

The legitimation of digital platforms across different markets in the Netherlands



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ABSTRACT

Digital platforms such as Uber, Deliveroo and Airbnb are part and parcel of present times. Previous studies mention how digital platforms transcend market boundaries, making them 'market-agnostic'. Practice has shown how digital platforms often disrupt the markets that they enter, thereby formulating new rules of the game. This forms a discrepancy with what is proclaimed in institutional theory, that is, an organization needs to conform to its institutional environment to be perceived as legitimate. While existing literature is often concerned with studying the legitimation of platforms through case studies that take place in a single market, how the legitimation of digital platforms is affected on a macro-level has hitherto remained unexplored. Hence, this study addresses the current gap in the literature by examining how digital platforms leverage legitimacy spillovers from markets. More formally, the study asks: *to what extent does the market entry of a digital platform in the Netherlands depend on external legitimacy spillovers?* In defining external legitimacy spillovers, the theoretical perspectives of institutional theory and organizational ecology are synthesized in the form of the density dependence model. This study specifically extends the basic density dependence model by taking the markets where the platforms are active in as unit of analysis. In the model, the density of platforms in a market is used as a proxy for legitimacy spillovers and competition. The model is applied in the form of logistic regression analyses on two samples during the period of 2010 to 2020: the population of gig platforms and the population of sharing platforms in the Netherlands. The results prove that digital platforms benefit from legitimacy spillovers by other platforms in the same market on the short term, while concomitantly being negatively affected by spillover effects from other markets. However, as local competition between platforms becomes more intense, subsequent market entry also becomes dependent on legitimacy spillovers from platforms in other markets. This study suggests that the latter effect is induced by platforms that engage in institutional transposition, which denotes the process in which the status and experience garnered in one market is converted to another dimension. These results are integrated into a proposed visual model that illustrates the relationship between digital platforms and spillover effects within and between markets. In doing so, this study marks the beginning of uncovering how digital platforms can leverage legitimacy spillovers from markets through transposition.

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1. INTRODUCTION

The age of digitization engenders the spawn of an increasing number of digital platforms, from food delivery services to car sharing. Such digital platforms entail peer-to-peer technology, thereby “bringing the romance of entrepreneurialism to the masses” (Ravenelle, 2017, p. 281). In general, digital platforms can be defined as infrastructures that accommodate social and economic interactions online (Kenney & Zysman, 2016). As digital platforms become increasingly embedded in society, they are slowly finding their way into the innovation studies literature. Scholars are often concerned with the rapid and extensive diffusion of platforms across markets, and thereby point toward the idiosyncratic nature of digital platforms. To elaborate, as digital platforms are essentially a form of digital innovation, their underlying digital technology can easily be (re)combined with digital data from heterogeneous sources to form novel products or services (Kallinikos et al., 2013; Yoo et al., 2010). Correspondingly, digital platforms can transcend market boundaries by changing either the scope of the platform in terms of activities, the configuration of the platform in terms of user access, or the digital interfaces that specify the bilateral exchange of data (Gawer, 2021). Put simply, digital platforms can be labelled as “market-agnostic” (Antonopoulou et al., 2016; Yoo et al., 2010).

From this market-agnostic characteristic follows how digital innovations can enter markets with relative ease. This poses a specifically interesting discrepancy when reasoning from institutional theory. Particularly, institutional theory has long proclaimed how each market is constituted by its institutions, such as laws, regulations, cultural norms, social rules and technical standards (Edquist, 1997). For instance, Meyer & Rowan (1977) formulated how the modernization of society eventuates into rationalized institutional structures across market domains. In a similar vein, early innovation studies claim that each market is institutionally supported in different ways and that these differences in institutional arrangements subsequently affect innovation (Edquist & Johnson, 1998). In other words, institutional theorists suggest that the legitimacy of any form of innovation, be it organizational, technological, or digital, is likely to be affected by the extent of variety across institutional environments over multiple markets, rendering it difficult for an innovation to spread across multiple markets.

Regardless, contemporary platforms are known for heavily influencing traditional markets. Digital platforms often transform or disrupt the institutional environment of the respective markets they enter, formulating new rules of the game (Hinings et al., 2018; Skog et al., 2018). To specify, while digital platforms quite often signify a stark deviation from established norms, beliefs, and regulations (Edelman & Geradin, 2016; Pelzer et al., 2019), they tend to become accepted as legitimate through their popularity among users (Frenken & Schor, 2017). As a result, the taken-for-granted activities of digital platforms affect actors, structures, practices, and institutions on an industry or market level (Skog et al., 2018), potentially culminating in the creation of new organizational forms and business models (Hinings et al., 2018). The rapid growth of platforms and their simultaneous impact on markets makes it interesting to scrutinize how digital platforms build legitimacy.

Numerous scholars have elaborated on how an organization gains legitimacy. They all mention that an organization needs to conform to both the values and demands of stakeholders, as well as to common ethical ideals (Aldrich & Fiol, 1994; Scott, 1995; Suchman, 1995). To put this into perspective, a digital platform would need to conform to existing institutions to obtain endorsement. There is a small body of literature that aims to elucidate this discrepancy in how digital platforms attain legitimacy. For example, Aversa et al. (2021) investigated how both Uber and BlaBlaCar pursued two distinct strategies in an attempt to acquire legitimacy. Comparably, Pelzer et al. (2019) scrutinized the

strategies that Uber deployed for changing the Dutch taxi regulations in their favour to roll out their platform service called UberPOP, and how this eventuated in failure.

While such studies offer a comprehensive explanation as to why the platform under study has gained legitimacy (or not), they tend to focus on cases that take place in one market. Consequently, the generalization of the findings of these studies to other markets and sectors is limited. Again, each market is constituted by its institutional composition. Hence the extent to which digital platforms disrupt existing institutional arrangements probably differs per market (Hinings et al., 2018; Skog et al., 2018). In addition, as digital platforms are stipulated as market-agnostic, the disruption or transformation of a market by a digital platform is subject to macro-level interactions between markets, platforms, and a multitude of stakeholders with diverse roles (Boon et al., 2019). As such, a more macro-level perspective is warranted to assimilate how the legitimation of digital platforms is affected by these macro-level interactions. More specifically, it is interesting to uncover the effect of legitimacy spillovers generated by these macro-level interactions, and how this impacts the market entries of digital platforms. This culminates in the following research question that remains to be answered:

To what extent does the market entry of a digital platform in the Netherlands depend on external legitimacy spillovers?

Assorted studies already hint at how platforms rely on legitimacy spillovers when entering new markets, industries, or regions. For example, Punt, van Kollem, et al. (2021) show that platform companies can leverage their existing internationally mobile customers as advocates of the new service through word-of-mouth recommendation, thus acting as carriers of legitimacy. By the same token, Stallkamp & Schotter (2021) assert that digital platforms with network externalities that transcend national borders can leverage their existing global user base to break into local markets.

These studies emphasize the effects of internal legitimacy spillovers generated by the platform company itself when diversifying into other regions or countries. However, organizations can also benefit from external legitimacy spillovers generated by other organizations in the same market (Bigelow et al., 1997; Kuilman & Li, 2009; Soublière & Gehman, 2020). How digital platforms are dependent on external legitimacy spillovers is particularly interesting, since they are market-agnostic and are therefore expected to be able to leverage external legitimacy spillovers also from other markets than the ones they are active in. Moreover, the relationship between the legitimation of digital platforms and these external legitimacy spillovers has hitherto remained unexplored. As such, answering the research question would address this gap in the literature. In doing so, this study centres specifically on gig economy and sharing economy platforms in the Netherlands as a focus is required to approach the research question.

This study also contributes to the understanding of how platform entrepreneurs can benefit from the endeavours of other platforms, by scrutinizing the relationship between external legitimacy spillovers and market entry. The overall thesis of this study is that platforms need to leverage external legitimacy spillovers to attain legitimacy. The findings illustrate how the legitimation of a digital platform is affected by both local legitimacy spillovers from platforms in the same market, and spillover effects from platforms in other markets. It is also shown how these relationships shift over time. This knowledge may be of relevance for platform entrepreneurs in determining the most optimal time for market entry.

The findings of the study are also of relevance for policymakers. Digital platforms are often in transgression with regulation and public interests (Frenken, van Waes, et al., 2020; Schor, 2020), and more recent studies show how they can also engender negative externalities such as higher house prices (van Haaren et al., 2021). Hence learning how to

effectively implement policy that targets digital platforms, when necessary, seems to be essential for policymakers. The findings of this study enucleate on the relationship between institutional changes and the legitimation of digital platforms, thus providing valuable knowledge to be considered by policymakers.

The rest of the thesis is structured as follows. Chapter 2 summarizes the theory on institutions, legitimacy, and legitimacy spillovers, which is followed by a conceptual definition of the gig and sharing economy. The section concludes by formulating several hypotheses regarding external legitimacy spillovers and the market entry of a digital platform. Subsequently, the employed methodology is outlined in chapter 3. The results of the study are presented in chapter 4, followed by a conclusion based on the findings in chapter 5. Finally, the findings are discussed in terms of implications in chapter 6. This section also includes a proposed model that illustrated the dependency of digital platforms on legitimacy spillovers.

2. THEORY

2.1. Institutions

During the 1980s, the conundrums surrounding the linear model of innovation led scholars to re-examine the factors that shape innovation (Schot & Steinmueller, 2018). A broad consensus emerged about the relationship between innovation and institutions; innovations are shaped by institutions, whereas innovations in turn can instigate institutional change (Vermeulen & Raab, 2007). Organizations, infrastructure, institutions and their correlated interactions, all need to function together as a conducive environment for the generation and diffusion of innovation (Edquist, 1997). Prevailing innovation studies suggest how the different configurations of so-called 'innovation systems' in terms of institutional setup are reasons for differential developmental patterns across countries, regions, industries and markets (Freeman, 1995; Lundvall, 2007).

These institutional compositions arise as a product of historical accidents, also known as random occurrences in the past under certain circumstances (Arthur, 1989). As institutions evolve, they become increasingly embedded within markets and technologies, driven by increasing returns and forming a self-sustaining force that is inert to change (Unruh, 2000). Be that as it may, institutions can change through the birth of new institutions, the dissolution of existing institutions, or the replacement of existing institutions (Rao et al., 2003). Institutional change is a process of social construction (Rao et al., 2003), which is often initiated by innovation. In general, institutional change is formed by collective action, comprising political strategies to deal with the dialectic challenges and conflict that it spawns (Hargrave & Van De Ven, 2006). The relationship between conflict, power, and political behaviours and institutions is reciprocal; conflict, power, and politics drive institutional change, while institutions set the frame for conflict, power, and politics (Hargrave & Van De Ven, 2006). Such a reciprocal relationship between agency and institutions indicates the complexity of institutional change.

This "paradox of embedded agency" (Battilana et al., 2009, p. 67) also highlights how institutional change instigated by digital platforms is inherently complex. On the one hand, the introduction of a digital platform often involves the disruption or transformation of the institutional compositions of the respective markets they enter (Hinings et al., 2018; Skog et al., 2018). On the other hand, a digital platform is expected to conform to the institutional setting of the market they are in to gain endorsement (Frenken, Vaskelainen, et al., 2020). This contradiction makes it difficult to assimilate how platforms obtain legitimacy.

2.2. Legitimacy

The concepts of legitimacy and institutions are virtually synonymous in prevailing literature (Suchman, 1995). However, institutions are often labelled as legitimated conventions (Johnson et al., 2006). This paper follows Suchman (1995) in the following definition of legitimacy:

“Legitimacy is a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs and definitions” (Suchman, 1995, p. 574).

Legitimacy is often treated as a dichotomous outcome, that is, organizations are legitimate, or they are not. Rather, legitimacy has both continuous and dichotomous properties (Soublière & Gehman, 2020). Legitimacy is continuous since the magnitude of social endorsement can differ (Aldrich & Fiol, 1994; Soublière & Gehman, 2020). Legitimacy is also dichotomous as there is a threshold of endorsement where an organization has garnered enough legitimacy to survive (Soublière & Gehman, 2020). The extent to which a social object can garner legitimacy depends on both the cognitive dimension of legitimacy that frames the social object as a valid social feature and the normative (socio-political) dimension that depicts the social object as (ethically) right (Aldrich & Fiol, 1994; Deephouse & Suchman, 2012; Suchman, 1995).

Tradition institutional theory suggests that organizations are driven to adopt practices or routines to achieve increased legitimacy in an attempt to improve their survival prospects (Meyer & Rowan, 1977). In doing so, organizations become increasingly homogeneous in terms of their formal structures, driven by institutional isomorphic change (DiMaggio & Powell, 1983; Meyer & Rowan, 1977). However, the legitimation of organizations in emerging markets is different vis-à-vis organizations in established markets (Aldrich & Fiol, 1994; Maguire et al., 2004). Similarly, the legitimation of a digital platform deviates from how other organizations and innovations gain legitimacy in markets, owing to the idiosyncratic nature of digital platforms. Building legitimacy in emerging markets is a form of *institutional bricolage*, denoting a process by which actors and organizations intentionally and unintentionally leverage existing social and cultural arrangements to alter institutions in response to changing situations (e.g., practices, routines, values) (Garud & Karnøe, 2003; Maguire et al., 2004). Thereby, so-called institutional entrepreneurs tend to bridge and translate the interests of diverse stakeholders in an attempt to gain legitimacy (Maguire et al., 2004).

The legitimation process of digital platforms is postulated to be similar to that of emerging markets, in the sense that digital platforms do not only disrupt traditional markets by advancing innovative solutions, but they also use cognitive strategies to exploit existing institutions in an attempt to resonate with a heterogeneous set of stakeholders (Aversa et al., 2021). Put differently, the legitimization strategies of digital platforms involve discursively aligning novel practices to existing institutions and stakeholder values, thereby ‘borrowing’ the legitimacy from matured markets. This phenomenon is conceptually referred to as *transposition* and denotes the process in which the status and experience garnered in one market or industry is converted to another dimension (Boxenbaum & Battilana, 2005; Powell et al., 2012). An example of transposition by a digital platform is mentioned in Aversa et al. (2021), where a platform called BlaBlaCar was able to transpose and harness the status of the sharing economy, consequently being associated with positive externalities such as traffic reduction and pollution. As digital platforms are market-agnostic, it is expected that they are particularly able to purposefully leverage *legitimacy spillovers* through transposition, eventually providing legitimacy spillovers for ensuing platforms.

2.3. Legitimacy spillovers

Legitimacy spillovers are often discussed in terms of geographical spillovers, as highlighted by studies from both institutional theory and organizational ecology strands (Bigelow et al., 1997; Haveman & David, 2008; Kostova & Zaheer, 1999; Punt, Bauwens, et al., 2021; Wenting & Frenken, 2011). The general postulation concerning geographical spillovers is that organizations can leverage institutional capabilities present in nearby districts, regions, or countries, e.g., through labour mobility of personnel. In effect, organizations benefit in terms of legitimation due to geographical proximity to other organizations (Bigelow et al., 1997; Boschma, 2005; Hannan et al., 1995).

In addition to geographical spillovers, digital platforms are expected to also benefit from market spillovers. This study refers to market spillovers as the phenomena in which an organization can transpose legitimacy from markets other than the one they are active in. Again, the recombinational nature of digital platforms renders them market-agnostic (Antonopoulou et al., 2016; Yoo et al., 2010), consequently enabling them to transcend market boundaries. Digital platforms, and other digital innovations, are therefore idiosyncratic in terms of being able to leverage legitimacy spillovers from other markets. This unique characteristic of digital innovations makes it especially interesting to uncover the exact relationship between market spillovers and the legitimation of digital platforms.

A conceptual distinction should be made regarding how this study treats external legitimacy spillovers. External legitimacy spillovers can occur in two ways: digital platforms can either leverage spillovers present in the same market, or they can transpose the legitimacy from organizations in other markets. Indeed, digital platforms can also benefit from internal legitimacy spillovers when diversifying to other regions. In this case, the spillovers are engendered by the overarching or multinational entity of the focal platform (Kostova & Zaheer, 1999; Punt, van Kollem, et al., 2021; Stallkamp & Schotter, 2021). Despite the possible effects of both geographical spillovers and internal spillovers on the legitimation of digital platforms, emphasis is placed on external legitimacy spillovers in this study, as these have hitherto remained understudied on a more macro level.

However, measuring legitimacy spillovers can prove to be difficult, especially when studying them on a macro level. Hence, a theoretical perspective is warranted to make sense of legitimacy spillovers. The most common theoretical perspectives to study legitimacy are institutional theory and organizational ecology. While institutional theory offers a more comprehensive definition of legitimacy and how to study this concept, it is less applicable for studying macro-level trends (Haveman & David, 2008). Therefore, this study utilizes theoretical models from organizational ecology while referring to institutional theory for conceptual definitions.

A theoretical model that is considered to be the synthesis of institutional and ecological ideas is the density dependence model (Singh & Lumsden, 1990). The model proposes that organizations' founding and failure rates in a given population depend on the number of organizations present in that population (Bigelow et al., 1997; Hannan et al., 1995). More specifically, the early range of increases in population density increases the population's legitimacy and helps improve the founding rate (Hannan & Freeman, 1977). The presumption here is that growth in numbers legitimates the organizational form itself, subsequently leading to decreasing failure rates (Singh & Lumsden, 1990). However, as the density continues to increase, competition starts to overwhelm legitimation as the driver of organizational survival rates (Haveman & David, 2008). Combined, the mutual effects of legitimation and competition suggest curvilinear effects of density on the founding and failure rates of organizations in a given population (Baum & Shipilov, 2006).

2.4. The sharing economy and the gig economy

A condition for the density dependence model is that the organizations in a defined population are of the same organizational form. That is because, the cognitive legitimation of a population of organizations accrues to an organizational form as it increases in numbers (Hannan & Freeman, 1987). While digital platforms are often treated as an umbrella concept (Gawer, 2021), regarding them as a single organizational form is specious. This is evidenced by how various scholars describe different types of digital platforms (Kenney & Zysman, 2016; Knee, 2021). Hence this study delineates two types of organizational forms of digital platforms: gig platforms and sharing platforms.

Frenken & Schor (2017) point out that there has been widespread conceptual ambiguity and confusion about the term 'sharing economy' and therefore propose a definition. This study follows these authors in defining the sharing economy, specifically in distinguishing between the sharing economy and the gig economy.

The sharing economy is defined as "consumers granting each other temporary access to under-utilised physical assets ('idle capacity'), possibly for money" (Frenken & Schor, 2017, p. 5). This definition is undergirded by three elements. First, transactions in the sharing economy are consumer-to-consumer or also known as 'peer-to-peer'. Second, the transactions only allow temporary access to an asset. And third, the sharing economy concerns the sharing of idle assets and not services. To illustrate, the usage of shared mobility vehicles that are owned by private companies does not fall under the sharing economy, since these transactions are not consumer-to-consumer. Neither does the sale of second-hand products, as this gives the buyer permanent access to the asset.

The gig economy concerns the provision of services between consumers rather than providing access to goods. In other words, transactions in the gig economy involve doing actual labour instead of sharing 'idle capacity'. As an example, ride-sharing platforms fall under the sharing economy because idle capacity is involved, i.e., the trip will be made regardless. Whereas peer-to-peer ride-hailing platforms belong to the gig economy as labour is required to offer the taxi service, meaning that the trip would not be made if the ride were not ordered.

A digital platform that conforms to the three elements of the sharing economy can therefore be labelled as a sharing platform. Similarly, a digital platform is considered to be part of the gig economy when they match the supply and demand for (paid) labour (Florisson & Mandl, 2018; Wood et al., 2019). This labour is based on the performance of individual tasks or projects rather than a permanent employment relationship (Florisson & Mandl, 2018; Friedman, 2014). The type of labour that is transacted via gig platforms consists both of work delivered offline, meaning that the worker needs to be physically present, and work that is delivered online (Huws et al., 2016).

Following this conceptual delineation, the remainder of the study discerns between gig platforms and sharing platforms. Consequently, hypotheses are formulated and tested for both types of digital platforms separately.

2.5. Hypotheses

Several hypotheses can be formulated following the theory outlined above. These are illustrated in the theoretical model in **Figure 1**. The density dependence model suggests that the entry of new platforms when the overall number of platforms operating in a market is low can increase the legitimacy of that market (Bigelow et al., 1997; Hannan et al., 1995). Nevertheless, the more platforms that enter a given market, the more intense the competition becomes in that market. However, as the overall number of gig economy platforms in the Netherlands is still relatively small, it is expected that legitimation currently overwhelms competition as the main driver of the platform survival rates.

Correspondingly, ensuing digital platforms can leverage the legitimacy spillovers in the pre-existing market which are generated by the successful endeavours of their predecessors (Soublière & Gehman, 2020). Conversely, the potential failure of predecessors negatively affects the legitimacy spillovers in that market. Altogether, the first hypothesis is phrased as follows:

H1a: The market entry of a gig platform is positively related to the number of platforms present in the same market.

H1b: The market entry of a sharing platform is positively related to the number of platforms present in the same market.

As previously stated, transposition refers to converting the status and experiences that are garnered in one market to another domain (Battilana et al., 2009; Powell et al., 2012). It is expected that digital platforms are particularly able to transpose the legitimacy from platforms in other markets, owing to their market-agnostic characteristic, which allows them to transcend market boundaries. Moreover, as the total number of digital platforms increases, so do the successful past experiences with platforms (Rossman, 2014). Simply put, the legitimation of the general concept of what a digital platform entails provides legitimacy spillovers for other platforms, no matter what market they are in. As such, the second hypothesis is formulated as:

H2a: The market entry of a gig platform is positively related to the total number of platforms in all other markets.

H2b: The market entry of a sharing platform is positively related to the total number of platforms in all other markets.

Like any other organizational form, platforms can more easily emerge when they benefit from the legitimacy spillovers of related institutional settings in other markets (Carvalho & Vale, 2018; Punt, Bauwens, et al., 2021). To explain, a platform is more likely to leverage legitimacy spillovers from platforms that operate under similar institutional settings, owing to their relational proximity (Boschma, 2005; Carvalho & Vale, 2018). By transposing resources from related markets across industries, platforms can piggyback on the legitimacy of platforms in related markets. Hence, the third hypothesis is as follows:

H3a: The market entry of a gig platform is positively related to the total number of platforms in related markets.

H3b: The market entry of a sharing platform is positively related to the total number of platforms in related markets.

The final proposition relates to changes in pressure from the institutional environment, which are referred to as '*institutional shocks*' here. These institutional shocks can be described as unforeseen changes in the institutional landscape, such as the implementation of new legislation. Organizational ecologists acknowledge that institutional shocks may alter the dynamics between density and vital rates (Singh & Lumsden, 1990), thereby suggesting that changes in the institutional environment have a stronger effect on an organization's legitimation than legitimacy spillovers. Unexpected changes in the legal environment are listed as one of the most frequent causes of the failure of platforms in the gig and sharing economy (Täuscher & Kietzmann, 2017). Yet, these platforms are known for their ability to capitalize on legal loopholes, which is also described as '*regulatory arbitrage*' (Schor, 2020, p. 155). This discrepancy makes it interesting to uncover the relationship between the market entry of digital platforms and institutional shocks. In general, the following hypothesis can be formulated:

H4a: The market entry of a gig platform is (negatively) / positively related to (unfavourable) / favourable institutional shocks.

H4b: The market entry of a sharing platform is (negatively) / positively related to (unfavourable) / favourable institutional shocks.

