationships with incumbent platforms (1,0) (BH)	4.642**	5.132**
	(2.110)	(2.162)
Existing relationships with incumbent platforms * Capacity constraint (H1)	-0.964*	-1.200**
	(0.533)	(0.542)
Existing relationships with incumbent platforms * Chain (H2)	-0.171***	-0.120**
	(0.052)	(0.044)
Existing relationships with incumbent platforms * Average review star (H3)	-0.132***	
	(0.034)	
Existing relationships with incumbent platforms * Total number of Yelp reviews (H3)		-0.000**
		(0.000)
Capacity constraint	-0.165	-0.072
	(0.231)	(0.193)
Chain (1,0)	0.047	0.028
	(0.030)	(0.028)
Average review star	0.021	
	(0.018)	
Total number of Yelp reviews		-0.000
		(0.000)
Price	0.034	0.034
	(0.025)	(0.022)
Store size	-0.000***	-0.000***
	(0.000)	(0.000)
Number of competitors within 1km	0.000	0.000
	(0.000)	(0.000)
% of nearby restaurants on incumbent platforms	-0.057	-0.007
	(0.196)	(0.182)
Industry FE	YES	YES
Zip-code FE	YES	YES
Constant	0.909	0.608
	(0.927)	(0.789)
Observations	1,797	2,024
R-squared	0.098	0.092

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 7 Alternative Mechanisms

DV=Join (DD)	Uncertainty Mitigation		Ghost posting
	(1)	(2)	(3)
Existing relationships with incumbent platforms (1,0) (BH)	6.025***	6.142**	6.265***
	(2.000)	(2.583)	(1.687)
Existing relationships with incumbent platforms * Capacity constraint (H1)	-1.326**	-1.313*	-1.385***
	(0.508)	(0.655)	(0.431)
Existing relationships with incumbent platforms * Chain (H2)	-0.165***	-0.246***	-0.179***
	(0.052)	(0.066)	(0.054)
Existing relationships with incumbent platforms * Average review star (H3)	-0.114***	-0.148***	-0.111***
	(0.038)	(0.051)	(0.039)
Capacity constraint	-0.085	-0.254	-0.007
	(0.195)	(0.197)	(0.185)
Chain (1,0)	0.047	0.055	0.020
	(0.030)	(0.047)	(0.037)
Average review star	0.007	0.031	0.004
	(0.019)	(0.028)	(0.020)
Price	0.022	-0.008	0.021
	(0.021)	(0.034)	(0.022)
Store size	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)
Number of competitors within 1km	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
% of nearby restaurants on incumbent platforms	0.008	-0.061	0.007
	(0.188)	(0.177)	(0.209)
Industry FE	YES	YES	YES
Zip-code FE	YES	YES	YES
Constant	0.659	1.253	0.244
	(0.808)	(0.784)	(0.760)
Observations	1,948	1,040	1,626
R-squared	0.100	0.109	0.124

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 8 Mechanism tests for BH

DV=Join (DD)	Existing relationships with incumbent platforms=1	
	HHI by Zip-code	HHI by NAICS code
	(1)	(2)
HHI	0.776	0.345**
	(0.584)	(0.162)
Capacity constraint	-1.635***	-1.476***
	(0.583)	(0.498)
Chain (1,0)	-0.172***	-0.192***
	(0.048)	(0.051)
Average review star	-0.140***	-0.116***
	(0.038)	(0.034)
Price	0.009	0.015
	(0.038)	(0.037)
Store size	-0.000	-0.000
	(0.000)	(0.000)
Number of competitors within 1km	-0.000	0.000
	(0.000)	(0.000)
% of nearby restaurants on incumbent platforms	-0.075	-0.073
	(0.204)	(0.230)
Industry FE	YES	NO
Zip-code FE	NO	YES
Constant	7.452***	6.820***
	(2.300)	(1.968)
Observations	600	600
R-squared	0.064	0.102

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 9 Sensitivity Analysis Using Oster's Method

			Estimates of Oster's δ	
Specification	Variable	R_M	$R_{max} = R_M$	$R_{max} = 1.3 * R_M$
Table 3: Model 3	*Existing relationships with incumbent platforms*	0.085	8.05	5.35

NOTES: Results obtained from using methodology developed by Oster (2019). Following the suggestions, R_{max} is calculated as (1) R_M, the R-squared for my estimated model, and (2) $1.3 * R_M$. Larger values of δ means that unobservable variables are relatively less important than observed (i.e., included control) variables in explaining variation in the outcome.

FIGURE 1 Summary of the availability of scraped data

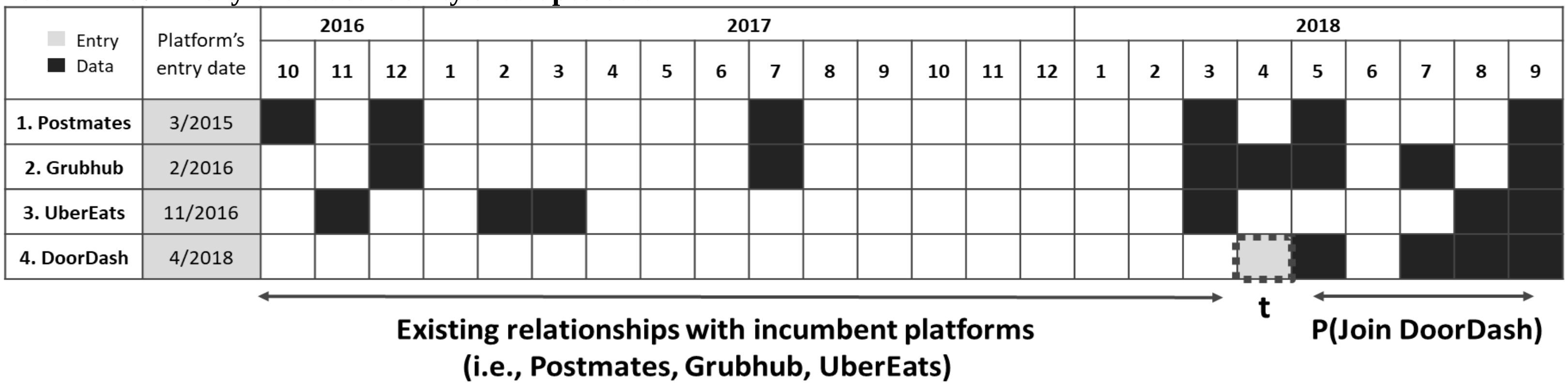

FIGURE 2 Interaction effects based on predicted values from the linear models