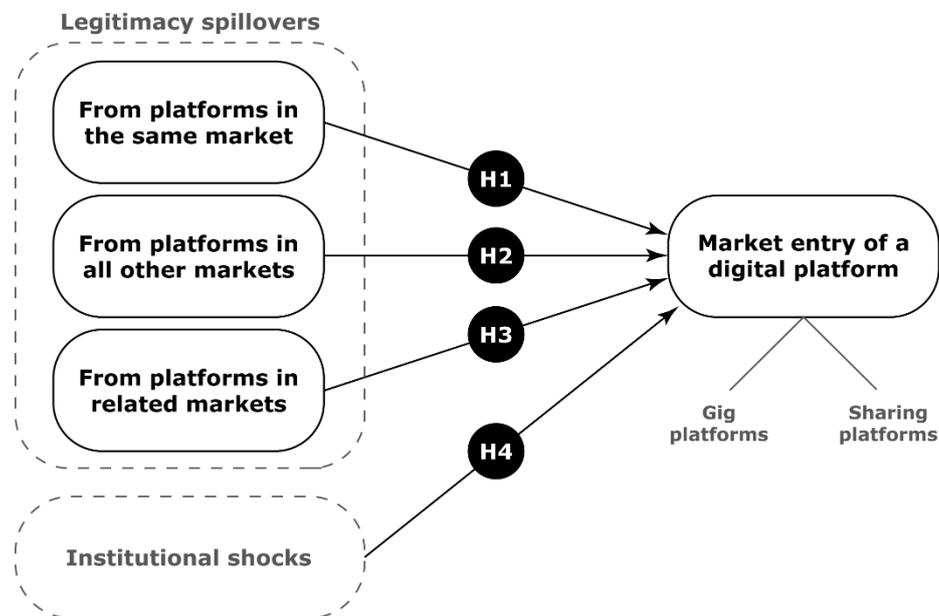


Figure 1. Theoretical model.

3. METHOD

3.1. Research design

The study aims to uncover the relationship between the market entries of digital platforms and legitimacy spillovers. In doing so, a macro perspective is employed to analyse the diffusion of platforms across markets over time. In particular, the study aspires to ascertain the causality between market entry and density, i.e., the number of platforms present in a market at a given point in time. Therefore, a quantitative and longitudinal research design appears to be the most appropriate. To account for the effects of legitimation and competition on the market entry of digital platforms, the density-dependent model from organizational ecology is employed. A comprehensive explanation of how the density dependence model is operationalized is given in section 3.3. The analysis is based on statistical research of secondary data, with a particular focus on quarterly data during the 11 years between 2010 and 2020. This period appears to be the most appropriate, since most initiatives in the gig and sharing economy started to emerge at the beginning of the 2010s (de Waal & Arets, 2022). The number of gig and sharing platforms has also grown tremendously during this timeframe. To study the complete population of the gig and sharing platforms during this period, both active platforms and dissolved platforms are included in the ecological model. By dissolved platforms, this study refers to the platforms that were dissolved at a given point in time during the selected timeframe, while being active until that point. How data is collected and subsequently analysed is further specified in the remainder of the methodology chapter.

3.2. Data and sampling

In testing the hypotheses on the market entry of digital platforms, this study distinguishes between platforms from the gig and sharing economy. Correspondingly, two samples were

constructed: a sample of the total population of gig platforms in the Netherlands and a sample of the total population of sharing platforms in the Netherlands.

3.2.1. *Sample of gig platforms*

The total population of gig platforms in the Netherlands consists of 197 platforms, of which forty platforms are dissolved. This sample was derived from several pre-existing databases. Each database and the way it contributes to the sample of gig platforms will be described briefly. First, the Dutch website platformwerk.nl offers a free and up-to-date database that contains data on 87 gig platforms that are active in the Netherlands (Platformwerk, n.d.). This data consists of basic information, such as date of registration, revenue model, legal form, and location of the gig service (online, offline or both). Second, in a report by CEPS on digital labour platforms in the EU27 countries, a total of 516 active (as of March 2021) digital labour platforms were identified (European Commission, 2021b). However, the report only provides a list of platform names of the 516 platforms. Hence each platform was briefly scrutinized based on their corresponding official websites to determine whether these platforms could be classified as gig or sharing platforms following this study's delineation between the gig and sharing economy (see Section 2.4). Concomitantly, it was also verified whether the platform is or has been active in the Netherlands. Finally, a list of 125 platform names that were used for a study on the Dutch 'platform economy' (SER, 2020) was provided on request.

To ensure the completeness of the sample, the list of platform names from all databases was complemented through additional data collection. This data was collected through academic literature, news articles, and even online advertisements. A more comprehensive description of how this data was collected is given in **Table 1**.

3.2.2. *Sample of sharing platforms*

The total population of sharing platforms in the Netherlands comprises 138 platforms, of which fifty are dissolved. Also here, the sample was derived from existing databases and complemented with additional data collection. The sample of sharing platforms is largely based on the database from deeleconomiein nederland.nl, which offers data on 218 platforms that supposedly are active in the Netherlands (Deeleconomiein nederland.nl, n.d.). Each platform was briefly scrutinized whether it could be classified as either a gig or sharing platform and if they were still active in the Netherlands. However, as this database was less up-to-date in comparison with the databases on gig platforms, more emphasis was placed on the additional data collection through academic literature and news articles. How this data was collected is summarized in **Table 1**.

3.3. *Ecological model*

The density dependence model from organizational ecology explains how initial increases in population density can increase the legitimacy of that population of organizations, thereby having a positive effect on the founding rate (Baum & Shipilov, 2006; Hannan et al., 1995). However, as the population of organizations continues to grow, resources become scarcer and the nature of interdependence of the population becomes competitive, driving down founding rates. Both effects are integrated into the expression of the founding rate as follows (Bigelow et al., 1997):

$$\lambda(t) = \exp(\beta_0 + \beta_1 N_t + \beta_2 N_t^2)$$

With $\lambda(t)$ as the market entry rate per time interval (here, quarters), N_t as the population density at time t (here, the number of digital platforms already present), β_1 as the expected positive legitimation effect, and β_2 as the expected negative competition effect.

Table 1. Data collection of Dutch platform names.

Source	Summary	Search engine	Search key terms
Academic literature	<p>All articles on the first ten pages are checked. Only academic sources that mention the “Netherlands” or “Dutch” are opened. The documents are then briefly scrutinized if they refer to online gig economy platforms in the Netherlands.</p> <p>A total of nineteen academic sources were gathered that have conducted studies on gig economy platforms in the Netherlands. All the platform companies that are mentioned in these studies are listed. Through cross-references, an additional amount of seventeen documents were found. These seventeen documents range from academic literature to grey literature to news articles.</p>	Google Scholar	<p>Online platforms AND the Netherlands OR Dutch AND gig economy; Dutch online platforms AND gig economy</p>
News articles	<p>A total of 757 articles on the Dutch gig economy were found during the 11 years between 2010 - 2020. Each article was scrutinized briefly, and new platform names were documented.</p> <p>The selected period for articles on the Dutch sharing economy was set between 2016 and 2020, as the comprehensive database on sharing platforms in the Netherlands by deeleconomiein nederland seemed up to date until 2016. A total of 1,701 were found. Only the first 1,000 articles with the highest relevance to the search term were subsequently scrutinized.</p>	Lexis Nexis	<p>Klusplatform OR deelplatform AND verboden OR failliet OR faillissement OR stopt; online platform AND verboden OR failliet OR stopt OR faillissement</p> <p>Deelplatform OR Deeleconomie</p>
Online advertisements	Additional platform names were found through online advertisements during the private use of various forms of social media (Instagram, Facebook, and YouTube).	Based on internet cookies	

Normally, the baseline ecological model is applied to a certain geographical context. That is, to study the differences between spatial levels in which the processes of legitimation and competition take place, and how this affects the founding (or mortality) rate (Bigelow et al., 1997; Hannan et al., 1995). However, this study places focus on the markets in which the platforms are active, thereby shifting the application of the density dependence model from regions to markets. Certainly, one might argue that such a change in the operationalization of the model may alter the dynamics between density and legitimation since legitimacy spillovers are often discussed in terms of geographical spillovers. Be that as it may, the central thesis of the density dependence model is that cognitive legitimacy is a collective good that is freely accessible to all organizations of the same organizational form within an industry (Amburgey & Rao, 1996), which inherently suggests that the model has no geographical constraints. Moreover, it was postulated in the theory section that digital platforms leverage legitimacy spillovers from markets. As such, the axiomatic formulation of the density dependence model remains the same, whether the model's unit of analysis is regions or markets.

To test the hypotheses, some extensions to the baseline ecological model are made. Legitimacy spillovers within markets are operationalized through density at the 'local' level, which is the number of platforms active in a market. Density at the 'global' level signifies legitimacy spillovers between a given market and all other markets. More specifically, global density is measured by the cumulative sum of market entries by platforms in all other markets. Indeed, this means that the global density is higher than the actual number of platforms. However, measuring global density in terms of the total amount of platforms neglects the fact that digital platforms are market-agnostic and therefore often active in multiple markets. Furthermore, the selected definition of global density allows the study to test the second hypothesis in terms of the total spread of platforms over markets, instead of merely the total number of platforms active nationally. Like the definition of global density, the densities of related markets are considered to account for legitimacy spillovers from related markets. The specific requirements for markets to be considered related are outlined in Section 3.4.1. As such, this study extends the basic ecological model based on Punt, Bauwens, et al. (2021) with separate models for gig and sharing platform markets:

$$\lambda_{gig}(t) = \exp(\beta_0 + \beta_1 n_{it} + \beta_2 n_{it}^2 + \beta_3 N_{it} + \beta_4 N_{it}^2 + \beta_5 \check{n}_{it} + \beta_6 \check{n}_{it}^2)$$

$$\lambda_{sharing}(t) = \exp(\beta_0 + \beta_1 n_{it} + \beta_2 n_{it}^2 + \beta_3 N_{it} + \beta_4 \check{n}_{it} + \beta_5 \check{n}_{it}^2)$$

With the quarterly market entry rate of digital platforms for each market i as the dependent variable; with n_{it} as the density of market i in quarter t as the independent variable for the first hypothesis; N_{it} is the density of all markets in quarter t as the independent variable for the second hypothesis; \check{n}_{it} is the sum of densities of markets related to market i in quarter t as the independent variable for the third hypothesis.

The gig model includes a legitimation and competition effect at every level. While gig platforms do not compete directly with each other at the global or related level, they may do so in terms of acquiring labour capital. Notwithstanding, gig workers are not constrained to deliver work through a single platform nor in a single market. For example, an Uber driver can also deliver meals through Deliveroo and give tutoring lessons on Udemy. Schor (2020) finds that gig workers tend to make use of a variety of different platforms. A competition effect at the global level is included as it is conjectured that gig platforms eventually engage in competition for users. Thus, excluding the squared term would lead to the erroneous assumption that the effect induced by global density is monotonic.

The sharing model does not include a competition effect on the global level, since sharing platforms neither compete directly nor indirectly via labour capital on a global level.

However, a competition effect between related markets is expected in the sharing model, as the sharing of one good may diminish the need for another. For example, markets for car sharing are likely to compete with markets for the sharing of bicycles to some extent, as they both offer mobility solutions.

3.3.1. Institutional shocks

To test the fourth hypothesis, important institutional shocks that occurred during the observed period are added to the gig and sharing models. Three events for both the gig and sharing platforms are included, as these events can be regarded as the most signifying institutional shocks of the last decade. The first institutional shock for gig platforms is the prohibition of UberPOP in the Netherlands. UberPOP is an additional ride-hailing service offered by Uber, which allows unlicensed chauffeurs to connect with passengers to provide taxi trips. The company's aggressive rollout of this new service precluded a societal debate to discuss the legitimacy of UberPOP on cognitive and moral grounds, which prevented Uber from entering serious negotiations with the Ministry of Infrastructure and the Environment (Pelzer et al., 2019). Correspondingly, the UberPOP service was ruled forbidden by a court decision at the end of 2014 (NOS, 2014). While being in transgression with the current legal framework, Uber continued their UberPOP service until the company decided to bring it to a halt on November 20th in 2015 (Uber, 2015). The misconduct surrounding UberPOP could have instigated a 'stigma effect' for other gig platforms. That is, accusations against a platform generate negative consequences for non-accused platforms (Naumovska & Lavie, 2021). This stigma effect could make it more difficult for a platform to garner legitimacy, thereby acting as a barrier to market entry. As such, the official dissolution date of the UberPOP service is included as a dummy variable.

The second institutional shock for gig platforms is the implementation of the Balanced Labour Market Act (Wet Arbeidsmarkt in Balans in Dutch) (WAB). As of January 1st, 2020, rules regarding employment contracts and dismissal have changed. More specifically, employers are stimulated to offer permanent service contracts more frequently by paying lower unemployment insurance premiums for employees with a permanent contract. In addition, the WAB deemed the working conditions and legal position of temporary or gig workers as at least equal to contracted employees (Wet Arbeidsmarkt in Balans, 2020). By instigating better working conditions for gig workers, the WAB is likely to affect the population of gig platforms. The start of the WAB policy is therefore included as a dummy variable in the gig model.

The first and second institutional shocks for sharing platforms are the restrictions of the Airbnb rental term in Amsterdam. Since the start of 2017, the maximum rental term of short-stay apartments and B&B's via Airbnb in Amsterdam was reduced to 60 days following numerous complaints of nuisance caused by tourists (Kraniotis, 2017). Later on and in response to an increasing amount of societal and political pressure, the municipality of Amsterdam decided to decrease the maximum rental term to 30 days as of 2019 (Couzy, 2018). Following the argument of a stigma effect, these restrictions are likely to have affected the entire population of sharing platforms. Other home-sharing platforms received similar restrictions later on, such as the restrictions for the rental of short-stay apartments through Booking.com in 2018 (NOS, 2017). The dates when the restrictions were set in motion are included as a dummy variable.

The final institutional shock that affected both platform populations is the first COVID-19 lockdown period. The global COVID-19 pandemic effectuated an 'intelligent' lockdown as of March 23th 2020 (Rijksoverheid, 2020), which significantly limited economic activities. Most economic activities resumed in June 2020 when the first lockdown was lifted, only to be prohibited again by a new lockdown in October. Only the first lockdown period is included as a dummy variable since the last lockdown period started in the final quarter of the observations.

3.3.2. Control variables

Both models also include four control variables to control for alternative explanations of the findings and additionally increase the statistical power of the model (Becker, 2005). The first control variable is market size, characterized by the number of companies that are active in each market. Larger markets may signal a larger chance for fruitful endeavours for ensuing platforms. Conversely, larger markets generate stronger competition effects as resources become scarcer, forming a barrier to market entry. The quarterly market size data is retrieved from CBS data (CBS, 2022).

The second control variable controls for international legitimacy spillovers. The CBS reported that in 2020 more than half of the platform users in the Netherlands come from abroad (Klijs, 2021). This would suggest that a more aggregated definition of the 'global' level in the ecological model could be more appropriate. Therefore, the global density is aggregated to the European level in an additional control model, of which the density variable will be referred to as *European density*. In specific, European density is measured by the cumulative sum of market entries by platforms in all other markets in all the EU27 countries. Additional samples for all European (EU27) platforms were therefore constructed, excluding those platforms that are or have been active in the Netherlands. These samples consist of 386 gig platforms, of which fifty-eight are dissolved, and 161 sharing platforms, of which thirty-three are dissolved. An overview of the European gig and platform population is given in **Figure 9**. How this sample was constructed is explained in Appendix B – Data collection of European platforms. It should however be mentioned that the collection of market entry and market exit data for the European platforms was conducted less robustly since the emphasis was placed on the main samples.

The third control variable is constructed to account for unobserved heterogeneity between the markets. The operationalized ecological model implicitly assumes that all markets are homogeneous, that is, the relationship between the density variables and market entry should be the same in each market. However, in reality, some markets have higher barriers to market entry than others, owing to assorted reasons. In addition, some scholars suggest that the decreasing mortality rate caused by increasing density is the product of unobserved heterogeneity in and between populations instead of legitimation (Petersen & Koput, 1991). Hence the delineation between certain types of markets to control for unobserved heterogeneity between markets.

The categories for gig markets are based on the level of skill required to perform the markets' corresponding economic activities. Schor (2020) mentions how gig workers are often highly educated yet doing work that traditionally is done by people with lower education. Similarly, the results from the COLLEEM II survey show that European platform workers are on average higher educated than non-platform workers (Urzi Brancati et al., 2020). From this follows a striking discrepancy concerning the level of skill required for the modus operandi of markets in which gig platforms are active. The general postulation on the one hand is that barriers to market entry are proportional to the specialization of that market since specialized or skilled workers are a lot harder to acquire. On the other hand, the results from both studies show that platforms are supported by a high percentage of skilled workers in their user base, which may in turn decrease barriers to entry in specialized markets.

To control for this effect, markets are placed in either of the following three categories. These categories are based on the conceptualisation of digital labour by De Groen et al. (2016), who mention that gig platforms can be differentiated based on the worker skills required. The skill of labour in a market depends on the time required to acquire the skills necessary to perform a certain job (Farris & Bergfeld, 2022; ONS, n.d.). First, markets for unskilled labour, for which no education or experience is required. Examples of such markets include cleaning or social work. Second, markets for semi-skilled labour, where

certain abilities or training are required beforehand, but not advanced education or specialized skills. For instance, work that requires the need of certain types of driver's licenses can be classified as semi-skilled labour. And third, markets for skilled labour, which requires advanced education or specialized skills. An example of skilled labour is IT work, for which advanced knowledge on software and programming is often required. Each market is placed in one of these categories based on its economic activities. For instance, the market for legal services belongs to the 'skilled' category, since advanced education is involved, whereas the cleaning market belongs to the 'unskilled' category, as no specialized skills are involved. There are however certain cases where a market can be placed in multiple categories following this method. For instance, the delivery of goods can be placed in both unskilled and semi-skilled markets, since goods can either be delivered by bike or through truck transport, for which a driver's license is required. Regardless, there might always be cases in which the 'skill' required for work is questionable, e.g., when IT work only involves helping elderly people with how to access the internet. As such, the questionable cases will be handled by placing them in the category with higher skill (which means that the delivery of goods is categorized as 'semi-skilled'). An overview of the categories and their corresponding markets is provided in **Table 20** in Appendix A - Markets.

The sharing markets are placed in either of the following categories: Moveable property; Immoveable property; and Other. Markets that involve the sharing of moveable property (e.g., sharing of cars, photography equipment) are placed in the moveable property category. Markets that involve the sharing of immoveable property (e.g., home sharing, parking space sharing) are listed as immoveable property markets. All markets in the observations that belong to neither category (e.g., ride sharing, electricity sharing) are placed in the 'other' category. **Table 21** in Appendix A - Markets gives an overview of these categories and their corresponding markets.

The final control variable in the gig model is based on the proportion of gig platforms in each market with an online, or partly online, service type. Labour transacted via gig platforms with an online service type consists of work that is delivered online. This variable thereby measures the extent to which a certain market allows online labour. The conjecture here is that markets for online labour have lower barriers to market entry, given that online activities are easier to initiate. That is because the internet allows anybody to start online endeavours. How the data concerning a platform's service type is collected is described in section 3.3.3.

The final control variable in the sharing model is based on the proportion of sharing platforms in a certain market that take on the form of a non-profit body. Preliminary analysis of the sharing platform population indicates that the population consists of numerous non-profit platforms. In addition, several studies mention that the sharing economy consists partly of platforms with a non-profit market orientation (Geissinger et al., 2019; Schor, 2016). The number of non-profits in a market may affect the market entry in two ways. On one hand, a large number of non-profits in a market signifies less competition in the eyes of ensuing platforms, which makes a market more attractive to enter. Moreover, a larger number of non-profits may engender greater legitimacy spillovers based on normative grounds, as non-profits are more likely to be ethically ratified. On the other hand, a high number of non-profits may signal mediocre prospects of fruitful endeavours for platforms that take on the form of a for-profit body. The sharing model is therefore controlled for the proportion of non-profits in each market. How the data concerning a platform's revenue model is collected is described in section 3.3.3

An overview of the variables from the ecological model, the institutional shock dummy variables, and the control variables is given in **Table 3**.

3.3.3. Collection of platform data

To construct the variables, the collection of additional data is required. Hence, more specific data on the samples of platforms was gathered through web searches, news articles, internet archives, social media, grey literature, and the national trade register. The specific platform data required to construct the variables from the ecological models consists of the date of registration (and dissolution), and in which markets the platform is active. How these markets are defined is explained in Section 3.4. Specific data concerning the number of countries in which the platform is active, the revenue models, and the location of the service (online or offline), was also gathered to construct the final control variables and to provide additional descriptive information on both platform populations. An overview of the sources for the data collection of specific platform information is provided in **Table 2**.

Table 2. Data collection of specific platform information.

Information type	Description	Sources
Date of registration	The date the platform became active in the Netherlands.	Trade register (Company.info, n.d.) Crunchbase (Crunchbase, n.d.) Social media
Date of dissolution	The date at which the platform was officially dissolved.	Trade register Crunchbase News articles Wayback machine
Revenue model type	The type of revenue model (see Table 7)	The platform's Terms of Service (through Wayback machine for dissolved platforms.
Active countries	The number of countries in which the platform is active in.	The platform's website (through Wayback machine for dissolved platforms.
Service type	The service type offered via the platform (online, offline or both).	The platform's website (through Wayback machine for dissolved platforms.

Table 3. Measurement model for all variables.

Variable	Type	Operationalisation	Category	Measure
<u>Ecological model</u>				
Market entry	Dependent	$\lambda(t)$ for market i	Discrete	Count
Local density	Independent	Density of market i at t	Discrete	Count
Global density	Independent	Density of all markets at t	Discrete	Count
Related density	Independent	Density of related markets at t	Discrete	Count
European density	Control	Density of all markets at t , measured on a European level	Discrete	Count
<u>Market control variables</u>				
Market size	Control	Number of companies in market i at t	Discrete	Count
Market skill (gig)	Control	1 = Unskilled labour markets (no education or experience is required for working in these markets) 2 = Semi-skilled labour markets (certain abilities or training is required, e.g., a truckers driver's license) 3 = Skilled labour markets (advanced education or specialized skills are required, e.g., knowledge of programming code)	Categorical	Multivalent
Market type (sharing)	Control	1 = Moveable property markets 2 = Immovable property markets 0 = All other markets	Categorical	Multivalent
Service type (gig)	Control	The share of platforms in market i at t that allows online work	Continuous	Ratio
Non-profits (sharing)	Control	The share of platforms in market i at t that have a non-profit market orientation	Continuous	Ratio
<u>Institutional shock dummy variables</u>				
COVID-19 lockdown	Dummy	Value of 1 for the first and second quarter of 2020	Categorical	Binary
UberPOP exit (gig)	Dummy	Value of 1 from the third quarter of 2015 and onwards	Categorical	Binary
Airbnb restrictions (sharing)	Dummy	0 = No restrictions 1 = 60 days restriction from 2017 and onwards 2 = 30 days restriction from 2019 and onwards	Categorical	Multivalent
WAB policy (gig)	Dummy	Value of 1 from the first quarter of 2020 and onwards	Categorical	Binary

3.4. Classification of markets

As the study's dependent variable is the market entries by digital platforms, a classification of the markets in which the platforms are active is warranted. The classification of the markets is based on the 'Standaard Bedrijfsindeling' (SBI) 2008 by the Dutch Central Bureau of Statistics (CBS) (CBS, 2021). The SBI 2008 market classifications are specified on a scale of five levels, of which the first four levels are equivalent to the European NACE Rev 2 statistical classification of economic activities (Eurostat, 2008). Each level of classification comprises a higher degree of specification of the market. As markets are the study's unit of analysis, selecting the appropriate level of market specification is of vital essence. A too general specification of markets can neglect important institutional differences between markets. Furthermore, it increases the risk of unobserved heterogeneity (Petersen & Koput, 1991), i.e. observed relationships are the product of differences between platforms in a market. Conversely, a too specific specification of markets may render markets too small to observe legitimacy spillovers within them.

Considering this, the most appropriate level of market specification is selected for both gig and sharing platform populations separately. Level 3 from the SBI codes is used for the market specification in which the gig platforms are active. The steps for determining in which markets the gig platforms are active are listed in **Table 4**.

For the sharing platform population, the most specific level of market specification (4 and 5) was deemed more appropriate. To elaborate, most sharing platforms comprise giving temporary access to specific assets. Only the most specific level of market specification allows for distinguishing between these specific assets. Broader levels of specification would erroneously group markets together, thereby neglecting the differences between the assets that are shared on the platforms. To illustrate this with an example, the economic activities of boat-sharing and PC-sharing are clustered as one market in the level 3 market specification, while a platform for boat sharing does certainly not compete with a platform for PC sharing. How are placed in markets is outlined in **Table 4**.

Table 4. Steps for determining in which markets the platforms are active in.

- 1 Look at the SBI codes under which the platforms are officially registered in the Dutch trade register. Steps 2 and 3 apply for cases where this step is not possible (e.g., platforms that are not officially registered in the Netherlands).
- 2 Consult the platforms' official websites for their main activities. Most gig and sharing platforms offer a detailed categorization of their utilities.
- 3 The official websites of dissolved platforms are scrutinized through snapshots from the internet archive of the Wayback Machine (Internet Archive, n.d.).

3.4.1. Related markets

This study treats markets as institutionally related when they belong to the same overarching industries. To explain, markets are considered related when they have commonalities in their institutional environment, that is, they need to comply with the rules and legislation of the overarching industry. The overarching industries are based on the broadest SBI 2008 market specification (level 1). To give an example of two markets that are related, passenger transport (e.g., Uber) and delivery of goods (e.g., Deliveroo) both belong to the transport industry and therefore both need to comply with the laws and regulations of the overarching transport and storage industry.

3.5. Transformation of samples

By employing the ecological models as the basis for the study's analysis, emphasis is placed on the markets that are entered by gig and sharing platforms. The two samples are therefore transformed with markets as the focal point. In doing so, an ex-ante demarcation of the markets which could be entered by gig and sharing platforms is made. To explain, the list of markets from the SBI specification is extensive and contains numerous markets that are very unlikely to be entered by a platform. Therefore, including all markets in the ecological models would increase the risk of discrepant results of the density-related arguments. That is, the excessive number of markets with no entries by platforms influences the relationships observed at the 'global' and 'related' levels. On the other hand, by only including the markets with observed entries, the markets that did not experience a market entry by a digital platform but who might experience such an introduction at a later stage will be excluded from the analysis. Inherent in the ecological model is that the possible entry by platforms in these markets is also affected by legitimacy spillovers and competition. As such, a demarcation is made of the markets that are eligible for the entry of a gig or a sharing platform.

3.5.1. *Sample of gig markets*

The selection of eligible gig markets is performed in two steps. First, each industry (e.g., agriculture) is reflected upon concerning the possibility of gig work taking place in that industry. As an example, it is highly unlikely for gig work to take place in the 'extraction of minerals' industry. Second, the three-level SBI-codes are scrutinized following the same logic. For instance, markets concerning the trade of products are not eligible for gig work as this transgresses the boundary between the gig and sharing economy. The selection process is based on the six basic types of digital labour platforms as formulated by Schmidt (2017). These are freelance marketplaces, micro-tasking crowd work, contest-based creative crowd work, accommodation, transportation and delivery services, and household services and personal services. Every three-level SBI market is reflected on whether one of these six types could be active in that market. Following these steps results in a total of eighty gig markets that are analysed during the observed period, leading to 3,520 observations in total. An overview of all the gig markets can be found in **Table 18** in Appendix A - Markets.

As mentioned earlier, the market-agnostic characteristic of digital platforms allows them to transcend market boundaries. Therefore, this study allows platforms to be active in multiple markets simultaneously. Hence the total number of market entries by the sample of gig platforms exceeds the number of gig platforms present in the sample. In specific, 408 market entries and 127 market exits by gig platforms were observed in the sample.

3.5.2. *Sample of sharing markets*

Like the selection of eligible gig markets, the eligible sharing markets are chosen in two steps. First, each industry is reflected upon whether the sharing of idle capacity is possible. For example, the market category "Advice, research and other specialist business services" is a service-based market category in which the sharing of idle capacity is not applicable. Second, markets at the four and five-levels SBI-code are scrutinized following the same logic. A total of seventy-three markets are analysed, leading to 3,212 observations in total. Within this sample, 262 market entries and 115 market exits by sharing platforms were observed. The number of observations in the subsequent regression models has been reduced to 3,196 since the market size control variable contains some missing values.

3.6. Analysis

Multiple regression analyses were conducted for the ecological models as outlined above. The distribution of the number of market entries per observation as outlined in **Table 5**

and **Table 6** shows that 83-90% of the observations have no market entry. Moreover, most of the observations with a market entry had only one market entry during that quarter. Considering the limited number of cases with multiple market entries and the excessive number of zeros, both datasets are transformed into binary data. Correspondingly, logistic regression is employed to model the market entries for both gig and sharing platforms. Again, the analysis focuses on quarterly data between 2010 and 2020. All regressions were estimated using software package R.

Table 5. *Distribution of the market entries of gig platforms over the total observations*

Number of Market entries	Frequency	Percentage of observations	Percentage of observations with market entries
0	2,937	83.44%	-
1	408	11.59%	69.98%
2	140	3.98%	24.01%
3	23	0.653%	3.95%
4	9	0.226%	1.54%
5	3	0.085%	0.515%
<i>Total observations</i>	3,520		
<i>Total observations with market entries</i>	583		

Table 6. *Distribution of the market entries of sharing platforms over the total observations*

Number of Market entries	Frequency	Percentage of observations	Percentage of observations with market entries
0	3,002	90.97%	-
1	262	7.94%	87.92%
2	27	0.818%	9.06%
3	9	0.273%	3.02%
<i>Total observations</i>	3,300		
<i>Total observations with market entries</i>	298		

3.7. Quality criteria

This study ensures the reliability and validity of the research, owing to the following reasons. First, internal reliability is optimised by focusing on quarterly data, as longer time spans might influence the consistency between the measured variables (Bryman, 2016). Second, external reliability is guaranteed since accessible secondary data is used, enabling other scholars to replicate the study. Third, by employing a longitudinal research design, temporal differences are considered, thereby increasing the internal validity. In addition, the study controls for the causality between the independent variables and the dependent variable through control variables. In doing so, the risk of results being caused by unobserved heterogeneity in the density-related variables is limited. Fourth, by taking on a macro perspective on studying the legitimation of digital platforms, the study maximizes external validity. To substantiate, previous studies on digital platforms often focused on single platform cases, thus comprising limited generalizability. In this study the entire population of digital gig economy platforms is analysed, thereby ensuring the generalization of the findings. And finally, numerous scholars have questioned the credibility of density as a proxy for legitimacy spillovers (Amburgey & Rao, 1996). In particular, some suggest that part of the legitimation effect measured through density results from externalities that are unrelated to legitimation (Singh, 1993). Nevertheless, defendants of the density dependence model point towards its parsimony and generalizability over historical contexts (Singh & Lumsden, 1990). The limitations of the density dependence model are taken into account and controlled for to the extent that this

is possible. The inclusion of these variables reduces the possibility of observing results that are induced by externalities. This study also reflects on the results based on these limitations in the discussion section.

4. RESULTS

The results section is structured as follows. First, an overview of the digital platform population is given, in which their distribution over time and some platform characteristics are discussed. Thereupon, the descriptive statistics and the correlation matrices are examined. Thereafter, the results from the logistic regression models are presented and discussed, followed by a visualization of the ecological effects. Concomitantly, the hypotheses are tested. Unexpected findings are checked for their robustness. The results section ends with a summary of the findings and whether these support the hypotheses.

4.1. Distribution of the digital platform population

Figure 2 shows the diffusion of both gig and sharing platforms at the national level of the Netherlands. Both digital platform types follow a similar diffusion pattern up until the second quarter of 2016. The diffusion of gig platforms displays an acceleration of population growth at the end of the last decade. In contrast, the diffusion of sharing platforms has stagnated near the end of the last decade. Unsurprisingly, the ratio of market exits to market entries during the 11 years is higher for the sharing platform population (0.439) in comparison with the gig platform population (0.311). The institutional shocks are also plotted in the figure. These shocks illustrate how the gig platform population witnessed a stark increase after the implementation of the WAB policy, whereas the sharing platform population decreased after the first Airbnb restriction.

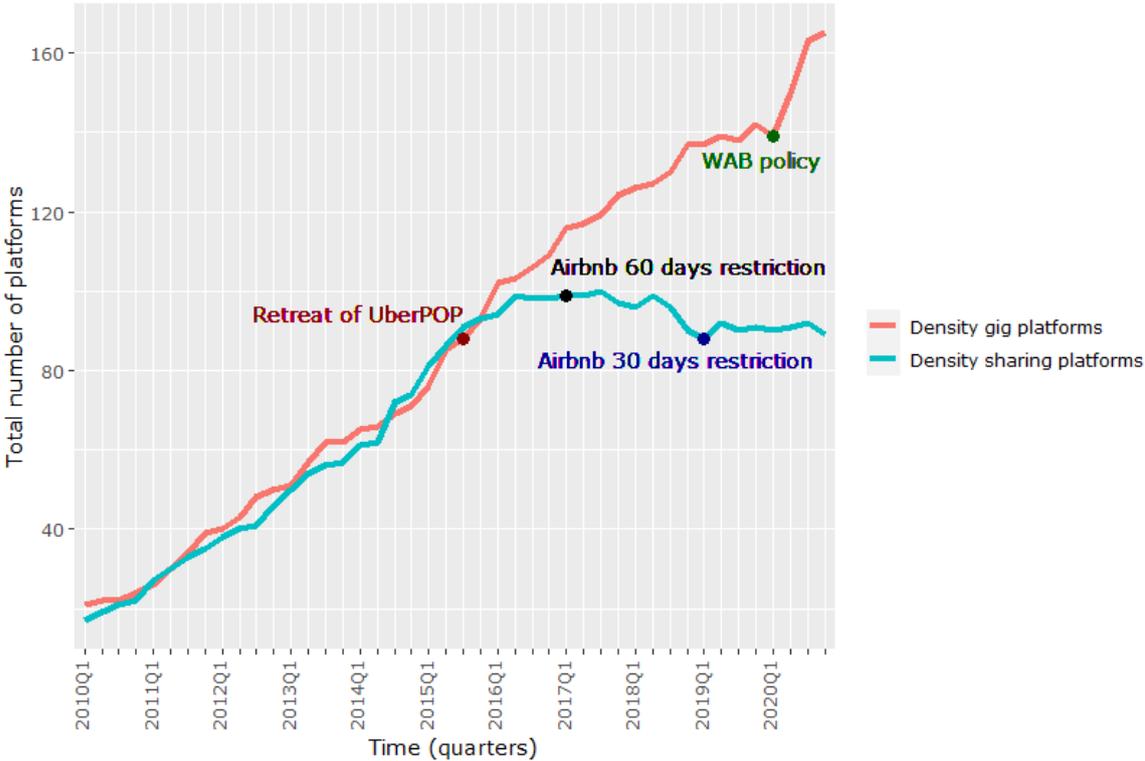


Figure 2. Digital platforms population in the Netherlands, 2010-20.

A considerable proportion of the digital platform population consists of platforms that are active in multiple countries. To be precise, 40.72% of the gig platforms and 42.96% of the sharing platforms during the observed period were active internationally. This corroborates the presumption to control for legitimacy spillovers on a European level in additional control models.

The distribution of the revenue models among the digital platform population is given in **Figure 3** and **Figure 4**. This study discerns 6 possible revenue model types, which are based on Handgraaf & Antikainen (2022). An outline of the revenue model types is given in **Table 7**. These figures illustrate how gig platforms have a more commercialised revenue model in general, with a commission-based revenue model being the most frequent. While this also applies to platforms in the sharing economy to some extent, a larger proportion of sharing platforms is non-profit or based on semi-voluntarily donations. The term semi-voluntarily is used here because these particular platforms deny users of access when they fail to provide a donation after using the platform for a while (e.g., Eigenhuisruil.nl (Eigenhuisruil.nl, n.d.)). These results are consistent with a study on Dutch digital platforms in 2021, which mentions that three-quarters of the digital platforms take the form of a for-profit-making body (Klijs, 2021).

Table 7. Typology of different revenue models (Handgraaf & Antikainen, 2022)

Number	Revenue model type	Explanation
1	Commission only	The platform charges a set fee or percentage of the transaction value.
2	Subscription only	One or both sides pay a subscription fee, no transaction fees are collected.
3	Commission and subscription	Hybrid model of above.
4	Freemium	Use of the platform is completely free. The platform monetizes by selling additional services (e.g., insurances)
5	Lead fee	Supply party is charged a fee for a (successful) lead.
6	Other	Platform monetizes through other means like enabling ads or retrieving donations.

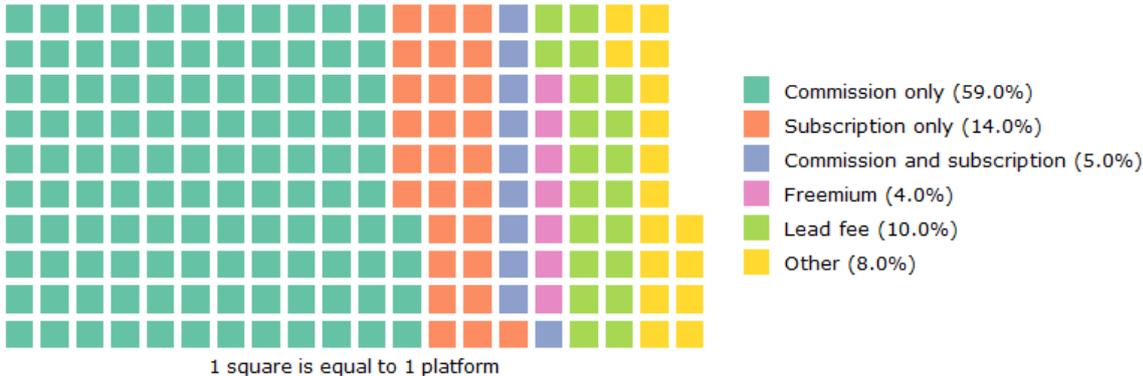


Figure 3. Distribution of revenue models among gig platforms.

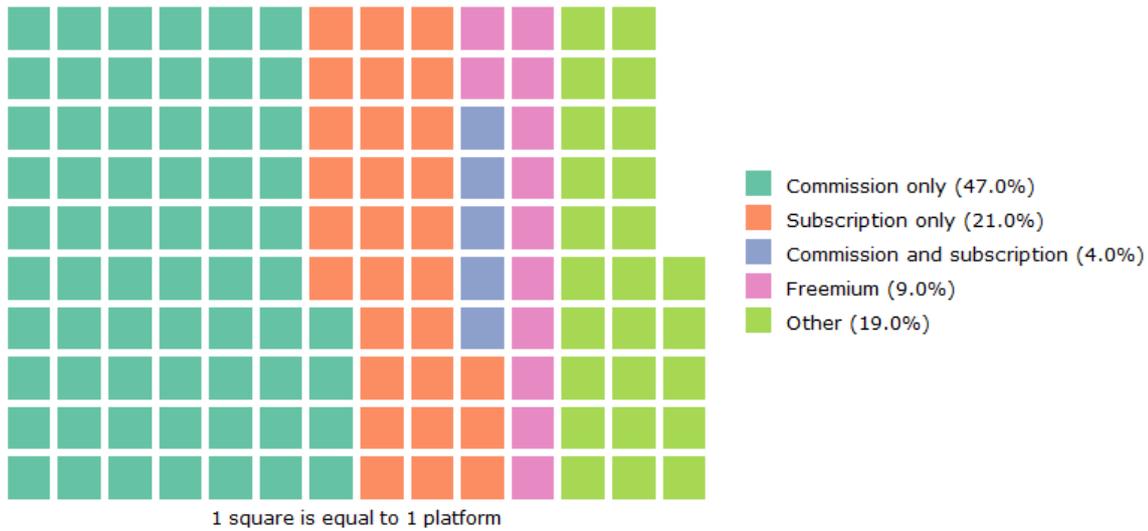


Figure 4. Distribution of revenue models among sharing platforms.

The share of non-profit platforms amongst the sharing population is visualized in **Figure 5**. The values here are taken from the average proportions of all markets that belong to the same market type category. Markets for the sharing of moveable property show to have a higher proportion of non-profit platforms than markets for the sharing of immovable property. However, the overall share of non-profits in the sharing platform population has declined at the end of the last decade. This signals that in the face of stagnating sharing platform population growth, non-profits tend to have worse survival prospects compared to sharing platforms that take on the form of a for-profit body.

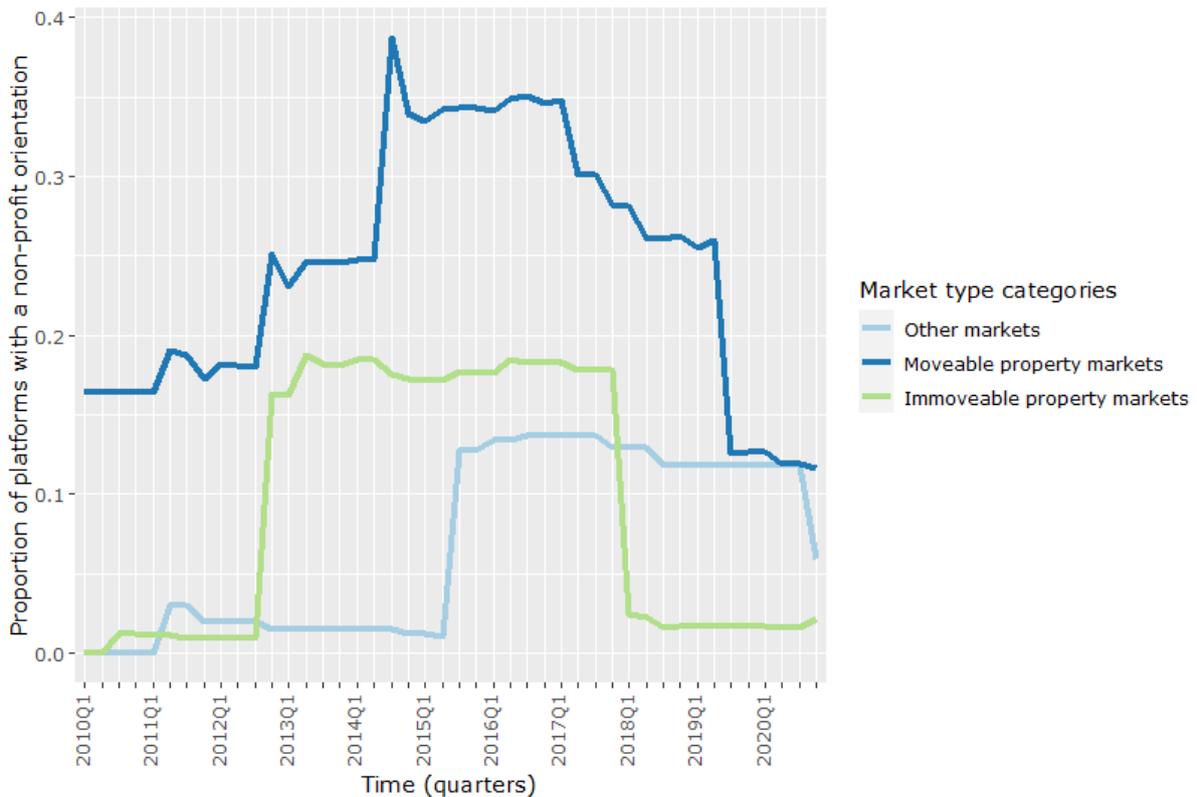


Figure 5. Average proportion of sharing platforms with a non-profit market orientation over the different market type categories.

While it can be expected that most gig platforms allow for online gig work, the opposite turns out to be true. Only 31% of the gig platforms provide possibilities for online gig work, of which half only allows for carrying out online labour. The results of the monitor online platforms 2021 are similar and show that 16,8% of the gig platforms solely allow for online work (Klijs, 2021). Obviously, with a few exceptions, all the sharing platforms focus on the sharing of physical assets. The ratio of gig platforms with an online service type over the three market skill categories is illustrated in **Figure 6**. Markets for skilled labour have a higher average share of platforms that allow online work, which implicitly suggests that a large part of the work delivered online is based on skilled labour. This is in line with Kässä & Lehdonvirta (2018), who mention that most of the demand for online labour is based on high-skilled work (e.g. software development).

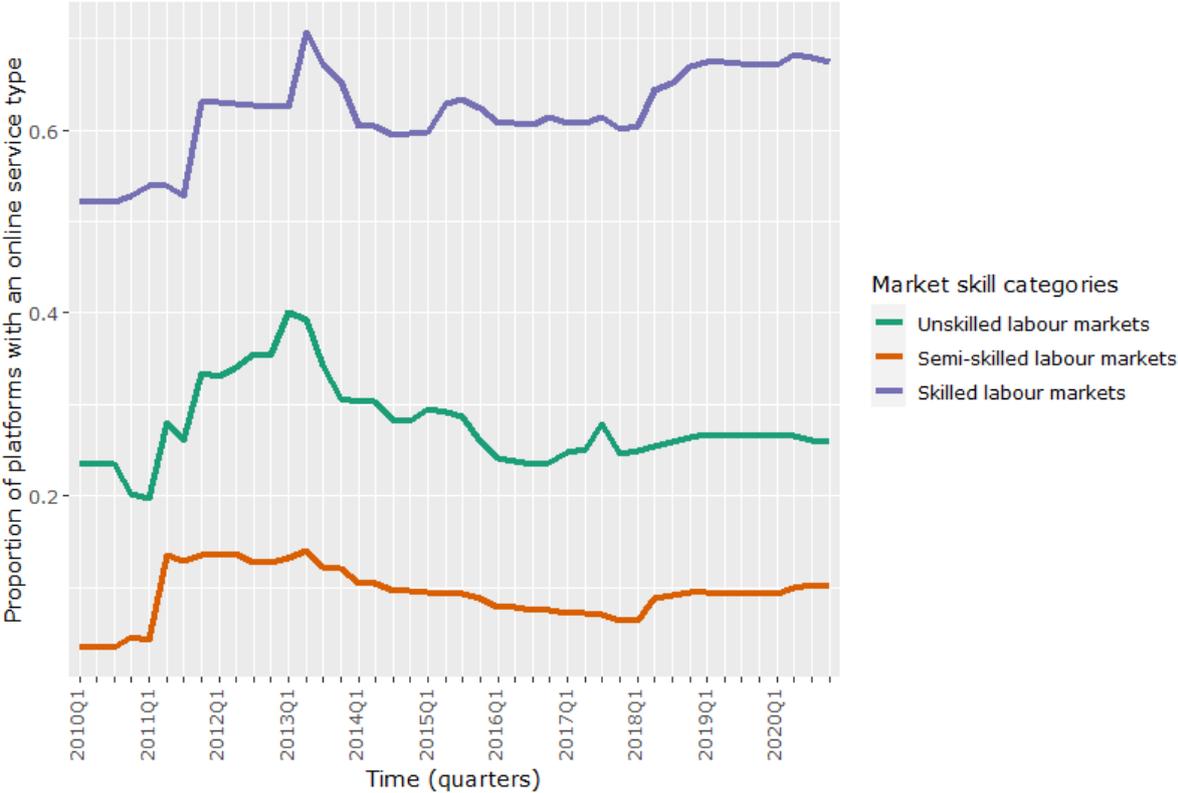


Figure 6. Average proportion of gig platforms with an online service type over the different market skill categories.

The distribution of gig platforms in the ten largest markets is illustrated in **Figure 7**. The diffusion pattern of gig platforms over individual markets is like that of the total population. While the market for *Delivery of goods* started as the smallest market among the top ten, it has experienced the fastest growth during the last decade. Interestingly, a number of the largest markets belong to the 'skilled labour' category (e.g., Information technology services activities and Data processing), while gig work is often considered to be unskilled work (Schor, 2020).

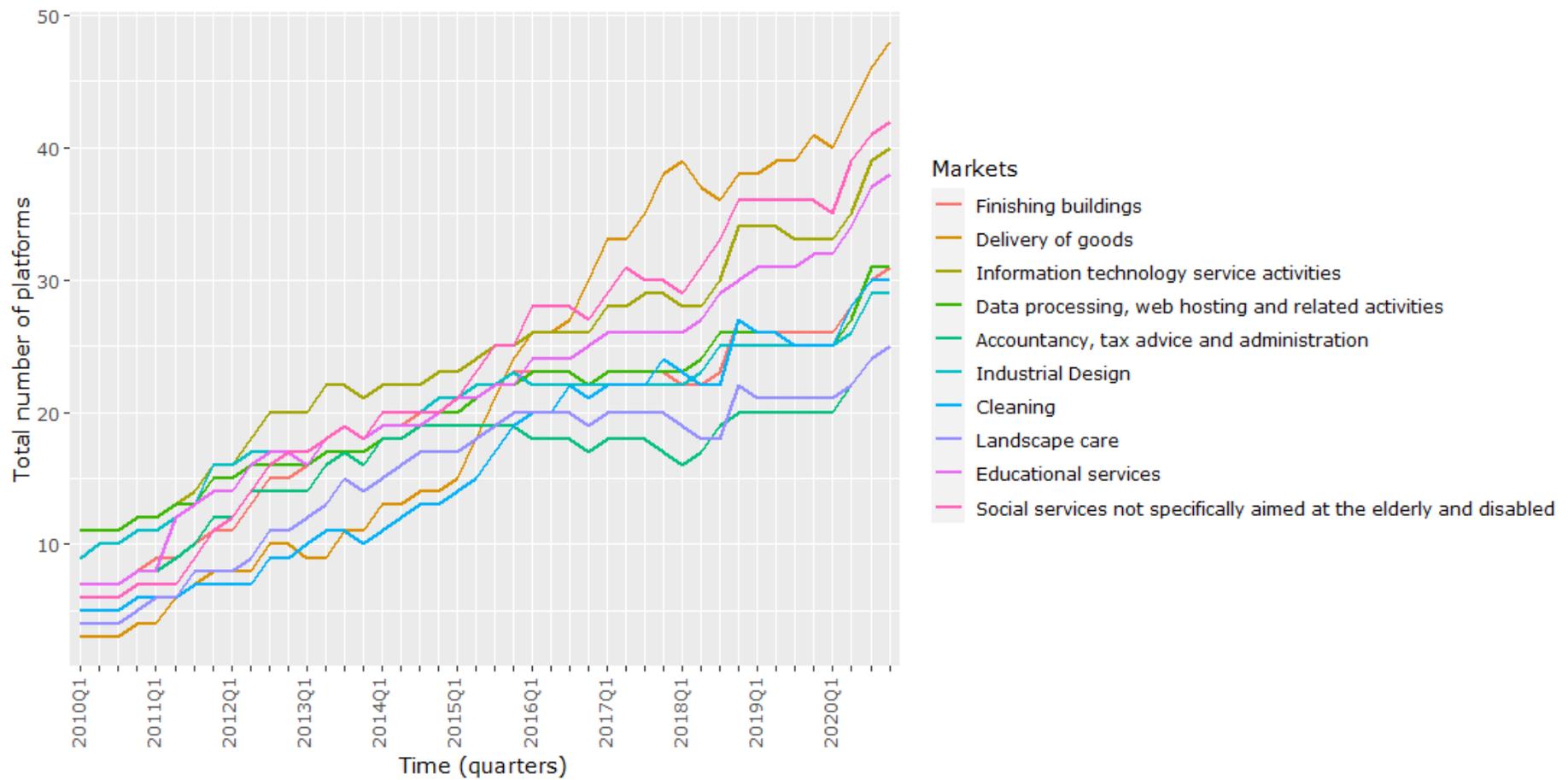


Figure 7. Population of gig platforms in the ten largest gig markets.

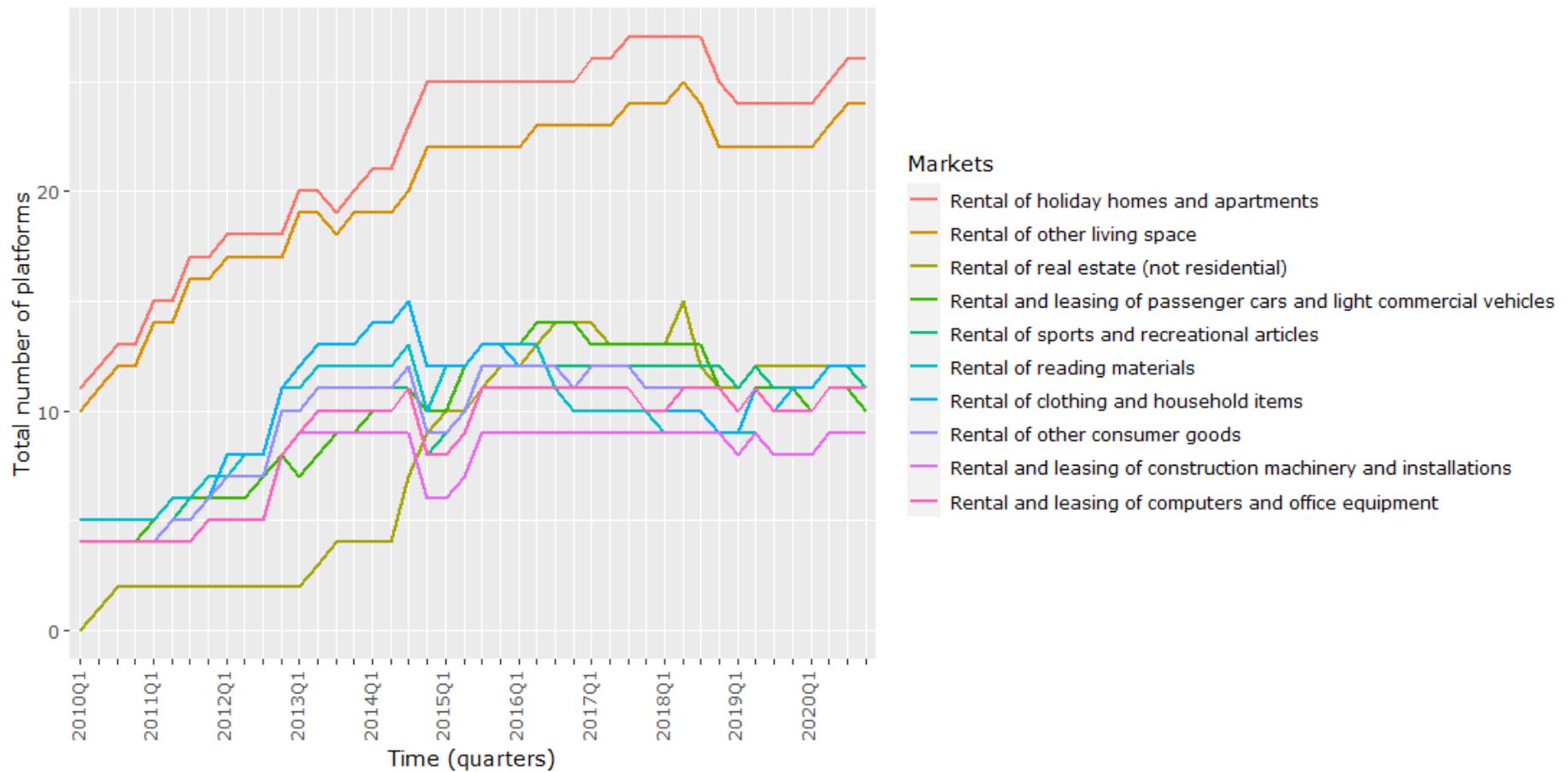


Figure 8. Population of sharing platforms in the ten largest sharing markets.

Figure 8 shows the distribution of sharing platforms in the ten largest markets. Most sharing platforms are active in the markets for home or property sharing. Also here, the diffusion pattern of sharing platforms over individual markets is like that of the total population. In particular, the growth of the number of sharing platforms in these largest markets came to a halt in the second half of the last decade. However, it should be mentioned that the distribution of platforms as depicted in the figure does not consider the platform sizes. It is common for both gig and sharing platforms alike to take over or merge with competing platforms since many platforms prove to be in winner-takes-all markets (Kenney & Zysman, 2016). Examples include ParkflyRent, which was bought by SnappCar (Keswiel, 2018); the acquisition of Huizenruil.com by HomeExchange (Huizenruil.com, n.d.); and the take-over of ANWB samenrijden by BlaBlaCar (ANWB, 2016). Various studies report a growth in the number of sharing platform users, such as for platforms for mobility sharing (Jorritsma et al., 2021), or for sharing platforms for short-stay rentals (European Commission, 2021a).

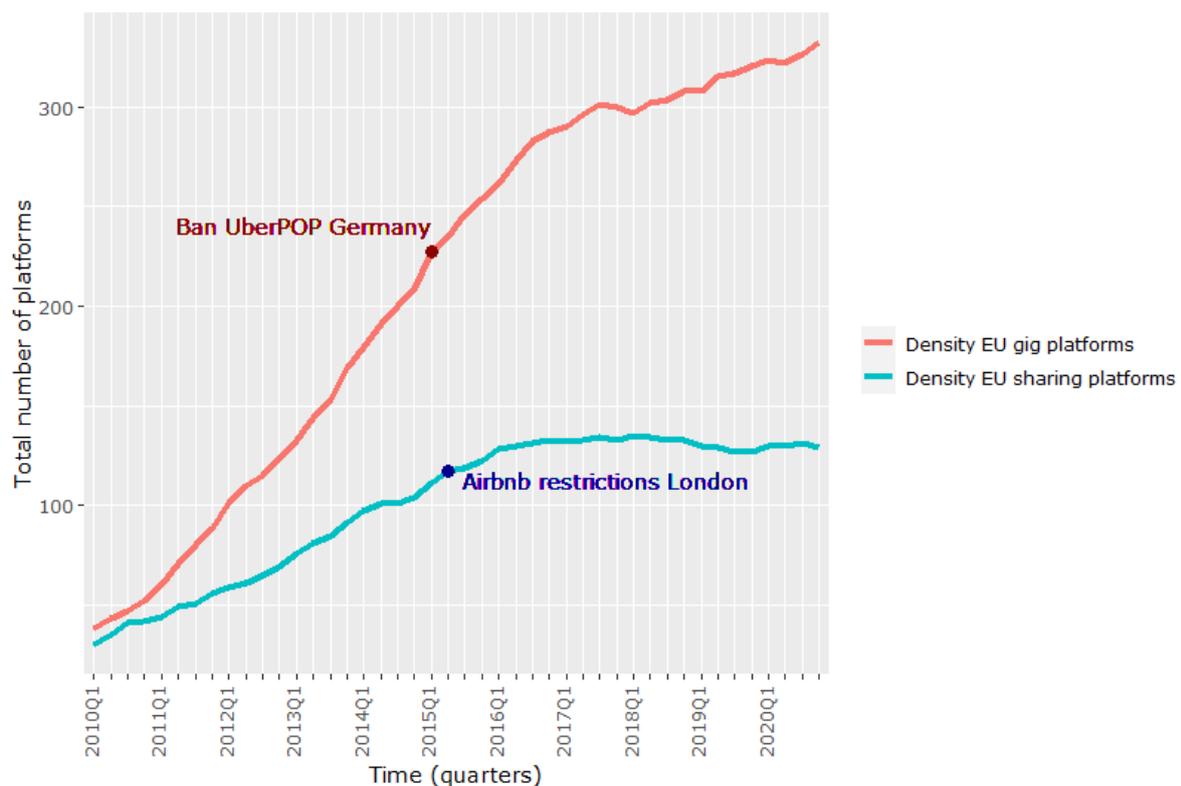


Figure 9. Digital platforms population in the EU 27 (excluding the Dutch population), 2010-20.

Figure 9 shows the diffusion of both gig and sharing platforms at the European level, excluding those that are active in the Netherlands. Again here, the diffusion of European sharing platforms has stagnated near the end of the last decade, whereas the number of European gig platforms has grown tremendously. In fact, the number of gig platforms was more than 2.5 times as high as the number of sharing platforms at the end of 2020. Similar institutional shocks are also plotted in the figure. These are the ban of the UberPOP service in Germany in March 2015 (Eddy, 2015), and a 90-day rental term restriction for short-stay rentals through Airbnb in London (Sherwood, 2019). These institutional shocks are only specific examples from two of the most well-known platforms, but they illustrate how European countries started to respond to the gig and sharing platforms with stronger regulations halfway last decade.

Descriptive information on the European platform samples shows that the distribution of gig and sharing platforms over markets is similar to the distribution observed in the

Netherlands. This indicates that the subsequent results are at least generalizable to other European countries.

4.2. Descriptive statistics

The descriptive statistics for both models are given in **Table 8** and the correlation matrices for the gig and sharing models are provided in **Table 9** and **Table 10** respectively. '*Global density situation one*' refers to the models in which related density is excluded. '*Global density situation two*' refers to the models that include related density, hence the related density term is subtracted from the global density in these models to prevent multicollinearity. The descriptive statistics show that the ratio of market entries to observations is higher for gig platforms in comparison to sharing platforms. However, the sample of sharing platforms shows a higher mean value for related density, while the mean values of all other density terms are lower compared to the gig platform population. This is caused by a lower number of overarching industries in the sharing data (8) compared to the gig data (13).

The correlations in both gig and sharing models between most variables are low to moderate. The exceptions are the expectedly high correlations between variables in the ecological model with the squared terms. These correlations do not generate less reliable statistical inferences, since both density-related terms capture different effects on market entry, i.e., first-order (legitimation) and second-order (competition) effects, which are expected to be curvilinear. Other high correlations are present between both global density variables, as with the European density variant of global density. The dummy variable for the retreat of UberPOP correlates highly with some of the ecological variables and is therefore only included in the final model as a robustness check.

4.3. Regression results

4.3.1. Results of the gig models

The results of the regression analysis of gig platforms are shown in **Table 11**. Gig M1 only includes the local and global ecological variables. The effect of local density is positive and significant, indicating how an increase in local density increases the odds of a market entry by a gig platform. Put differently, gig platforms are more likely to enter a market with a higher density, owing to a legitimation effect. As this effect remains stable over the models, enough statistical evidence is presented to accept Hypothesis 1a. However, the squared term of local density is negative and significant, suggesting that the competition effect eventually becomes a barrier to market entry. Surprisingly, the effects of global density and its squared term are reversed. That is, a negative and significant effect of the first-order term and a positive and significant effect of the second-order term. This suggests that an initial increase in global density lowers the odds of market entry. However, this effect changes as the global density continues to increase, and eventually enhances the odds of market entry. The positive long-term effect of global density suggests that it may be invalid to reject Hypothesis 2a. Thus this effect will be discussed more extensively in the discussion section.

The regression model is extended in the second model by also including the related density. Again here, the results induced by global density are at odds with what was expected. Similarly, the first-order effects of related density are also negative and significant. This signifies that an initial increase in the density of related markets reduces the odds of market entry by a gig platform. In other words, there is evidence of a market barrier that is posed by platforms in related markets. The squared term of related density shows no significant effect. Since the results for related density are opposed to what was hypothesized, there is not enough statistical evidence in favour of Hypothesis 3a.

Table 8. Descriptive statistics for both gig and sharing models

Variable	<u>Gig Data</u>				<u>Sharing data</u>			
	Mean	SD	Min	Max	Mean	SD	Min	Max
<u>Dependent variable</u>								
Market entry (binary)	0.17	0.37	0.00	1.00	0.09	0.29	0.00	1.00
<u>Ecological model</u>								
Local density	6.43	7.84	0.00	48.00	3.40	4.48	0.00	27.00
(Local density ²)/100	1.03	2.11	0.00	23.04	0.32	0.84	0.00	7.29
Global density s1	508.27	177.86	199.00	846.00	244.69	58.80	117.00	310.00
(Global density s1 ²)/100	2899.65	1798.99	396.01	7157.16	633.31	260.36	136.89	961.00
Global density s2	456.84	168.45	137.00	846.00	189.55	61.34	64.00	309.00
(Global density s2 ²)/100	2370.73	1569.10	187.69	7157.16	396.89	236.37	40.96	954.81
Related density	51.43	52.64	0.00	224.00	55.15	39.43	0.00	112.00
(Related density ²)/100	54.15	87.94	0.00	501.76	45.96	41.35	0.00	125.44
EU density s1	1500.43	575.70	386.00	2288.00	567.10	139.10	260.00	711.00
(EU density s1 ²)/100	25826.27	15904.32	1489.96	52349.44	3409.46	1439.30	676.00	5055.21
EU density s2	1449.00	560.73	324.00	2288.00	511.95	133.93	207.00	711.00
(EU density s2 ²)/100	24139.34	14986.84	1049.76	52349.44	2800.28	1279.06	428.49	5055.21
<u>Market control variables</u>								
Market size	11460.03	17820.70	5.00	131165.00	2082.96	3103.37	0.00	28215.00
Market skill	2.25	0.70	1.00	3.00				
Market type					0.95	0.64	0.00	2.00
Service type	0.33	0.36	0.00	1.00				
Non-profits					0.17	0.25	0.00	1.00
<u>Institutional shock dummies</u>								
COVID-19 lockdown	0.05	0.21	0.00	1.00	0.05	0.21	0.00	1.00
Exit of UberPOP	0.50	0.50	0.00	1.00				
Policy WAB	0.09	0.29	0.00	1.00				
Airbnb restrictions					0.55	0.78	0.00	2.00

Table 9. Gig platforms - descriptive statistics and correlation matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Dependent variable																			
(1) Market entry (binary)	1.00																		
Ecological model																			
(2) Local density	0.43	1.00																	
(3) (Local density ²)/100	0.35	0.91	1.00																
(4) Global density s1	-0.01	0.25	0.26	1.00															
(5) (Global density s1 ²)/100	-0.01	0.23	0.25	0.98	1.00														
(6) Global density s2	-0.04	0.15	0.20	0.96	0.94	1.00													
(7) (Global density s2 ²)/100	-0.04	0.13	0.19	0.93	0.94	0.98	1.00												
(8) Related density	0.10	0.35	0.21	0.32	0.31	0.03	-0.01	1.00											
(9) (Related density ²)/100	0.07	0.30	0.17	0.31	0.31	0.03	0.00	0.95	1.00										
(10) EU density s1	-0.01	0.27	0.27	0.99	0.94	0.94	0.89	0.33	0.31	1.00									
(11) (EU density s1 ²)/100	-0.01	0.27	0.27	0.99	0.98	0.94	0.92	0.33	0.31	0.99	1.00								
(12) EU density s2	-0.02	0.24	0.26	0.98	0.94	0.96	0.91	0.24	0.23	1.00	0.98	1.00							
(13) (EU density s2 ²)/100	-0.02	0.24	0.26	0.98	0.97	0.97	0.95	0.22	0.21	0.98	0.99	0.98	1.00						
Market control variables																			
(14) Market size	0.13	0.33	0.28	0.08	0.08	0.04	0.05	0.12	0.16	0.08	0.09	0.08	0.08	1.00					
(15) Market skill	0.04	0.18	0.08	-0.01	-0.01	-0.14	-0.13	0.41	0.41	0.00	0.00	-0.04	-0.05	0.00	1.00				
(16) Service type	0.27	0.51	0.29	0.01	0.01	-0.13	-0.14	0.47	0.44	0.03	0.02	-0.02	-0.03	0.23	0.49	1.00			
Institutional shock dummies																			
(17) Exit of UberPOP	-0.01	0.25	0.25	0.86	0.85	0.81	0.80	0.28	0.27	0.87	0.90	0.86	0.90	0.08	0.00	0.01	1.00		
(18) Policy WAB	0.05	0.14	0.18	0.49	0.58	0.47	0.54	0.16	0.19	0.39	0.46	0.39	0.45	0.05	0.00	0.02	0.32	1.00	
(19) COVID-19 lockdown	0.02	0.08	0.09	0.29	0.32	0.27	0.30	0.09	0.10	0.25	0.28	0.25	0.28	0.04	0.00	0.01	0.22	0.69	1.00

Table 10. Sharing platforms - Correlation matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
<u>Dependent variable</u>														
(1) Market entry (binary)	1.00													
<u>Ecological model</u>														
(2) Local density	0.32	1.00												
(3) (Local density ²)/100	0.24	0.89	1.00											
(4) Global density s1	-0.06	0.10	0.07	1.00										
(5) Global density s2	-0.09	-0.02	0.09	0.79	1.00									
(6) Related density	0.06	0.18	-0.04	0.27	-0.39	1.00								
(7) (Related density ²)/100	0.05	0.18	-0.02	0.36	-0.29	0.98	1.00							
(8) EU density s1	-0.06	0.15	0.11	0.99	0.77	0.27	0.35	1.00						
(9) EU density s2	-0.08	0.10	0.12	0.95	0.92	-0.02	0.08	0.96	1.00					
<u>Market control variables</u>														
(10) Market size	-0.01	-0.03	-0.05	0.05	0.15	-0.15	-0.17	0.06	0.10	1.00				
(11) Market type	0.10	0.31	0.29	-0.01	-0.10	0.13	0.07	0.00	-0.04	0.05	1.00			
(12) Non-profits	0.14	0.20	0.02	0.15	-0.08	0.34	0.30	0.14	0.05	0.20	0.06	1.00		
<u>Institutional shock dummies</u>														
(12) Airbnb restrictions	-0.05	0.09	0.06	0.51	0.40	0.14	0.19	0.58	0.56	0.06	0.01	-0.06	1.00	
(13) COVID-19 lockdown	0.08	0.02	0.02	0.13	0.10	0.03	0.04	0.19	0.19	0.03	0.00	-0.06	0.41	1.00

Table 11. Gig platforms - Regression models

Variable	Gig M1	Gig M2	Gig M3	Gig M4	Gig M5	Gig M6	Gig M7	Gig M8	Gig M9	Gig M10
<u>Ecological model</u>										
Local density	0.293*** (0.016)	0.319*** (0.020)	0.295*** (0.017)	0.320*** (0.020)	0.271*** (0.021)	0.288*** (0.023)	0.288*** (0.023)	0.288*** (0.022)	0.289*** (0.022)	0.259*** (0.019)
(Local density ²)/100	-0.494*** (0.055)	-0.569*** (0.065)	-0.488*** (0.055)	-0.559*** (0.066)	-0.435*** (0.629)	-0.482*** (0.067)	-0.483*** (0.068)	-0.489*** (0.065)	-0.489*** (0.065)	-0.416*** (0.059)
Global density s1	-0.007*** (0.002)				-0.007*** (0.002)					
(Global density s1 ²)/100	0.0004** (0.0002)				0.0004** (0.0002)					
Global density s2		-0.007*** (0.002)				-0.007*** (0.002)	-0.006*** (0.002)	-0.003 (0.002)	-0.003 (0.002)	
(Global density s2 ²)/100		0.0005*** (0.0002)				0.0005** (0.0002)	0.0004 (0.0002)	-0.0001 (0.0002)	-0.00003 (0.0003)	
Related density		-0.009*** (0.004)		-0.007* (0.004)		-0.009*** (0.004)	-0.009*** (0.004)	-0.008** (0.004)	-0.007** (0.004)	
(Related density ²)/100		0.002 (0.002)		0.001 (0.002)		0.003 (0.002)	0.003 (0.002)	0.001 (0.002)	0.001 (0.002)	
EU density s1			-0.001 (0.0005)							
(EU density s1 ²)/100			-0.001 (0.00002)							
EU density s2				-0.001* (0.0005)						
(EU density s2 ²)/100				0.00000 (0.00002)						
<u>Market control variables</u>										
Market size /1000					-0.006** (0.003)	-0.006** (0.003)	-0.006** (0.003)	-0.005* (0.003)	-0.005* (0.003)	-0.006** (0.003)
Semi-skilled markets					-0.477*** (0.154)	-0.407*** (0.154)	-0.408*** (0.154)	-0.429*** (0.154)	-0.428*** (0.154)	-0.495*** (0.154)
Skilled markets					-0.917*** (0.163)	-0.812*** (0.170)	-0.810*** (0.170)	-0.767*** (0.170)	-0.766*** (0.170)	-0.899*** (0.163)
Service type					0.982*** (0.218)	1.043*** (0.218)	1.039*** (0.218)	1.017*** (0.217)	1.000*** (0.220)	-0.979*** (0.222)
<u>Institutional shock dummies</u>										
COVID-19 lockdown							0.338 (0.253)	-0.505 (0.355)	-0.447 (0.368)	-0.139 (0.314)
Policy WAB								1.210*** (0.349)	1.114*** (0.381)	0.450* (0.236)
Exit of UberPOP									-0.146 (0.233)	-0.950*** (0.127)
Intercept	-1.190*** (0.369)	-1.300*** (0.334)	-2.217*** (0.292)	-2.099*** (0.289)	-0.3932*** (0.384)	-1.126*** (0.366)	-1.157*** (0.368)	-1.791*** (0.414)	-1.826*** (0.415)	-2.714*** (0.146)
Observations (N)	3,520	3,520	3,520	3,520	3,520	3,520	3,520	3,520	3,520	3,520
Log Likelihood	-1,218.881***	-1,213.612***	-1,212.744	-1,208.256**	-1,199.299***	-1,195.999*	-1,195.116	-1,188.837***	-1,188.620	-1,203.297
AIC	2,447.761	2,441.224	2,435.489	2,430.512	2,430.512	2,416.598	2,413.998	2,414.232	2,403.674	2,426.594

Notes:

*p<0.1; **p<0.05; ***p<0.01 (all two-tailed); Standard errors shown in parentheses are robust standard errors clustered by quarter and Market (SBI 2008)

The first two models are repeated in models 3 and 4 respectively, with the global density now set at the European level. As mentioned earlier, the digital platform population consist of approximately 40% of international platforms. It is therefore not surprising if either a legitimization or competition effect could be perceived on a larger global scale. Nevertheless, the effects of the density terms at the European scale are not statistically significant. In the following models, the global density at the national level is used again since the models show no differences between including either European density or global density.

In Gig M5 and Gig M6, the control variables are added. Market size shows a negative effect that is significant at $p < 0.1$. Simply put, this means that a larger market decreases the odds of market entry. More formally, this signals that gig platforms also compete with non-platform companies, thereby acting as a barrier to market entry. As for the market skill control variable, the results of the model show that the odds of market entry in semi-skilled markets are lower in comparison with unskilled markets and that this effect is significant. Comparatively, the odds of market entry of a gig platform in skilled markets in comparison to unskilled markets is even lower and significant. This poses a discrepancy with results on platform workers, who are on found to be more educated than the general population (Codagnone & Martens, 2016; Schor, 2020; Urzì Brancati et al., 2020). Put differently, the reduced odds of market entry in skilled markets are not caused by a lack of skilled workers. In addition, some of the markets with the highest number of gig platforms belong to the skilled market category. A plausible explanation would be that competition is more intense in these markets as more platforms have entered, which is detrimental for subsequent market entry. However, this could also signal that the dependency on legitimacy spillovers is different in the three markets. This is explored in the robustness check models in section 4.5.1 and section 4.5.2. The models show a positive and significant effect of service type, meaning that a larger proportion of gig platforms with an online service type increases the odds of market entry. As such, the variable for service type confirms what was conjectured, being that markets that allow for online labour have lower barriers to market entry.

In the final three models, the dummy variables are added. The effects of the ecological variables at the local level remain constant in terms of significance levels, effect sizes, and direction. However, the significance levels at global and related levels seem to drop after including more dummy variables. The final models only show minor changes in the effect sizes of the control variables. Concerning the institutional shock dummies, the dummy variable for the COVID-19 lockdown period displays no significant effect. A large and significant effect is induced by the WAB policy dummy. This simply means that the odds of observing a market entry are higher after the WAB policy was set in motion. It also coincides with the accelerated growth of the number of gig platforms as displayed in **Figure 2**. The dummy variable for the retreat of the UberPOP service shows no significant effect. However, this result may be influenced by collinearity between the UberPOP dummy and the global density terms, which consequently generates less reliable statistical inferences. In a control model without the global and related density terms, the UberPOP dummy shows a negative and significant effect. Together with the results induced by the WAB policy, this supports what was conjectured in Hypothesis 4a. That is, the market entry of gig platforms is affected proportionally by certain institutional shocks.

The model with the best fit to the data can be determined based on the log-likelihood and Akaike's Information Criterion (AIC) values. In general, a lower AIC value is preferred as this means that the complexity of the model, which is increased by loading in more estimators, is offset by an increase in goodness-of-fit that has been achieved, thereby striking a better balance between complexity and goodness-of-fit (Akaike, 1974). Unsurprisingly, model 8 appears to have the best model fit according to the AIC values

Furthermore, an asymptotic likelihood ratio test between model 8 and model 7, in which twice the difference in log-likelihoods is compared with the Chi-squared distribution (Self & Liang, 1987), is significant. The likelihood ratio tests of models 8 and 9 show no significant result, which is unsurprising since the inclusion of the UberPOP dummy cause no significant effect. As such, a regression model with the ecological variables, control variables and both the COVID-19 lockdown and the WAB policy dummies captures additional heterogeneity compared to the other models.

4.3.1. *Results of the sharing models*

The results of the regression analysis of sharing platforms are shown in **Table 12**. Again, model 1 only includes the local and global ecological variables. At the local level, both the positive legitimation and negative competition effects are significant. The effects at the local level remain consistent throughout the models, thereby providing supporting evidence for Hypothesis 1b. As was the case with the gig model, the effect of global density is negative and significant, thereby establishing itself as a barrier to market entry. The squared term of global density is therefore added in Sharing M2. While statistically not significant, the effect of global density follows a similar pattern to the gig models. The fact that the squared term of global density is not significant validates that competition between sharing platforms at the global level is unlikely. The related density terms that are added in Sharing M3 do not have any significant effect. This means that there is not enough statistical evidence to support Hypothesis 2b and 3b.

The first two models are extended in Sharing M4 and Sharing M5 by aggregating global density to the European level. As was the case with global density on a national level, the effect of European density is negative and significant. To interpret this, an increase in the number of sharing platforms in Europe reduces the odds of observing a market entry by a sharing platform in the Netherlands. By amassing global density to the European scale in Sharing M5, the significance level of related density has slightly increased. The subsequent models continue with global density on a national level since this has a larger effect size. The control variables are added in Sharing M6 and Sharing M7. However, only the variable for the proportion of non-profits displays a significant effect. This effect is positive, thereby implying that a larger proportion of sharing platforms with a non-profit market orientation lowers the barriers to market entry. Thus, this supports the presumption that a higher share of non-profits engenders greater legitimacy spillovers for ensuing platforms. The validity of this presumption is further explored in the robustness check models in section 4.5.4. The effects of the market type control variable were also controlled for changing the reference category, however, all effects remained not significant.

In Sharing M7 and Sharing M8, the institutional shock dummies are included. Notably, the models show a high and significant effect for the lockdown period, which suggests that the odds of market entry by a sharing platform were significantly higher during these months. Conversely, the diffusion of the sharing platforms population in **Figure 2** clearly illustrates how the population growth has stagnated and even decreased since 2016. By including the dummy variables, the positive second order of related density becomes significant. Sharing M8 shows a negative and significant effect of both Airbnb restriction categories. Simply put, this means that the odds of market entry were lower after restricting the rental of short-stay apartments in Amsterdam to 60 days. Furthermore, the odds of market entry became even lower after the allowed rental period was reduced to 30 days. The results induced by the institutional shock dummies support Hypothesis 4b.

Table 12. Sharing platforms - Regression Models

Variable	Sharing M1	Sharing M2	Sharing M3	Sharing M4	Sharing M5	Sharing M6	Sharing M7	Sharing M8	Sharing M9	Sharing M10
<u>Ecological model</u>										
Local density	0.478*** (0.032)	0.480*** (0.032)	0.481*** (0.039)	0.492*** (0.033)	0.490*** (0.040)	0.486*** (0.040)	0.485*** (0.042)	0.492*** (0.044)	0.488*** (0.043)	0.502*** (0.045)
(Local density ²)/100	-1.435*** (0.152)	-1.437*** (0.151)	-1.454*** (0.193)	-1.459*** (0.154)	-1.448*** (0.200)	-1.457*** (0.198)	-1.465*** (0.211)	-1.490*** (0.224)	-1.471*** (0.227)	-1.451*** (0.238)
Global density s1	-0.008*** (0.001)	-0.016 (0.013)				-0.009*** (0.001)				
(Global density s1 ²)/100		0.002 (0.003)								
Global density s2			-0.008*** (0.002)				-0.010*** (0.002)	-0.012*** (0.003)	-0.009*** (0.003)	
Related density			-0.015 (0.010)		-0.017* (0.0007)		-0.031* (0.020)	-0.037** (0.021)	-0.037** (0.021)	-0.024 (0.019)
(Related density ²)/100			0.007 (0.009)		0.014 (0.009)		0.020 (0.013)	0.024* (0.013)	0.025** (0.014)	0.026** (0.013)
EU density s1				-0.004*** (0.0005)						
EU density s2					-0.004*** (0.009)					-0.006*** (0.001)
<u>Market control variables</u>										
Market size/1000						-0.016 (0.025)	-0.005 (0.025)	-0.010 (0.025)	-0.004 (0.025)	0.0003 (0.026)
Moveable property						-0.351 (0.282)	-0.131 (0.905)	-0.114 (0.920)	0.005 (0.940)	-0.755 (0.763)
Immoveable property						0.109 (0.323)	0.235 (0.353)	0.290 (0.365)	0.286 (0.362)	0.219 (0.356)
Non-profits						1.997*** (0.349)	2.100*** (0.358)	2.416*** (0.345)	2.156*** (0.355)	2.338*** (0.371)
<u>Institutional shock dummies</u>										
COVID-19 lockdown								1.662*** (0.290)	2.289*** (0.369)	2.490*** (0.373)
Airbnb restriction 60 days									-0.544** (0.232)	-0.271 (0.249)
Airbnb restriction 30 days									-0.959*** (0.284)	-0.648** (0.303)
Intercept	-2.209*** (0.262)	-1.337 (1.265)	-1.992*** (0.384)	-1.979*** (0.254)	-1.542*** (0.369)	-2.169*** (0.356)	-1.724*** (0.535)	-1.480*** (0.552)	-1.480*** (0.580)	-0.968* (0.521)
Observations (N)	3,212	3,212	3,212	3,212	3,212	3,196	3,196	3,196	3,196	3,196
Log Likelihood	-806.536***	-806.242	-806.285	-798.313***	-797.173	-784.506	-782.892	--765.735***	-758.499***	-746.529***
AIC	1,621.071	1,622.483	1,624.571	1,604.626	1,606.346	1,585.012	1,585.784	1,553.470	1,542.998	1,519.057

Notes:

*p<0.1; **p<0.05; ***p<0.01 (all two-tailed)

Standard errors shown in parentheses are robust standard errors clustered by quarter and Market (SBI 2008).

In Sharing M9, global density is swapped for European density again as a robustness check. The effect induced by European density remains negative and significant. The only other noteworthy changes are the reduced significance of the effect caused by the Airbnb rental period restrictions and the short-term effect of related density not being significant. Regardless, this model shows the best model fit. Sharing M9 has the lowest AIC value, suggesting a better balance between the complexity and the goodness-of-fit of the model. In addition, the final model holds the lowest log-likelihood value. Furthermore, the asymptotic likelihood ratio test between model 9 and model 8 is significant, thereby confirming that the final model captures additional heterogeneity compared to model 9.

4.3.2. Comparison between the gig and sharing models

When juxtaposing the results from both gig and sharing regression models, several similarities can be observed. First, the legitimation and competition effects at the market level appear to be significant throughout the models. Second, the global and related density terms show reversed effects. This means that an initial increase in global density acts as a barrier to market entry, which eventually diminishes and even becomes a legitimating effect in the long term. The effects of global density becoming not significant in the final gig models is likely to be caused by medium correlation with the dummy variables. And third, the odds of market entry by both gig and sharing platforms are affected by policy changes, as is indicated by the significant effects of the WAB policy dummy and the Airbnb restrictions dummy.

Similarly, several differences can be identified. First, the effect induced by the COVID-19 lockdown is the opposite in the gig and sharing models. Where the effect of the lockdown dummy is negative but not significant in the gig models, it is positive and significant in the sharing models. This phenomenon is more than peculiar, as it was expected to perceive a negative effect for both types of platforms. To briefly explain, the lockdown in response to the COVID-19 pandemic has almost halted all forms of interaction, which should have affected the market entry of platforms. The higher odds of market entry by sharing platforms during the lockdown signals how more attention was placed on starting initiatives in the sharing economy when faced with the economic pressure of the COVID-19 crisis. And second, the effect of market size is negative and significant in the gig models, whereas market size has no significant effect in the sharing models. This can be explained by the fact that gig platforms compete with non-platform companies on two fronts: in terms of economic activity and the acquisition of labour capital. While it was conjectured that sharing platforms compete with non-platform equivalents only in terms of economic activity, statistical evidence suggests otherwise.

4.4. Ecological effects

The unexpected effects of the global and related density terms are scrutinized more extensively by visualizing them. The effects at the global level from Gig M1 are plotted in **Figure 10**. These plots are obtained via the marginal effects, which is keeping all other independent variables constant at their mean values. The figure illustrates how the global density follows a negative exponential distribution, with the odds for observing a market entry by a gig platform reaching zero per cent at a global density of eight hundred. Conversely, the squared term of global density follows a positive exponential distribution, where the odds of observing a market entry exceed 5% at a global density of 400,000. This reveals that the 'legitimation' effect observed in the long term is exceptionally weak.

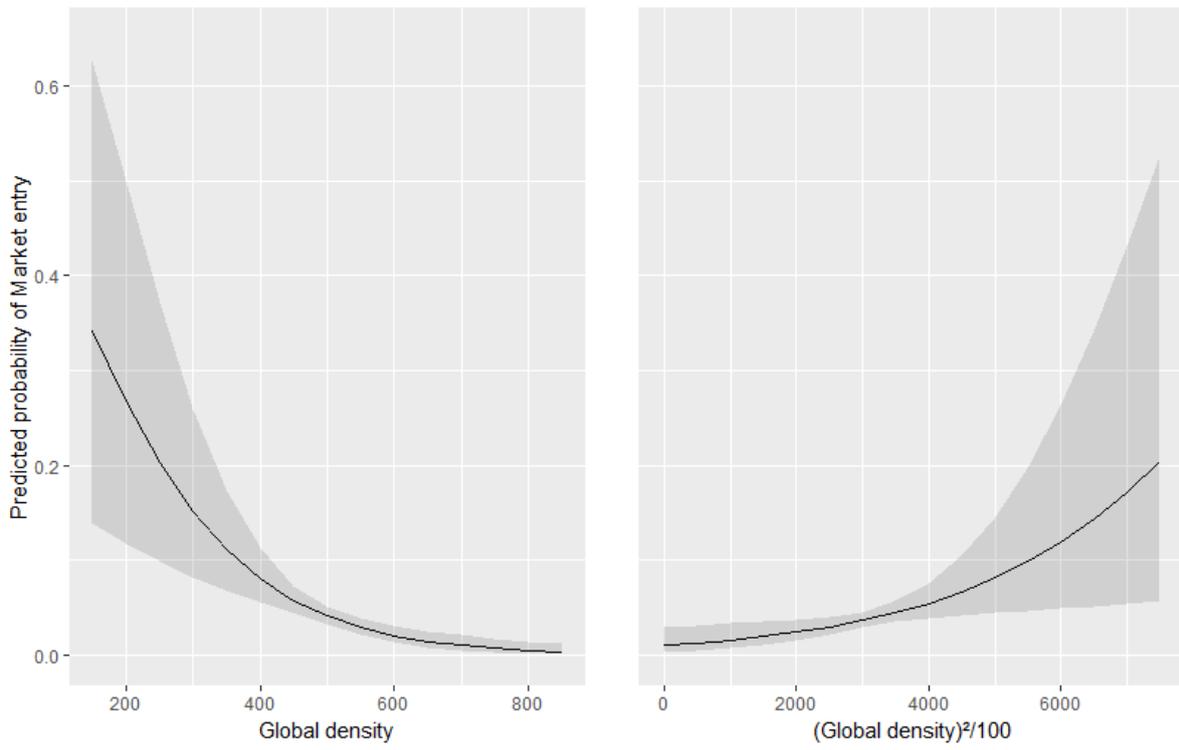


Figure 10. Ecological effects of global density from Gig M1.

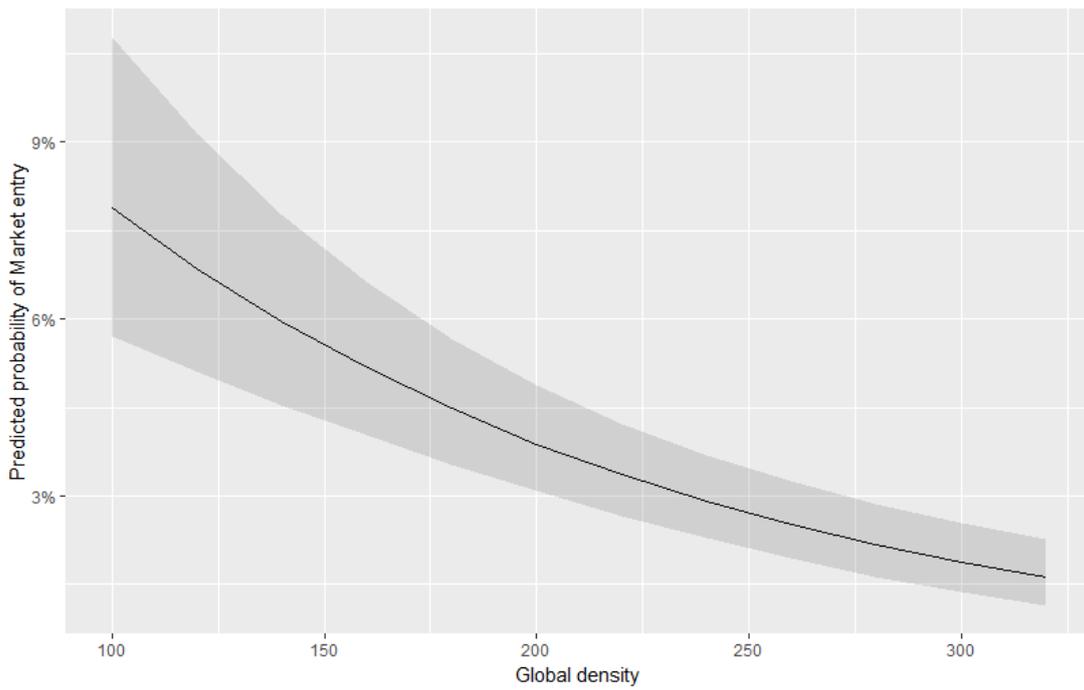


Figure 11. Ecological effects of global density from Sharing M1.

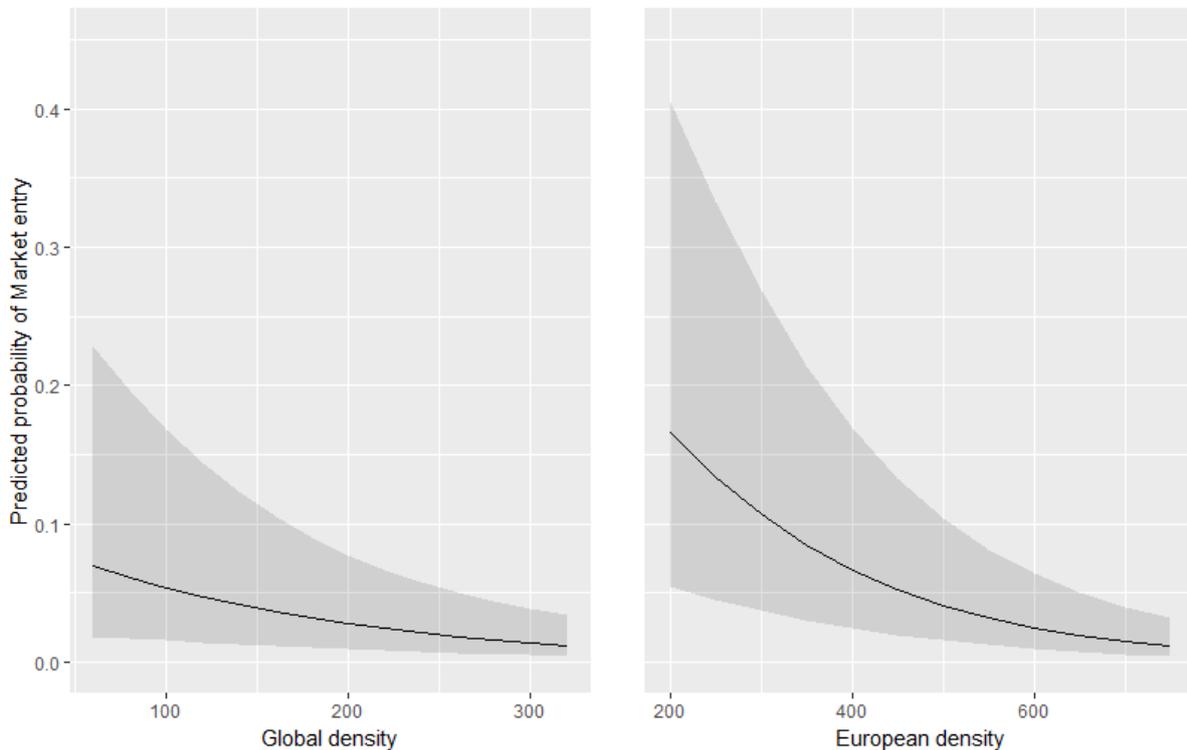


Figure 12. Ecological effects of global density from Sharing M8 (left) and Sharing M9 (right).

The ecological effect of global density from Sharing M1 is illustrated in **Figure 11**. In comparison with the effect of global density in the Gig models, the global density curve here is flatter. This is surprising since both the effect size and significance level of the global density predictor in Sharing M1 are nearly equal to the values of global density in Gig M1. The difference in global density between Sharing M8 and Sharing M9 is visualized in **Figure 12**. Both models include all ecological, control, and dummy variables. The difference between the models is that global density is clustered to the European level in model 9. The figure confirms that global density on the European level results in a better predictor than global density on a national level, by showing a steeper curve with the predicted probabilities of market entry.

4.5. Robustness checks

The gig and sharing models show unexpected results of global and related density. As such, additional regression models are analysed to control for the robustness of the findings.

4.5.1. Robustness checks of the gig models

The first robustness check for gig platforms is given in **Table 13**. The logistic regression models in the table are based on data where the markets with no entries are removed. When juxtaposing these results with the regression results from **Table 11**, the ecological model is stable in terms of effect sizes and significance levels. The effect sizes and significance levels for the institutional shock dummies also remain stable. A notable difference between both regression models is that the effect induced by semi-skilled markets is no longer significant. This suggests that most of the empty markets belong to the semi-skilled category, hence the lower odds to observe a market entry by a gig platform in semi-skilled markets compared with unskilled markets. Nonetheless, the effect induced by skilled markets remains significant, thereby confirming the lower odds of market entry in skilled labour markets vis-à-vis unskilled labour markets.

By excluding the markets with no observed entries, over a thousand observations with a value of zero are removed from the data. Consequently, the distribution of the number of market entries per observation changes. As such, count regression models are conducted in **Table 23** in Appendix C – Robustness checks as an additional robustness check. After checking for overdispersion of the data, all models show a dispersion of approximately 1.1, suggesting that Poisson regression is preferred over Quasi-Poisson or Negative binomial (Zeileis et al., 2008). The Poisson models show a significant first-order effect of European density. This means that while there is no significant effect of European density on the odds of a market entry, the European density does significantly reduce the market entry *rate*. That is, an increase in the European density decreases the overall number of market entries per given quarter.

When looking at the AIC values of the models as listed in **Table 11**, **Table 13**, and **Table 23**, the logistic regression models without the empty markets show the lowest values, which indicates a better model. Furthermore, the logistic regression models without the empty markets have log-likelihood values closer to zero, which suggests that the model's estimated coefficients are a better fit with the observed values. However, determining the best models utilizing a Vuong test, which compares the log-likelihoods (Vuong, 1989), is not possible since the models are estimated based on a different number of observations. In addition, the models that exclude the empty markets neglect an important ecological assumption. That is, legitimation and competition effects also affect the markets that did not experience a market entry by a digital platform, but who might experience such an introduction at a later stage. Moreover, since there is minor difference in either AIC or log-likelihood values between the logistic regression models with and without the empty markets, the models that include the empty markets are taken as a better fit.

4.5.2. Interaction effects gig models

All regression models were controlled for interaction effects with the institutional shock dummies. How the institutional shock dummy variables are embedded in the regression models implicitly assumes that the effects induced by institutional shocks are equal for each market or industry. From a methodological point of view, the argument of unobserved heterogeneity applies here again. That is, the relationship between institutional shocks and market entry does not consider differences between markets. Furthermore, institutional theory proclaims how each market is constituted by its institutions (Edquist, 1997). This implies that each market might not be affected equally by institutional shocks. The models are therefore controlled for interaction effects between the dummies and markets, but no significant interactions are reported. Additional interaction was checked between the dummies and the industries. No interaction effects are reported here as well. This means that there are no differences between either the markets or the industries in terms of the effects induced by the institutional shocks.

Table 13. Gig platforms - Logistic regression models without the empty markets.

Variable	G EM1	G EM2	G EM3	G EM4	G EM5	G EM6	G EM7	G EM8	G EM9
<u>Ecological model</u>									
Local density	0.227*** (0.018)	0.254*** (0.021)	0.229*** (0.018)	0.255*** (0.021)	0.222*** (0.021)	0.240*** (0.023)	0.240*** (0.023)	0.240*** (0.022)	0.241*** (0.022)
(Local density ²)/100	-0.344*** (0.054)	-0.419*** (0.062)	-0.336*** (0.054)	-0.408*** (0.062)	-0.325*** (0.060)	-0.372*** (0.064)	-0.373*** (0.065)	-0.380*** (0.062)	-0.380*** (0.062)
Global density s1	-0.006*** (0.002)				-0.006*** (0.002)				
(Global density s1 ²)/100	0.0004** (0.0002)				0.0004** (0.0002)				
Global density s2		-0.006*** (0.002)				-0.006*** (0.002)	-0.006*** (0.002)	-0.002 (0.002)	-0.002 (0.002)
(Global density s2 ²)/100		0.0004** (0.0002)				0.0004** (0.0002)	0.0004** (0.0002)	-0.0001 (0.0002)	-0.00005 (0.0003)
Related density		-0.010*** (0.004)		-0.008** (0.004)		-0.010*** (0.004)	-0.010*** (0.004)	-0.009** (0.004)	-0.008** (0.004)
(Related density ²)/100		0.003 (0.002)		0.002 (0.002)		0.004* (0.002)	0.003* (0.002)	0.002 (0.002)	0.002 (0.002)
EU density s1			-0.001 (0.0005)						
(EU density s1 ²)/100			-0.00001 (0.00002)						
EU density s2				-0.001 (0.0005)					
(EU density s2 ²)/100				-0.00001 (0.00002)					
<u>Market control variables</u>									
Market size/1000					-0.006** (0.003)	-0.006** (0.003)	-0.006** (0.003)	-0.005* (0.003)	-0.005* (0.003)
Semi-skilled markets					-0.293* (0.155)	-0.226 (0.156)	-0.228 (0.156)	-0.248 (0.156)	-0.246 (0.156)
Skilled markets					-0.805*** (0.153)	-0.724*** (0.161)	-0.721*** (0.161)	-0.754*** (0.160)	-0.735*** (0.161)
Service type					0.740*** (0.204)	0.782*** (0.204)	0.779*** (0.204)	0.754*** (0.205)	0.735*** (0.207)
<u>Institutional shock dummies</u>									
COVID-19 lockdown							0.346 (0.254)	-0.476 (0.353)	-0.403 (0.365)
Policy WAB								1.179*** (0.345)	1.058*** (0.376)
Exit of UberPOP									-0.184 (0.230)
Intercept	-0.921*** (0.371)	-1.042*** (0.332)	-1.890*** (0.296)	-1.771*** (0.293)	-0.647 (0.384)	-0.752* (0.364)	-0.784** (0.367)	-1.408*** (0.414)	-1.453*** (0.416)
Observations (N)	2,508	2,508	2,508	2,508	2,508	2,508	2,508	2,508	2,508
Log Likelihood	-1,166.056***	-1,160.598***	-1,159.991	-1,155.037***	-1,149.957***	-1,146.747**	-1,145.827	-1,139.891***	-1,139.547
AIC	2,342.113	2,335.196	2,329.981	2,324.075	2,317.914	2,315.494	2,315.655	2,307.093	2,307.093

Notes:

*p<0.1; **p<0.05; ***p<0.01 (all two-tailed); Standard errors shown in parentheses are robust standard errors clustered by quarter and Market (SBI 2008)

The results of the gig platform population show how skilled labour markets have lower odds to be entered by a gig platform in comparison with unskilled labour markets. This makes it interesting to scrutinize whether there is a difference in the legitimation effect between the three market skill categories. Furthermore, since the descriptive data on gig platforms show that some of the largest markets belong to the 'skilled labour' category, it is presumed that those markets benefit from a stronger legitimation effect. That is because the 'skill hierarchy of labour' implies that skilled work is perceived as more legitimate in comparison with unskilled work. (Farris & Bergfeld, 2022). Hence an interaction term is included in additional logistic regression models in **Table 14**. Since the robustness checks indicated that most of the markets with no entries belong to the skilled labour market category, this category is set as the reference category. The first model includes all ecological and market control variables. In the second and third models, the dummy variables are added to check for changes in the interaction effects.

Table 14. Gig platforms - Logistic regression with interaction term of local density and market skill.

Variable	Gig MS1	Gig MS2	Gig MS3
<u>Ecological model</u>			
Local density	0.319*** (0.024)	0.321*** (0.024)	0.322*** (0.024)
(Local density ²)/100	-0.491*** (0.064)	-0.500*** (0.061)	-0.500*** (0.059061)
Global density s2	-0.006*** (0.002)	-0.002 (0.002)	-0.002 (0.002)
(Global density s2 ²)/100	0.0004** (0.0002)	-0.0001 (0.0002)	-0.00003 (0.0002)
Related density	-0.012*** (0.004)	-0.010** (0.004)	-0.009** (0.004)
(Related density ²)/100	0.004* (0.002)	0.002 (0.002)	0.002 (0.002)
<u>Market control variables</u>			
Market size/1000	-0.005* (0.003)	-0.004 (0.003)	-0.004 (0.003)
Unskilled markets	0.693*** (0.242)	0.756*** (0.240)	0.753*** (0.240)
Skilled markets	0.191 (0.224)	0.280 (0.220)	0.281 (0.220)
Service type	1.016*** (0.216)	0.977*** (0.216)	0.963*** (0.218)
<u>Institutional shock dummies</u>			
COVID-19 lockdown		-0.536 (0.357)	-0.475 (0.370)
Policy WAB		1.257*** (0.350)	1.156*** (0.381)
Exit of UberPOP			-0.153 (0.231)
<u>Interaction terms</u>			
Local density * Unskilled markets	-0.029* (0.017)	-0.033* (0.017)	-0.033* (0.017)
Local density * Skilled markets	-0.053*** (0.015)	-0.054*** (0.015)	-0.054*** (0.015)
Intercept	-1.872*** (0.362)	-2.599*** (0.407)	-2.636*** (0.409)
Observations (N)	3,520	3,520	3,520
Log Likelihood	-1,189.712***	-1,182.072***	-1,181.833
AIC	2,405.425	2,394.145	2,395.666

Notes:

*p<0.1; **p<0.5; ***p<0.01 (all two-tailed)

Standard errors shown in parentheses are robust standard errors clustered by quarter and Market (SBI 2008)

The regression results show significant interaction terms between local density and the market skill categories in all the models. The interaction terms have a negative effect, which means that the odds ratio induced by local density decreases in both unskilled and skilled labour markets in comparison with semi-skilled labour markets. This implies that the legitimization effect at the local level is weaker in unskilled and skilled labour markets compared to semi-skilled labour markets. Or conversely, semi-skilled markets have a stronger legitimization effect at the market level in comparison with the other market skill categories. The stronger dependency on legitimacy spillovers in semi-skilled markets also corroborates why some of these markets (e.g., delivery of goods, repair person services) have experienced the fastest growth. The inclusion of the institutional shock dummy variables does not produce significant changes in the interaction terms. Changing the reference category shows no significant difference in the dependency on local legitimacy spillovers between unskilled and skilled labour markets.

Table 15. Gig platforms – Logistic regression models with interaction effects between share of online service type and the first-order density terms.

Variable	Gig ST1	Gig ST2	Gig ST3
<u>Ecological model</u>			
Local density	0.359*** (0.025)	0.286*** (0.022)	0.285*** (0.022)
(Local density ²)/100	-0.521*** (0.062)	-0.481*** (0.062)	-0.480*** (0.065)
Global density s2	-0.002 (0.002)	0.001 (0.002)	-0.004* (0.002)
(Global density s2 ²)/100	-0.0001 (0.0002)	-0.0003 (0.0003)	0.00002 (0.0002)
Related density	-0.013*** (0.004)	-0.010*** (0.004)	-0.003 (0.004)
(Related density ²)/100	0.004** (0.002)	0.002 (0.002)	0.005** (0.002)
<u>Market control variables</u>			
Market size/1000	-0.004 (0.003)	-0.006** (0.003)	-0.004 (0.003)
Unskilled markets	-0.165 (0.173)	-0.416*** (0.156)	-0.349** (0.160)
Skilled markets	-0.382** (0.183)	-0.701*** (0.173)	-0.738*** (0.172)
Service type	2.093*** (0.243)	2.385*** (0.389)	1.960*** (0.269)
<u>Institutional shock dummies</u>			
COVID-19 lockdown	-0.503 (0.352)	-0.584* (0.352)	-0.393 (0.348)
Policy WAB	1.214*** (0.345)	1.382*** (0.347)	1.021*** (0.343)
<u>Interaction terms</u>			
Local density * Service type	-0.140*** (0.022)		
Global density * Service type		-0.003*** (0.0009)	
Related density * Service type			-0.018*** (0.003)
Intercept	-2.389*** (0.409)	-2.869*** (0.484)	-1.958*** (0.420)
Observations (<i>N</i>)	3,520	3,520	3,520
Log Likelihood	-1,168.447***	-1,182.969***	-1,177.156***
AIC	2,364.895	2,393.938	2,382.312

Notes:

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$ (all two-tailed)

Standard errors shown in parentheses are robust standard errors clustered by quarter and Market (SBI 2008)

In a comparable way, the interactions between the service type variable and the first-order density terms are investigated in additional models in **Table 15**. From the earlier logistic regression models, it was proven that markets with a higher share of online services have greater odds of market entry, which indicates that these markets have lower barriers to market entry. Given that market entry barriers are lower, it is likely that platforms are less dependent on spillovers from other platforms when entering these markets. Moreover, it could be that platforms for online work are perceived as a unique organizational form in comparison with other gig platforms, causing them to have a different dependency on legitimacy spillovers. This is indeed shown by the interaction terms in the models, which are all negative and significant. This means that the density terms become a less important predictor when there is a higher share of platforms with an online service type. The interaction term with local density has the highest effect size, suggesting that the market entry of gig platforms becomes less dependent on legitimacy spillovers from platforms in the same market, i.e., markets with a substantial proportion of online labour. As such, these results confirm that 'online' markets perceive lower barriers to market entry.

Overall, the robustness checks support the robustness of the findings of the gig platform population. From the regression models without the empty markets, it can be ascertained that the effects at the global and related levels are indeed reversed. These models also indicate that the effect induced by semi-skilled markets is likely to be the product of 'empty' markets. That is because no market entries are observed in some of the semi-skilled markets, which implies that it is unlikely that these markets might experience a market entry by a gig platform at all. Nevertheless, the interaction terms between the market skill categories and local density suggest that semi-skilled markets have a higher dependency on legitimacy spillovers at the market level. Similarly, interaction terms corroborate that a higher share of online work platforms leads to lower barriers to market entry, as evidenced by a lower dependency on spillovers. And finally, the robustness checks confirm that a model with the ecological variables, the market control variables, and the institutional shock dummies, captures additional heterogeneity in comparison to the other models.

4.5.3. Robustness checks of the sharing models

The robustness of the findings of the sharing models is checked in **Table 16**. This robustness check is performed with logistic regression models in which the markets with no entries are excluded from the analysis. In comparison with the results from the other sharing regression models, all variables show consistency in terms of effect size and significance levels. Conducting another robustness check with a count model thus seems to be irrelevant here. In addition, the distribution of the number of market entries per observation does not change after removing the empty markets from the sharing platform sample, since the number of cases with multiple market entries remains limited.

Table 16. Sharing platforms - Logistic regression models without the empty markets.

Variable	S EM1	S EM2	S EM3	S EM4	S EM5	S EM6	S EM7	S EM8	S EM9
<u>Ecological model</u>									
Local density	0.393*** (0.036)	0.406*** (0.041)	0.407*** (0.037)	0.416*** (0.042)	0.428*** (0.042)	0.427*** (0.043)	0.435*** (0.044)	0.428*** (0.044)	0.446*** (0.047)
(Local density ²)/100	-1.133*** (0.156)	-1.211*** (0.190)	-1.160*** (0.158)	-1.209*** (0.197)	-1.282*** (0.193)	-1.283*** (0.204)	-1.309*** (0.216)	-1.277*** (0.219)	-1.279*** (0.230)
Global density situation 1	-0.007*** (0.001)				-0.008*** (0.001)				
Global density situation 2		-0.008*** (0.002)				-0.011*** (0.002)	-0.012*** (0.002)	-0.009*** (0.002)	
Related density		-0.022** (0.011)		-0.025** (0.010)		-0.029* (0.017)	-0.035** (0.019)	-0.034* (0.019)	-0.026 (0.017)
(Related density ²)/100		0.013 (0.010)		0.021** (0.009)		0.019 (0.012)	0.024* (0.013)	0.025** (0.013)	0.028** (0.013)
EU density s1			-0.004*** (0.0005)						
EU density s2				-0.004*** (0.0007)					-0.006*** (0.001)
<u>Market control variables</u>									
Market size/1000					-0.038 (0.025)	-0.027 (0.025)	-0.031 (0.025)	-0.026 (0.025)	-0.022 (0.026)
Moveable property					-0.619** (0.283)	-0.572 (0.710)	-0.542 (0.741)	0.432 (0.753)	-1.030 (0.610)
Immoveable property					-0.085 (0.329)	-0.019 (0.338)	0.075 (0.355)	0.065 (0.349)	0.036 (0.351)
Non-profits					1.675*** (0.338)	1.790*** (0.351)	2.101*** (0.341)	1.827*** (0.349)	2.037*** (0.366)
<u>Institutional shock dummies</u>									
COVID-19 lockdown							1.616*** (0.287)	2.269*** (0.366)	2.464*** (0.369)
Airbnb restriction 60 days								-0.871** (0.229)	-0.303 (0.243)
Airbnb restriction 30 days								-1.004*** (0.282)	-0.697** (0.292)
Intercept	-1.889*** (0.261)	-1.466*** (0.404)	-1.657*** (0.253)	-0.987** (0.388)	-1.586*** (0.368)	-1.029** (0.504)	-0.794 (0.527)	-1.264** (0.548)	-0.342 (0.301)
Observations (N)	2,376	2,376	2,376	2,376	2,360	2,360	2,360	2,360	2,360
Log Likelihood	-787.342***	-786.275	-779.494***	-777.204	-769.812	-767.992	-751.602	-743.546	-731.733
AIC	1,582.683	1,584.550	1,566.988	1,566.409					

Notes:

*p<0.1; **p<0.05; ***p<0.01 (all two-tailed)

Standard errors shown in parentheses are robust standard errors clustered by quarter and Market (SBI 2008)

4.5.4. *Interaction effects sharing models*

The regression models of the sharing platform population were also controlled for interaction effects induced by the institutional shock dummies. However, none of the models report significant interaction effects of these dummy variables with either the markets or the overarching industries. As such, the institutional shocks engender no divergent effects over different markets or industries.

In **Table 17**, additional models are presented that explore the interaction effects between the share of non-profits and the first-order density terms. European density is used in these models instead of global density since this results in a better model fit according to the AIC and log-likelihood values. Based on the employed conceptual model, it can be expected to observe different dependencies on spillovers in markets with a larger proportion of non-profits. To explain, it is assumed in the ecological model that the populations of platform companies are of the same organizational form, i.e., sharing platforms. However, the extent to which non-profits and for-profits are perceived as the same type of sharing platform by audiences is questionable. Furthermore, the study of Baum & Oliver (1996) emphasizes how the effects of ecological and institutional processes vary for non-profit and for-profit organizational forms. The interaction terms in the models show local and European density become a less important predictor with higher shares of non-profit sharing platforms, thereby corroborating that non-profit sharing platforms are indeed perceived as a different organizational form by audiences when compared to for-profit sharing platforms.

The robustness checks for the sharing platform models support the robustness of the findings. Also here, the negative effects of the global and related density terms remain consistent. All models show that a higher share of non-profit sharing platforms results in greater odds of market entry. Moreover, markets with more non-profits show a lower dependency on legitimacy spillovers from platforms in the same market. These markets are also less affected by the negative effect caused by platforms from other markets. The control models prove that the inclusion of European density instead of global density results in better model performances. That is, the log-likelihood and AIC values indicate that these models have a better balance between complexity and goodness-of-fit. From the AIC and log-likelihood values also follows that a model with all the variables captures additional heterogeneity in comparison with the other models.

Table 17. Sharing platforms – Logistic regression models with interaction effects between share of non-profits and the first-order density terms.

Variable	Sharing NP1	Sharing NP2	Sharing NP3
<u>Ecological model</u>			
Local density	0.590*** (0.061)	0.498*** (0.044)	0.502*** (0.046)
(Local density ²)/100	-1.674*** (0.267)	-1.498*** (0.222)	-1.452*** (0.238)
EU density s2	-0.007*** (0.001)	-0.003*** (0.001)	-0.006*** (0.001)
Related density	-0.023 (0.020)	-0.040** (0.018)	-0.024 (0.020)
(Related density ²)/100	0.028** (0.014)	0.044*** (0.014)	0.026* (0.014)
<u>Market control variables</u>			
Market size/1000	-0.0005 (0.026)	-0.008 (0.025)	0.001 (0.026)
Moveable property	-1.007 (0.760)	-1.227* (0.699)	-0.762 (0.774)
Immoveable property	-0.027 (0.395)	0.239 (0.371)	0.216 (0.352)
Non-profits	2.992*** (0.454)	12.427*** (2.083)	2.313*** (0.638)
<u>Institutional shock dummies</u>			
COVID-19 lockdown	2.489*** (0.378)	2.455*** (0.358)	2.490*** (0.370)
Airbnb restriction 60 days	-0.285 (0.245)	-0.129 (0.252)	-0.270 (0.251)
Airbnb restriction 30 days	-0.745** (0.312)	-0.601** (0.306)	-0.647** (0.308)
<u>Interaction terms</u>			
Local density * Non-profits	-0.237*** (0.096)		
EU density s2 * Non-profits		-0.018*** (0.004)	
Related density * Non-profits			0.004 (0.010)
Intercept	-0.938* (0.543)	-2.358*** (0.602)	-0.966* (0.520)
Observations (<i>N</i>)	3,196	3,196	3,196
Log Likelihood	-743.132***	-730.512***	-746.528***
AIC	1,514.265	1,489.024	1,521.055

Notes:

*p<0.1; **p<0.5; ***p<0.01 (all two-tailed)

Standard errors shown in parentheses are robust standard errors clustered by quarter and Market (SBI 2008)

4.6. Summary of the findings

4.6.1. Reflection on the hypotheses

In all the models, the regression results show a significant legitimation effect at the local level, thereby supporting the first hypothesis. That is, the market entry of a digital platform is positively related to the number of platforms present in the same market. For both gig and sharing platform populations, an increase in the number of platforms present in the same markets engenders higher chances for subsequent market entry by ensuing platforms. From the density dependence follows that this effect is induced by legitimacy spillovers from platforms already present in the same market. However, the results also demonstrate how competition eventually becomes more intense as the number of digital platforms in each market continues to increase in the long term. Nevertheless, the short-term effect is in line with what was postulated, and Hypothesis 1 can therefore be accepted.

The negative long-term effect at the market level indicates how digital platforms eventually engage in fierce competition to leverage users. The fact remains that these platforms are digital, thus switching between platforms is only a click away. Moreover, digital platforms are contingent on network effects (Knee, 2021; Täuscher & Kietzmann, 2017), meaning that their relative value grows as their user base increases. When faced with an increasing number of platforms in the same markets, the pressure from low switching costs and network effects instigates intense competition.

The regression models and their corresponding robustness checks show counterintuitive results at the global level. As mentioned, the general presumption was that the market-agnostic traits of digital platforms allow them to transpose the legitimacy from platforms in other markets. However, global density has a nonmonotonic effect on market entry in the gig platform population, which starts negative and eventually becomes positive. The sharing platform population also shows a negative short-term effect of global density. This negative effect becomes stronger when the global level is aggregated to the European level. Simply put, the negative effect of global density means that the overall spread of digital platforms over markets acts as a market entry barrier for ensuing platforms in the short term. These findings are not sufficient to accept Hypothesis 2, but the positive long-term effect suggests that it may be too early to reject it. The plausible causes for the unexpected effects of global density are therefore discussed in the discussion chapter.

The results do not present enough statistical evidence to corroborate Hypothesis 3. The models show a negative effect of related density during the short term in both platform populations. This means that an increase in the spread of platforms over related markets acts as a market entry barrier. The long-term effect of related density becomes significant in the sharing models with dummies, which are a better model fit. Like global density, this suggests that sharing platforms leverage legitimacy spillovers from platforms in related markets when local competition becomes more intense. However, the inconsistency of the long-term findings in both types of models causes the third hypothesis to be rejected. Concomitantly with global density, the plausible causes for observing a negative effect of related density are discussed in the discussion chapter.

The overall results give supporting evidence for Hypothesis 4, which can therefore be accepted. However, the direct causality between the institutional shocks and the market entries from the models is questionable since the institutional shocks are measured through dummy variables. Put differently, while the results give evidence for a relationship between institutional shocks and the market entry of a digital platform externalities are involved. Regardless, the results emphasize that there is at least some causality induced by institutional shocks, whether it be direct or indirect.

4.6.2. Control variables

Both the gig platform and sharing platform populations were controlled for alternative explanations by including market control variables. The results show that the total number of companies present in a market is negatively related to market entry by gig platforms. This can be perceived as a competition effect that occurs between gig platforms and non-platform companies, which forms a barrier to market entry. The results also reveal that gig platforms are less likely to enter markets that involve 'skilled labour', i.e., work that requires advanced education or specialized skills. In addition, markets for semi-skilled labour appear to have a stronger dependency on local legitimacy spillovers, that is, from platforms in the same market.

Barriers to market entry for gig platforms decrease as the ratio of platforms that allow for online work increases. This is demonstrated by the results in two ways. First, the odds of market entry are higher as the share of platforms with an online service type increases. And second, markets with a substantial proportion of online services are both less dependent on local legitimacy spillovers and less affected by the negative effect induced by the spread of platforms over other markets. Similarly, barriers to market entry for sharing platforms decrease as the ratio of non-profits increases. The market entry becomes less driven by legitimation and competition effects in markets with a large share of sharing platforms with a non-profit orientation.

5. CONCLUSION

The objective of this study was to contribute to the collective understanding of how digital platforms attain legitimacy through leveraging legitimacy spillovers. More formally, the study asks, "*to what extent does the market entry of a digital platform in the Netherlands depend on external legitimacy spillovers?*" In answering this research question, the populations of the gig and sharing platforms in the Netherlands during the 11 years between 2010 and 2020 were analysed.

In the theoretical model it was postulated that the market entry of a digital platform is affected by legitimacy spillovers from three levels: from platforms in the same market; from platforms in all other markets; and from platforms in all related markets. The findings demonstrate that the market entry of a digital platform is dependent on legitimacy spillovers from other platforms in the same markets. However, market entry eventually becomes driven by competition between digital platforms in the long term. The results also show how spillovers from digital platforms in other markets are initially a barrier to market entry, but eventually, drive market entry. The findings also hint that this effect is similar for related markets. As such, a formal answer to the research question would be as follows.

The market entry of a digital platform in the Netherlands depends on legitimacy spillovers to the extent that these spillovers arise from platforms in the same market. Market entry has a higher dependency on these spillovers in markets for skilled labour. The dependency on local legitimacy spillovers decreases when markets are characterized by a higher share of non-profit platforms or a higher share of platforms for online work. When competition between digital platforms in a market intensifies, subsequent market entry also becomes dependent on legitimacy spillovers from platforms in other markets.

6. DISCUSSION

The discussion section is divided into five parts. The first part reflects on what was postulated based on the theory, and how the findings contribute to this theory. Thereafter, the lack of supporting evidence for the second and third hypotheses is discussed. This part explores why the findings do not support the hypothesized effects. Subsequently, the plausible explanations for why the effects are the opposite of what was expected are discussed. This is followed by an outline of the study's limitations. The discussion ends by listing the contributions and their corresponding implications.

6.1. Embedding in theory

The theory section of the thesis postulated how digital platforms attain legitimacy. The presumption that was made, is that the legitimation of digital platforms is like that of emerging markets. That is, digital platforms do not only disrupt traditional markets by advancing innovative solutions, but they also use cognitive strategies to exploit existing institutions in an attempt to resonate with a heterogeneous set of stakeholders (Aversa et al., 2021). In a similar vein, Uzunca et al. (2018) state that, in countries with higher degrees of institutionalization (e.g. European countries), platforms from the gig and sharing economy employ strategies to approach existing institutions and key stakeholders in their environment in an attempt to gain legitimacy. By referring to the use of such strategies, these studies indicate that the legitimation of a digital platform likely hinges on institutional transposition, which denotes the process in which the status and experience garnered in a market or industry is converted to another dimension (Boxenbaum & Battilana, 2005; Powell et al., 2012). Moreover, the fact that digital platforms are considered market-agnostic corroborates their ability to leverage legitimacy spillovers, from both platforms in the same market and platforms in other markets. However, the legitimation of a digital platform is also contingent on the extent to which the platform can conform to its institutional environment, as proclaimed by institutional theory.

This discrepancy was further explored in this study by employing the density dependence model from organizational ecology. By setting the level of analysis at markets instead of regions, the legitimacy spillovers under study are those that arise from markets and thus are not geographical spillovers. The density dependence model assumes that the vital rates of a population of organization are driven by legitimation and competition, which is contingent on density. Empirical evidence with this ecological model suggests that legitimation generally operates on a more global level, while competition takes place at a more local level (Bigelow et al., 1997; Hannan et al., 1995). While a competition effect at a more local level was observed, the results diverge from the ecological model in two ways. First, digital platforms seem to benefit from the legitimacy spillovers of other platforms at a more local level, i.e., in the same market. And second, the total spread of digital platforms over other markets is negatively associated with the market entry of ensuing platforms in the short term. The term 'spread' is used since global density is measured by the net sum of entries of digital platforms in all other markets.

The effects of the ecological model are visualized in **Figure 13**. When the overall number of digital platforms present in markets is low, the model visualizes how digital platforms benefit from positive legitimacy spillovers from other platforms in the same markets. Simultaneously, platforms are negatively affected by spillovers from platforms in other markets. When the overall number of digital platforms present in markets is high, competition becomes more intense, eventually leading to legitimacy spillovers from other markets. The extent to which these effects drive the legitimation of digital platforms depends on the presence of institutional shocks. Organizational ecologists acknowledge the influence of changes in the institutional environment on organizational change and founding rates (Singh & Lumsden, 1990). The findings indeed confirm causality between

institutional shocks and the market entry of digital platforms, which corroborates the proclamation posed by institutional theorists.

Data on the Dutch populations of gig and sharing platforms show how digital platforms spread out over multiple markets, which verifies that digital platforms can be considered market-agnostic. However, not enough evidence is posed by the findings to entirely support the assertion about the ability of digital platforms to leverage legitimacy spillovers from other markets through transposition. Regardless, the results hint that platforms might be able to do so in the long term when competition within markets becomes more intense, driving them to also leverage legitimacy spillovers from other markets. The dependency of digital platforms on legitimacy spillovers has hitherto remained unaddressed in scientific literature. More specifically, existing studies on the legitimation of digital platforms are often qualitative in nature and engender frameworks of the possible cognitive strategies pursued by platforms to build legitimacy (Aversa et al., 2021; Boon et al., 2019; Uzunca et al., 2018). The findings of this study indicate that such cognitive strategies can also comprise the leverage of legitimacy spillovers through transposition. As such, this study marks the beginning of uncovering how digital platforms can leverage legitimacy spillovers from markets through transposition, especially those spillovers that originate from other markets.

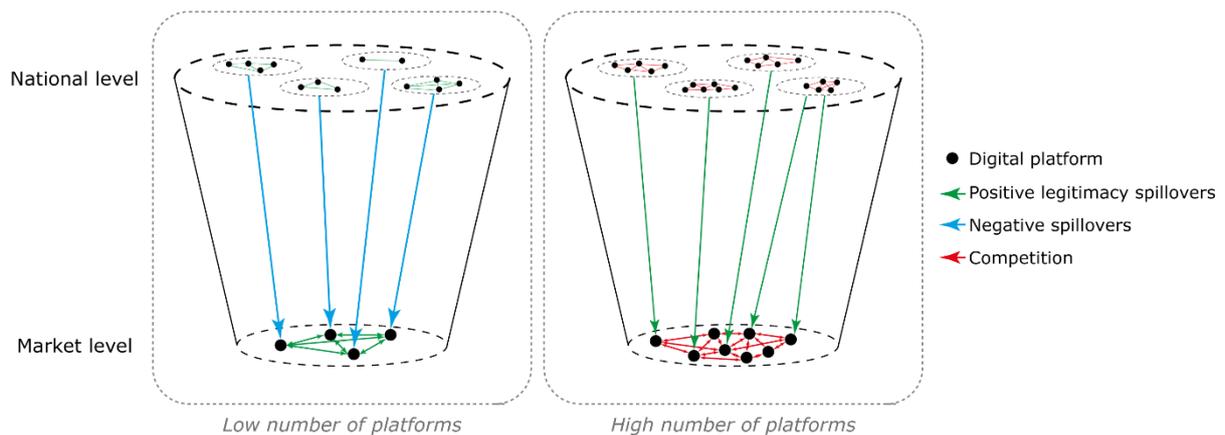


Figure 13. Visual model of digital platforms and legitimacy spillovers.

6.2. Unexpected results

The findings do not support the expected short-term effects of both related markets and all other markets. Again, it was expected that digital platforms act in institutional transposition, thereby leveraging legitimacy spillovers from other markets. But it was also conjectured that the organizational form of digital platforms benefits from global legitimation. To elaborate, as more people make use of digital platforms, successful past experiences with digital platforms start to accumulate, which enhances the legitimacy of a digital platform as an organizational form. While both arguments explain why digital platforms might benefit from legitimacy spillovers in other markets, it was anticipated that they are particularly dependent on legitimacy spillovers from related markets. The argument here was that platforms are more likely to leverage legitimacy spillovers from platforms that operate under similar institutional settings, owing to their relational proximity.

The fact that these expectations were not supported by the results suggests that the conceptual assumption of what a digital platform entails might be specious. In the employed ecological model, the cognitive dimension of legitimacy is emphasized (Haveman & David, 2008). This means that legitimacy accrues to an organizational form as it increases in numbers (Hannan & Freeman, 1987). As such, an assumption in the density

dependence model is that the populations of organizations under analysis are of the same organizational form, which is either gig platforms or sharing platforms here. However, what is conceptually referred to as gig platforms and sharing platforms in scientific literature might be perceived differently by audiences. It may very well be that audiences perceive platform companies not as digital platforms, but as another organizational form. To illustrate this with an example, the organizational form of Uber can be identified by general audiences as a taxi company, instead of a gig platform. From this follows that the perceived organizational form of a platform by audiences depends on the markets it is active in. Consequently, a cognitive legitimation effect of gig platforms or sharing platforms cannot be observed on higher levels than that of single markets, explaining the absence of a positive legitimation effect induced by the first-order terms of related density and global density.

6.3. Negative spillovers between markets

While the previous part explains why a legitimation effect is not observed at the related and global levels, it does not justify why the spread of platforms in related markets and all other markets is negatively associated with market entry. This thesis conjectures that this effect may be the cause of four different plausible explanations, which will be discussed below.

6.3.1. *Early competition*

First, the measured effect of global density can also be the product of early competition between platforms. The concept of what a gig or sharing platform entails was likely to be unfamiliar in the initial stages of the digital platform population, as hinted by the limited number of platforms in the 2010s. Consequently, the rivalry between platforms was likely to be more intense as the number of overall users was still limited. This conjecture is supported by the fact that the number of platform users has increased over the years. For instance, Urzì Brancati et al. (2020) find that share of platform workers in the overall Dutch labour force has risen by 4 per cent between 2017 and 2018. In like manner, Jorritsma et al. (2021) showcase how the number of platform users in the field of mobility sharing has grown in recent years. A plausible explanation for a negative short-term effect at the global level would therefore be that this is induced by competition for users. Given that the pool of platform users has increased over the years, the national competition for platform users is likely to become less intense, which explains why a legitimation effect takes over as the driver of market entry in the long term.

6.3.2. *Insufficient legitimacy*

A second explanation for the negative effect of global and related density relates to the strength of legitimacy spillovers. It was mentioned earlier that legitimacy has both dichotomous and continuous properties (Soublière & Gehman, 2020), meaning that platforms need sufficient endorsement to be regarded as legitimate. The results may suggest that, while digital platforms can leverage legitimacy spillovers over markets, these spillovers are not strong enough for the legitimation of a digital platform. More specifically, the spillovers are not sufficient for a new platform to garner legitimacy on both cognitive and normative grounds. Some case studies highlight that platforms in the gig and sharing economy have difficulty in gaining normative (moral) legitimacy (Hwang, 2019; Pelzer et al., 2019). When faced with negative institutional shocks, the threshold for being regarded as legitimate on moral grounds becomes even higher, as evidenced by the negative effect of the Airbnb restrictions on the market entry in the entire sharing platform population. It is therefore likely that legitimacy spillovers are not always sufficient for the legitimation of a digital platform.

6.3.1. *Illegitimacy spillovers*

Third and related to the former, the observed negative relationships can be the product of negative legitimacy spillovers, which can also be labelled as illegitimacy spillovers. Kostova & Zaheer (1999) mention in their work that legitimacy spillovers can occur in different directions, both positive and negative. The authors also add that positive and negative legitimacy spillovers are not symmetric in their effects, i.e., it is more likely that negative legitimacy spillovers have a stronger effect on legitimacy than positive spillovers. These illegitimacy spillovers have a particularly strong effect on new organizations that need to establish their legitimacy, in comparison with organizations that need to maintain their legitimacy (Kostova & Zaheer, 1999; Lounsbury & Glynn, 2001). That is because, under conditions of bounded rationality, people's opinions are shaped by their perceived judgement on similar experiences, which is also understood as the 'representative heuristic' (Tversky & Kahneman, 1974). More formally, novel organizations tend to have difficulty in attaining legitimacy when prior organizations are regarded as illegitimate.

The market entry of digital platforms may very well be affected by illegitimacy spillovers on a national level. Some of the more well-known platforms have become a cause célèbre over recent years, owing to assorted reasons. Examples include racial discrimination on home sharing platform Airbnb (Parkinson, 2016), fatal accidents caused by overworked Uber drivers (Homan, 2018; Schoonhoven, 2019), and numerous lawsuits due to bad working conditions of the so-called 'self-employed' gig workers against gig platforms as Deliveroo and Temper (NOS, 2018, 2020). These controversies could have instigated a 'stigma effect', i.e., accusations against a platform generate negative consequences for non-accused platforms (Naumovska & Lavie, 2021). Indeed, one might ask how these platforms remain active despite surrounding controversies that challenge their legitimacy. Colyvas & Jonsson (2011) state that innovations can diffuse without being institutionalized, thereby being ubiquitous but not accepted. In addition, maintaining legitimacy is easier in the face of illegitimate practices than establishing legitimacy (Kostova & Zaheer, 1999). The barrier to entry for digital platforms induced by global density could therefore be the product of spillovers from the illegitimate practices of existing digital platforms. The work of Ackermann et al. (2022) indicates the existence of illegitimacy spillovers in the sharing economy, by stating that the choice for tourists between platforms and non-platforms in the accommodation sector is affected by legitimacy issues raised by the sharing economy.

These illegitimacy spillovers are not only generated by the perceived illegitimate actions of platforms, but also by platforms with mediocre performance rates. To explain, poor performances of platforms discourage established backers whose support is unneeded, which subsequently shrinks the capacity to carry out other related endeavours (Soublière & Gehman, 2020). But conversely, the failures among digital platforms may engender positive legitimacy spillovers for ensuing platforms, as "the disbanding of an existing organization may create free-floating resources which could be reassembled into new organizations" (Singh & Lumsden, 1990, p. 164). The fact that illegitimacy spillovers can arise from both legitimate and illegitimate practices might also explain why global density has a positive effect in the long term. That is, inferior performances might initially signal limited possibilities for fruitful endeavours. But as the spread of platforms over markets continues to increase, chances are that the perceived success of these platforms is leveraged through transposition by ensuing platforms.

6.3.2. *Modelling errors*

A final explanation for observing a negative relationship between the density on the global and related levels and market entry is that it is the result of modelling errors. The density dependence model has encountered lots of criticism from scholars in its early years, especially since various studies have shown discrepant results (Singh, 1993). However,

Hannan & Carroll (1992) point out that in these studies the non-supportive results may arise from left-truncated data observation. Or in other words, part of the early history in which legitimation has the strongest effect has been left out of scope in the observation (Singh, 1993; Singh & Lumsden, 1990). While **Figure 2** does show that some digital platforms were present before the observation period, the distribution also illustrates that the populations of gig and sharing platforms started to increase during this timeframe. Therefore, it is safe to assume that the non-supportive results of global and related density do not arise from left-truncated data observation schemes.

The most realistic explanation would be a combination of the first three arguments. It is also likely that institutional shocks play an important part in the observed negative effect. The institutional shocks included in the study mostly comprise changes in the legal environment, but these shocks can also be induced by other types of events, as exemplified by the three controversial events mentioned earlier. Given the nature of the employed density dependence model, it is difficult to pinpoint which mechanism is the most responsible for observing a negative relationship between global density and the market entry of a digital platform. This is because density is used as a proxy for the effects of legitimation and competition, thus a direct measure of these effects is absent. As such, more attention to this phenomenon in future research is warranted. That is, to uncover the plausible mechanisms that drive the adverse effect of the spread of digital platforms over markets on subsequent market entry.

6.4. Limitations

The study has some limitations. First, the time of market entry was assumed to be equal to the platforms' date of registration, while platforms often rollout their services sequentially. In other words, a platform gradually enters more markets, instead of entering all markets simultaneously as was assumed. This assumption was made since finding out the exact dates of when each platform service or add-on was set in motion is impracticable, especially for platforms that were dissolved. However, such an assumption may have affected the observed effects at the global level to some extent, but the conjecture here is that this does not affect the directions of the effects. That is because the numerous robustness checks support the overall results of the regression analyses. Put differently, while the invalid assumption affects the internal reliability to some extent, it does not alter the causality of the findings.

Second, the study does not take the size and age of digital platforms into account. Various scholars have stressed platforms' reliance on network effects (Knee, 2021; Täuscher & Kietzmann, 2017), which suggests that legitimacy spillovers between platforms are also contingent on network effects. A more elaborate scrutinization of a platform's reliance on network effects and how this influences the legitimacy spillovers between digital platforms is therefore warranted. Future studies could thereby extend the findings of this study by employing alterations of the density dependence model. Examples of such alterations include the mass dependence or age dependence model to account for the impact of larger and more mature platforms (Amburgey & Rao, 1996).

And third, as exemplified by the discussion on legitimacy spillovers between markets, the quantitative nature of the study does not provide in-depth knowledge on how legitimacy spillovers are leveraged by platforms. Nevertheless, existing qualitative studies already explain how digital platforms follow certain strategies to garner legitimacy. For example, Aversa et al. (2021) assert that digital platforms identify themselves, or refrain from identifying themselves, in a certain market category, and how this consequently affects a platform's perceived legitimacy. In line with this, it is presumed in this thesis that digital platforms leverage legitimacy spillovers through institutional transposition.

6.5. Contributions and implications

This study also makes several scientific and social contributions. First, it contributes to the collective understanding of how digital platforms leverage legitimacy spillovers across markets, which was hitherto unexplored in scientific literature. At the beginning of this thesis, it was proclaimed that digital platforms can transcend market boundaries by either changing the scope of the platform in terms of activities, the configuration of the platform in terms of user access, or the digital interfaces that specify the bilateral exchange of data. Notwithstanding the focus on gig and sharing platforms, the findings presented in this paper are generalizable to other types of digital platforms, given that they share the idiosyncratic abilities that render them market-agnostic. Examples of other types of platforms include social media platforms (e.g., Facebook or Twitter) or retail platforms (e.g., Amazon or eBay), but also cryptocurrency (e.g., Bitcoin or Ethereum). The presumption for these platforms is that they show similar dependencies on legitimacy spillovers. But regardless, more research into this topic is warranted.

Second and related to the former, this thesis adds to the body of literature on organizational ecology that is specifically concerned with the empirical application of the density dependence model. As previously mentioned, the strengths of the density dependence model lie in its parsimony and generalizability. These strengths were utilized here, which enabled the study to set the level of analysis of the ecological model to markets instead of geographic regions. In doing so, the population density was defined in terms of market entries. At aggregated levels, this allowed for measuring the effects of density in terms of the spread of digital platforms over markets instead of the total number of digital platforms present. As such, this study offers an extension of the baseline density dependence model that is suitable for assimilating the effects of density on the market entry rate, while simultaneously proving its usefulness with empirics on gig and sharing platforms.

Third, this study contributes to the understanding of how platform entrepreneurs can benefit from the endeavours of other platforms by scrutinizing the relationship between external legitimacy spillovers and market entry. While platforms benefit from legitimacy spillovers of other platforms in the same market, they may be negatively affected by spillover effects from platforms in other markets. Indeed, given that the nature of the spillovers between markets is uncertain, it is difficult to derive how platform entrepreneurs should act accordingly. Regardless, the findings demonstrate that the general endorsement of a platform is negatively affected by the expansion of platforms over other markets, which should be considered by platform entrepreneurs. The findings also illustrate that the dependency on spillover effects changes over time. This knowledge may be of relevance for platform entrepreneurs in determining the most optimal time for market entry.

Fourth, the thesis gives supporting evidence for the effectiveness of policy and regulation on digital platforms. The results indicate that the market entry of a digital platform is indeed affected by changes in the institutional environment, which are called 'institutional shocks' here. More specifically, the results suggest that stronger regulations and restrictions are detrimental to the market entry rate of digital platforms, as illustrated by the rental term restrictions of Airbnb. This thesis thereby gives an initial answer to one of the open questions posed by Greenwood et al. (2017, p. 28), which was formulated as: "*How will differences in labour laws, regulations, and economic opportunity affect the geographic expansion of gig-economy platforms?*". The results also indicate that institutional shocks have a stronger effect on the market entry of digital platforms than the presence of legitimacy spillovers. Naturally, the fact remains that platforms need to conform to their institutional environment to be perceived as legitimate.

Fifth and related to the former, by assimilating how digital platforms leverage legitimacy spillovers across markets, policymakers can more effectively target those platforms that transgress the most fundamental public interests. Discussing the implications of how policymakers and regulators could respond to digital platforms is out of scope here, as this is discussed extensively in other works (Frenken, van Waes, et al., 2020). In addition, the findings highlight how regulatory changes seem to be effective in targeting the legitimation of digital platforms. However, this also implies that policy and regulation targeted at a single platform may eventuate an institutional shock that also affects other platforms. The extent to which changes in regulation influence other platforms should be considered in the decision by policymakers on whether to accommodate certain platforms.

Finally, this thesis contributes to the stream of literature in the innovation sciences that is concerned with the interactions between digital innovations and institutions. The digital platforms under study in this paper encompass novel digital organizational forms (Hinings et al., 2018), rendering them digital innovations. Innovation theory encourages scholars to study how innovations develop and diffuse, and in doing so, gain legitimacy. Gegenhuber et al. (2020) specifically called for papers on how digital innovations affect the very ways in which institutions are created, complemented, threatened, and destroyed. The findings of this study elucidate the dependency of digital platforms on legitimacy spillovers, thereby contributing to uncovering how digital innovations can affect institutions. While the results posed a lack of evidence to fully corroborate the transposition of legitimacy spillovers from digital platforms in other markets, it is conjectured that institutional transposition plays a significant role in the alteration of institutions by digital innovations. Scholars are therefore invited to further explore the relationship between digital innovations and institutional transposition.

7. REFERENCES

- Ackermann, C. L., Matson-Barkat, S., & Truong, Y. (2022). A legitimacy perspective on sharing economy consumption in the accommodation sector. *Current Issues in Tourism*, 25(12), 1947–1967. <https://doi.org/10.1080/13683500.2021.1935789>
- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6), 716–723. <https://doi.org/10.1109/TAC.1974.1100705>
- Aldrich, H. E., & Fiol, C. M. (1994). Fools Rush in? The Institutional Context of Industry Creation. *Academy of Management Review*, 19(4), 645–670.
- Amburgey, T. L., & Rao, H. (1996). Organizational Ecology: Past, Present, and Future Directions. *Academy of Management Journal*, 39(5), 1265–1286. <https://doi.org/10.2307/256999>
- Antonopoulou, K., Nandhakumar, J., & Henfridsson, O. (2016). Creating new value through repurposing digital innovations. *76th Annual Meeting of the Academy of Management, AOM 2016*, 1616–1621. <https://doi.org/10.5465/AMBPP.2016.277>
- ANWB. (2016). *ANWB en BlaBlaCar: samenrijden voor binnen- én buitenland*. <https://www.anwb.nl/verkeer/nieuws/nederland/2016/september/anwb-en-blablacar-samenrijden-voor-buiten--en-binnenland>
- Arthur, W. B. (1989). Competing Technologies, Increasing Returns, and Lock-In by Historical Events. *The Economic Journal*, 99(394), 116. <https://doi.org/10.2307/2234208>
- Aversa, P., Huyghe, A., & Bonadio, G. (2021). First Impressions Stick: Market Entry Strategies and Category Priming in the Digital Domain. *Journal of Management Studies*, 58(7), 1721–1760. <https://doi.org/10.1111/joms.12712>
- Battilana, J., Leca, B., & Boxenbaum, E. (2009). How Actors Change Institutions: Towards a Theory of Institutional Entrepreneurship. *The Academy of Management Annals*, 3(1), 65–107. <https://doi.org/10.1080/19416520903053598>
- Baum, J. A. C., & Oliver, C. (1996). Toward An Institutional Ecology of Organizational Founding. *Academy of Management Journal*, 39(5), 1378–1427. <https://doi.org/10.5465/257003>
- Baum, J. A. C., & Shipilov, A. V. (2006). Ecological Approaches to Organizations. In *The SAGE Handbook of Organization Studies* (Issue June 2015). <https://doi.org/10.4135/9781848608030.n3>
- Becker, T. E. (2005). Potential problems in the statistical control of variables in organizational research: A qualitative analysis with recommendations. *Organizational Research Methods*, 8(3), 274–289. <https://doi.org/10.1177/1094428105278021>
- Bigelow, L. S., Carroll, G. R., Seidel, M. D. L., & Tsai, L. (1997). Legitimation, geographical scale, and organizational density: Regional patterns of foundings of american automobile producers, 1885–1981. *Social Science Research*, 26(4), 377–398. <https://doi.org/10.1006/ssre.1997.0591>
- Boon, W. P. C., Spruit, K., & Frenken, K. (2019). Collective institutional work: the case of Airbnb in Amsterdam, London and New York. *Industry and Innovation*, 26(8), 898–919. <https://doi.org/10.1080/13662716.2019.1633279>
- Boschma, R. A. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, 39(1), 61–74. <https://doi.org/10.1080/0034340052000320887>
- Boxenbaum, E., & Battilana, J. (2005). Importation as innovation: Transposing managerial practices across fields. *Strategic Organization*, 3(4), 355–383. <https://doi.org/10.1177/1476127005058996>
- Bryman, A. (2016). *Social research methods*. Oxford university press.
- Busch, C., Demary, V., Engels, B., Haucap, J., Kehder, C., Loebert, I., & Rusche, C. (2018). *Sharing Economy in Germany*. www.bmw.de
- Carvalho, L., & Vale, M. (2018). Biotech by bricolage? Agency, institutional relatedness and new path development in peripheral regions. *Cambridge Journal of Regions, Economy and Society*, 11(2), 275–295. <https://doi.org/10.1093/cjres/rsy009>

- CBS. (2021). *Standaard Bedrijfs Indeling 2008 Versie 2018 Update 2021* (pp. 1–42). <https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/activiteiten/sbi-2008-standaard-bedrijfsindeling-2008/de-structuur-van-de-sbi-2008-versie-2019-update-2021>
- CBS. (2022). *Bedrijven; bedrijfstak*. <https://www.cbs.nl/nl-nl/cijfers/detail/81589NED>
- Crunchbase. (n.d.). *Crunchbase.com*. Retrieved March 1, 2022, from <https://www.crunchbase.com/>
- Colyvas, J. A., & Jonsson, S. (2011). Ubiquity and Legitimacy: Disentangling Diffusion and Institutionalization. *Sociological Theory*, 29(1), 27–53. <https://doi.org/10.1111/j.1467-9558.2010.01386.x>
- Company.info. (n.d.). *Bedrijfsgegevens*. Retrieved March 1, 2022, from <https://companyinfo.nl/>
- Couzy, M. (2018, January 10). Maximale verhuurtermijn Airbnb naar 30 dagen. *Het Parool*. <https://www.parool.nl/nieuws/maximale-verhuurtermijn-airbnb-naar-30-dagen~bd3cd8c2/?referrer=https%3A%2F%2Fwww.google.com%2F>
- De Groen, W. P., Maselli, I., & Fabo, B. (2016). The Digital Market for Local Services: A one-night stand for workers? *CEPS Special Report*, 133, 31. <https://doi.org/10.2788/536883>
- de Waal, M., & Arets, M. (2022). From a Sharing Economy to a Platform Economy: Public Values in Shared Mobility and Gig Work in the Netherlands. In *The Sharing Economy in Europe* (pp. 241–261). Springer International Publishing. https://doi.org/10.1007/978-3-030-86897-0_11
- Deeleconomiein nederland.nl. (n.d.). *Onderzoek*. <http://www.deeleconomiein nederland.nl/over/onderzoek/>
- Deephouse, D. L., & Suchman, M. (2012). Legitimacy in Organizational Institutionalism. *The SAGE Handbook of Organizational Institutionalism*, 49–77. <https://doi.org/10.4135/9781849200387.n2>
- Deleportalen. (n.d.). *Den Lille Tjeneste*. Retrieved May 12, 2022, from <https://deleportalen.dk/services/den-lille-tjeneste/>
- DiMaggio, P. J., & Powell, W. W. (1983). The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields Author (s): Paul J . DiMaggio and Walter W . Powell Published by: American Sociological Association Stable URL: <http://www.jstor.org/stable/2095101>. *American Sociological Review*, 48(2), 147–160.
- Eddy, M. (2015). An Uber Service Is Banned in Germany Again. *The New York Times*. <https://www.nytimes.com/2015/03/19/technology/germany-frankfurt-uber-ruling-taxi.html>
- Edelman, B. G., & Geradin, D. (2016). Efficiencies and Regulatory Shortcuts: How Should We Regulate Companies like Airbnb and Uber? *Stanford Technology Law Review*, 19(2), 293–328. <https://doi.org/10.2139/ssrn.2658603>
- Edquist, C. (1997). Systems of Innovation Approaches - Their Emergence and Characteristics. *Systems of Innovation: Technologies, Institutions and Organizations, January 2000*, 1–35.
- Edquist, C., & Johnson, B. (1998). Institutions and Organizations in Systems of Innovation. In *Systems of Innovation: Technologies, Institutions and Organizations* (Vol. 31, Issue 2, pp. 41–63). [https://doi.org/10.1016/s0024-6301\(98\)90244-8](https://doi.org/10.1016/s0024-6301(98)90244-8)
- Eigenhuisruil.nl. (n.d.). *Hoe werkt het?* Retrieved April 1, 2022, from <https://www.eigenhuisruil.nl/werkwijze.php>
- European Commission. (2021a). Commission (Eurostat) publishes first statistics on short-stay accommodation booked via collaborative economy platforms. *IP/21/3293, June*, 3.
- European Commission. (2021b). *Digital labour platforms in the EU: mapping and business models: final report*. <https://doi.org/10.2767/224624>
- Eurostat. (2008). NACE Rev. 2 – Statistical classification of economic activities in the European Community. In *Office for Official Publications of the European Communities*.
- Farris, S. R., & Bergfeld, M. (2022). Low-skill no more! essential workers, social reproduction and the legitimacy-crisis of the division of labour. *Distinktion: Journal of Social Theory*, 0(0), 1–17.

<https://doi.org/10.1080/1600910X.2022.2077400>

- Federale Overheidsdienst Financien. (2022). *Deeconomie – Lijst van de erkende platformen* (p. 8). <https://financien.belgium.be/sites/default/files/downloads/127-deeconomie-lijst-erkende-platformen-20220503.pdf>
- Felländer, A., Ingram, C., & Teigland, R. (2015). The Sharing Economy: Embracing change with caution. In *Näringspolitikst Forum Rapport #11*.
- Florisson, R., & Mandl, I. (2018). Platform work: Types and implications for work and employment – Literature review. In *Digital age - Eurofound* (No. WPEF18004).
- Freeman, C. (1995). The “national system of innovation” in historical perspective. *Cambridge Journal of Economics*, 19(1), 5–24. <https://doi.org/10.1093/oxfordjournals.cje.a035309>
- Frenken, K., & Schor, J. B. (2017). Putting the sharing economy into perspective. *Environmental Innovation and Societal Transitions*, 23, 3–10. <https://doi.org/10.1016/j.eist.2017.01.003>
- Frenken, K., van Waes, A., Pelzer, P., Smink, M., & van Est, R. (2020). Safeguarding Public Interests in the Platform Economy. *Policy and Internet*, 12(3), 400–425. <https://doi.org/10.1002/poi3.217>
- Frenken, K., Vaskelainen, T., Fünfschilling, L., & Piscicelli, L. (2020). An Institutional Logics Perspective on the Gig Economy. *Research in the Sociology of Organizations*, 66, 83–105. <https://doi.org/10.1108/S0733-558X20200000066005>
- Friedman, G. (2014). Workers without employers: shadow corporations and the rise of the gig economy. *Review of Keynesian Economics*, 2(2), 171–188. <https://doi.org/10.4337/roke.2014.02.03>
- Garud, R., & Karnøe, P. (2003). Bricolage versus breakthrough: distributed and embedded agency in technology entrepreneurship. *Research Policy*, 32(2), 277–300. [https://doi.org/10.1016/S0048-7333\(02\)00100-2](https://doi.org/10.1016/S0048-7333(02)00100-2)
- Gawer, A. (2021). Digital platforms’ boundaries: The interplay of firm scope, platform sides, and digital interfaces. *Long Range Planning*, 54(5). <https://doi.org/10.1016/j.lrp.2020.102045>
- Gegenhuber, T., Logue, D., Hinings, B., & Barrett, M. (2020). *Call for papers for a Research in the Sociology of Organizations Volume on: Digital transformation and institutional theorizing: Consequences, opportunities and challenges. August 2020*. <https://www.researchgate.net/publication/336588526>
- Geissinger, A., Laurell, C., Öberg, C., & Sandström, C. (2019). How sustainable is the sharing economy? On the sustainability connotations of sharing economy platforms. *Journal of Cleaner Production*, 206, 419–429. <https://doi.org/10.1016/j.jclepro.2018.09.196>
- Gimmingsrud, K., & Bernt, A. (2017). The age of the sharing economy. In *Advokatfirmaet Haavind AS*.
- Greenwood, B., Burtch, G., & Carnahan, S. (2017). Unknowns of the gig-economy. *Communications of the ACM*, 60(7), 27–29. <https://doi.org/10.1145/3097349>
- Handgraaf, S., & Antikainen, K. (2022). *The best marketplaces run on commission*. <https://www.sharetribe.com/academy/how-top-100-marketplaces-monetize/>
- Hannan, M. T., & Carroll, G. R. (1992). *Dynamics of organizational populations: Density, legitimation, and competition*. Oxford university press.
- Hannan, M. T., Carroll, G. R., Dundon, E. a, & Torres, J. C. (1995). Organizational Evolution in a Multinational Context: Entries of Automobile Manufacturers in Belgium, Britain, France, Germany, and Italy. *American Sociological Review*, 60(4), 509–528.
- Hannan, M. T., & Freeman, J. (1977). The Population Ecology of Organizations. *American Journal of Sociology*, 82(5), 929–964. <https://doi.org/10.1086/226424>
- Hannan, M. T., & Freeman, J. (1987). The Ecology of Organizational Founding: American Labor Unions, 1836-1985. *American Journal of Sociology*, 92(4), 910–943. <https://doi.org/10.1086/228587>

- Hargrave, T. J., & Van De Ven, A. H. (2006). A Collective Action Model of Institutional Innovation. *Academy of Management Review*, 31(4), 864–888. <https://doi.org/10.5465/amr.2006.22527458>
- Haveman, H. A., & David, R. J. (2008). Ecologists and Institutionalists: Friends or Foes? *The SAGE Handbook of Organizational Institutionalism*, 573–595. <https://doi.org/10.4135/9781849200387.n25>
- Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization*, 28(1), 52–61. <https://doi.org/10.1016/j.infoandorg.2018.02.004>
- Höflehner, V. (2015, December). DIE HEIMISCHE SHARING ECONOMY / #DOSSIER_ARBEITSWELT #5. *Werde Digital.At*. https://www.werdedigital.at/2015/12/digitales-arbeiten-in-oesterreich-die-heimische-sharing-economy-dossier_arbeitswelt-5/
- Homan, M. (2018). Vermoeide chauffeur rijdt 22-jarige dood: schuld van Uber? *RTL Nieuws*. <https://www.rtlnieuws.nl/economie/business/artikel/4468226/uber-chauffeur-dodelijk-ongeluk-amsterdam-rechter-aansprakelijk>
- Huizenruil.com. (n.d.). *Huizenruil.com*. Retrieved March 15, 2022, from <https://www.huizenruil.com/nl/>
- Huws, U., Spencer, N. H., & Joyce, S. (2016). Crowd Work in Europe. *Fundation for European Progressive Studies*, December, 22–23.
- Hwang, J. (2019). Managing the innovation legitimacy of the sharing economy. *International Journal of Quality Innovation*, 5(1), 21. <https://doi.org/10.1186/s40887-018-0026-0>
- InsuranceUp. (2018). *Sharing economy, the most funded Italian startups*. <https://www.insuranceup.it/en/startup/sharing-economy-the-most-funded-italian-startups/>
- Johnson, C., Dowd, T. J., & Ridgeway, C. L. (2006). Legitimacy as a social process. *Annual Review of Sociology*, 32, 53–78. <https://doi.org/10.1146/annurev.soc.32.061604.123101>
- Jorritsma, P., Witt, J.-J., Alonso Gonzalez, M. J., & Hamersma, M. (2021). *Deelauto- en deelfietsmobiliteit in Nederland: Ontwikkelingen, effecten en potentie*.
- Kallinikos, J., Aaltonen, A., & Marton, A. (2013). The Ambivalent Ontology of Digital Artifacts. *MIS Quarterly*, 37(2), 357–370. <https://www.jstor.org/stable/43825913>
- Kässi, O., & Lehdonvirta, V. (2018). Online labour index: Measuring the online gig economy for policy and research. *Technological Forecasting and Social Change*, 137(July), 241–248. <https://doi.org/10.1016/j.techfore.2018.07.056>
- Kenney, M., & Zysman, J. (2016). The Rise of the Platform Economy. *Issues in Science and Technology*, 32(2), 61–69.
- Keswiel, M. (2018). *Waarom ParkFlyRent de handdoek in de ring gooide*. MT/Sprout. <https://mtsprout.nl/startups-scaleups/waarom-parkflyrent-de-handdoek-de-ring-gooide>
- Klijns, B. (2021). *Monitor online platformen 2020: Cijfers over de economische betekenis, maatschappelijke rol en internationalisering van online platformen in Nederland*. <https://www.cbs.nl/nl-nl/longread/rapportages/2021/monitor-online-platformen-2020>
- Knee, J. A. (2021). *The Platform Delusion: who wins and who loses in the age of tech titans* (1st ed.). Penguin Publishing Group, 2021.
- Kostova, T., & Zaheer, S. (1999). Organizational Legitimacy Under Conditions of Complexity: The Case of the Multinational Enterprise. *Academy of Management Review*, 24(1), 64–81. <https://doi.org/10.5465/amr.1999.1580441>
- Kraniotis, L. (2017, September 29). De explosieve groei van Airbnb in Amsterdam is voorbij. *NOS Nieuws*. <https://nos.nl/artikel/2195345-de-explosieve-groei-van-airbnb-in-amsterdam-is-voorbij>
- Kuilman, J. G., & Li, J. (2009). Grades of Membership and Legitimacy Spillovers: Foreign Banks in Shanghai, 1847–1935. *Academy of Management Journal*, 52(2), 229–245. <https://doi.org/10.5465/amj.2009.37308018>

- Lounsbury, M., & Glynn, M. A. (2001). Cultural entrepreneurship: stories, legitimacy, and the acquisition of resources. *Strategic Management Journal*, 22(6-7), 545-564. <https://doi.org/10.1002/smj.188>
- Lundvall, B. Å. (2007). National innovation systems - Analytical concept and development tool. *Industry and Innovation*, 14(1), 95-119. <https://doi.org/10.1080/13662710601130863>
- Maguire, S., Hardy, C., & Lawrence, T. B. (2004). Institutional Entrepreneurship in Emerging Fields: HIV/AIDS Treatment Advocacy in Canada. *Academy of Management Journal*, 47(5), 657-679. <https://doi.org/10.5465/20159610>
- Maineri, M. (2016). *Sharing Economy: La Mappatura Delle Piattaforme Italiane 2016*. 73. http://www.collaboriamo.org/media/2015/11/Mappatura2015_00.pdf
- Meyer, J. W., & Rowan, B. (1977). Institutionalized Organizations: Formal Structure as Myth and Ceremony. *American Journal of Sociology*, 83(2), 340-363. <https://www.jstor.org/stable/2778293>
- Naumovska, I., & Lavie, D. (2021). When an Industry Peer Is Accused of Financial Misconduct: Stigma versus Competition Effects on Non-accused Firms. *Administrative Science Quarterly*, 66(4), 1130-1172. <https://doi.org/10.1177/00018392211020662>
- NOS. (2014, December 8). Rechter verbiedt UberPOP. *NOS Nieuws*. <https://nos.nl/artikel/2007891-rechter-verbiedt-uberpop>
- NOS. (2017, November 9). Na Airbnb heeft Amsterdam ook deal met Booking over illegale verhuur. *NOS Nieuws*. <https://nos.nl/artikel/2201962-na-airbnb-heeft-amsterdam-ook-deal-met-booking-over-illegale-verhuur>
- NOS. (2018, June 15). Nog een rechtszaak tegen maaltijdbezorger Deliveroo. *NOS Nieuws*. <https://nos.nl/artikel/2236569-nog-een-rechtszaak-tegen-maaltijdbezorger-deliveroo>
- NOS. (2020, October 22). Vakbonden FNV en CNV starten rechtszaak tegen bemiddelingsplatform Temper. *NOS Nieuws*. <https://nos.nl/artikel/2353345-vakbonden-fnv-en-cnv-starten-rechtszaak-tegen-bemiddelingsplatform-temper>
- OCU. (2021). *Plataformas digitales de consumo colaborativo, de acceso compartido y bajo demanda*. <https://www.ocu.org/consumo-familia/consumo-colaborativo/informe/plataformas-consumo-colaborativo>
- ONS. (n.d.). *ONS Standard Occupational Classification (SOC) Hierarchy*. Office for National Statistics. Retrieved July 1, 2022, from https://onsdigital.github.io/dp-classification-tools/standard-occupational-classification/ONS_SOC_hierarchy_view.html
- Parkinson, H. J. (2016). #AirBnBWhileBlack hashtag highlights potential racial bias on rental app. *The Guardian*. <https://www.theguardian.com/technology/2016/may/05/airbnbwhileblack-hashtag-highlights-potential-racial-bias-rental-app>
- Pelzer, P., Frenken, K., & Boon, W. (2019). Institutional entrepreneurship in the platform economy: How Uber tried (and failed) to change the Dutch taxi law. *Environmental Innovation and Societal Transitions*, 33(January), 1-12. <https://doi.org/10.1016/j.eist.2019.02.003>
- Petersen, T., & Koput, K. W. (1991). Density Dependence in Organizational Mortality: Legitimacy or Unobserved Heterogeneity? *American Sociological Review*, 56(3), 399-409. <https://doi.org/10.2307/2096112>
- Platformwerk. (n.d.). *Alle kluseconomie platformen*. Retrieved November 25, 2021, from <https://platformwerk.nl/>
- Powell, W. W., Packalen, K., & Whittington, K. (2012). Organizational and Institutional Genesis: The Emergence of High-Tech Clusters in the Life Sciences. In *The emergence of organizations and markets* (pp. 434-465). Princeton University Press.
- Punt, M. B., Bauwens, T., Frenken, K., & Holstenkamp, L. (2021). Institutional relatedness and the emergence of renewable energy cooperatives in German districts. *Regional Studies*, 0(0), 1-15. <https://doi.org/10.1080/00343404.2021.1890708>
- Punt, M. B., van Kollem, J., Hoekman, J., & Frenken, K. (2021). Your Uber is arriving now: An analysis

- of platform location decisions through an institutional lens. In *Strategic Organization*. <https://doi.org/10.1177/14761270211022254>
- PwC. (2017). Collaborative Economy in Finland - Current State and Outlook. In *MEAE reports 9/2017*. <http://urn.fi/URN:ISBN:978-952-327-196-8>
- Rao, H., Monin, P., & Durand, R. (2003). Institutional change in toque ville: Nouvelle cuisine as an identity movement in French gastronomy. *American Journal of Sociology*, *108*(4), 795-843+i. <https://doi.org/10.1086/367917>
- Ravenelle, A. J. (2017). Sharing economy workers: Selling, not sharing. *Cambridge Journal of Regions, Economy and Society*, *10*(2), 281–295. <https://doi.org/10.1093/cjres/rsw043>
- Rijksoverheid. (2020). *Maart 2020: Maatregelen tegen verspreiding coronavirus, intelligente lockdown*. <https://www.rijksoverheid.nl/onderwerpen/coronavirus-tijdlijn/maart-2020-maatregelen-tegen-verspreiding-coronavirus>
- Wet arbeidsmarkt in balans, Pub. L. No. 35.074 (2020). <https://www.rijksoverheid.nl/onderwerpen/arbeidsovereenkomst-en-cao/plannen-kabinet-voor-meer-balans-tussen-vast-werk-en-flexwerk>
- Rinne, A., Fischer, C., Laura, E., Fjalland, P., Lorenzen, M., & Bernhardt, M. (2017). *Sharing City*.
- Rossman, G. (2014). The diffusion of the legitimate and the diffusion of legitimacy. *Sociological Science*, *1*(March), 49–69. <https://doi.org/10.15195/v1.a5>
- Schmidt, F. A. (2017). Digital Labour Markets in the Platform Economy. *Mapping the Political Challenges of Crowd Work and Gig Work*, *7*, 1–30. <http://library.fes.de/pdf-files/wiso/13164.pdf>
- Schoonhoven, S. (2019, January 14). Weer ongeluk met Uber: 24-jarige fietsster overleden. *De Telegraaf*. <https://www.telegraaf.nl/nieuws/3016458/weer-ongeluk-met-uber-24-jarige-fietsster-overleden>
- Schor, J. B. (2016). Debating the Sharing Economy. *Journal of Self-Governance and Management Economics*, *4*(3), 7. <https://doi.org/10.22381/jsme4320161>
- Schor, J. B. (2020). *After the Gig: How Sharing the Economy Got Hijacked and How to Win It Back* (W. Attwood-Charles, M. Cansoy, L. Carfagna, S. Eddy, C. Fitzmaurize, I. Ladegaard, & R. Wengronowitz (eds.); 29th ed.). University of California Press.
- Schot, J., & Steinmueller, W. E. (2018). Three frames for innovation policy: R&D, systems of innovation and transformative change. *Research Policy*, *47*(9), 1554–1567. <https://doi.org/10.1016/j.respol.2018.08.011>
- Scott, R. W. (1995). *Institutions and organizations*. SAGE Publications, Thousand Oaks.
- Self, S. G., & Liang, K.-Y. (1987). Asymptotic Properties of Maximum Likelihood Estimators and Likelihood Ratio Tests under Nonstandard Conditions. *Journal of the American Statistical Association*, *82*(398), 605–610. <https://doi.org/10.1080/01621459.1987.10478472>
- SER. (2020). Hoe werkt de platformeconomie? In *SERmagazine*. <https://www.ser.nl/nl/Publicaties/hoe-werkt-platformeconomie>
- Sharing economy UK. (n.d.). *Our Members*. Retrieved May 11, 2022, from <https://www.sharingeconomyuk.com/members>
- Sherwood, H. (2019). How Airbnb took over the world. *The Guardian*. <https://www.theguardian.com/technology/2019/may/05/airbnb-homelessness-renting-housing-accommodation-social-policy-cities-travel-leisure>
- Singh, J. V. (1993). Review Essay : Density Dependence Theory-Current Issues , Future Promise. *American Journal of Sociology*, *99*(2), 464–473.
- Singh, J. V., & Lumsden, C. J. (1990). *Theory and research in organizational ecology*. *16*(1), 161–195. <https://www.jstor.org/stable/2083267>
- Skog, D. A., Wimelius, H., & Sandberg, J. (2018). Digital Disruption. *Business and Information Systems Engineering*, *60*(5), 431–437. <https://doi.org/10.1007/s12599-018-0550-4>

- Soublière, J. F., & Gehman, J. (2020). The legitimacy threshold revisited: How prior successes and failures spill over to other endeavors on Kickstarter. *Academy of Management Journal*, 63(2), 472–502. <https://doi.org/10.5465/amj.2017.1103>
- Stallkamp, M., & Schotter, A. P. J. (2021). Platforms without borders? The international strategies of digital platform firms. *Global Strategy Journal*, 11(1), 58–80. <https://doi.org/10.1002/gsj.1336>
- Stanoevska-Slabeva, K., Lenz-Kesekamp, V., & Suter, V. (2017). Platforms and the Sharing Economy: An Analysis. In *EU H2020 Research Project Ps2Share*. https://www.researchgate.net/publication/322845971_Platforms_and_the_Sharing_Economy_An_Analysis_EU_H2020_Research_Project_Ps2Share_Participation_Privacy_and_Power_in_the_Sharing_Economy_2017
- Suchman, M. C. (1995). Managing Legitimacy : Strategic and Institutional Approaches. *The Academy of Management Review*, 20(3), 571–610.
- Täuscher, K., & Kietzmann, J. (2017). Learning from failures in the sharing economy. *MIS Quarterly Executive*, 16(4), 253–264.
- Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, 185(4157), 1124–1131. <https://doi.org/10.1126/science.185.4157.1124>
- Uber. (2015). *uberPOP stopt in Nederland*. <https://www.uber.com/nl/blog/amsterdam/uberpop-stopt-in-nederland/>
- Unruh, G. C. (2000). Understanding carbon lock-in. *Energy Policy*, 28(12), 817–830. [https://doi.org/10.1016/S0301-4215\(00\)00070-7](https://doi.org/10.1016/S0301-4215(00)00070-7)
- Urzi Brancati, M. C., Pesole, A., & Fernández-Macías, E. (2020). New evidence on platform workers in Europe. In *JRC Science For Policy Report* (Issue April). <https://doi.org/10.2760/459278>
- Utopia.de. (n.d.). *Sharing Economy: Plattformen zum Teilen & Verleihen*. Retrieved May 13, 2022, from <https://utopia.de/bestenlisten/sharing-economy-plattformen-teilen-verleihen/>
- Uzunca, B., Rigtering, J. P. C., & Ozcan, P. (2018). Sharing and Shaping: A Cross-Country Comparison of How Sharing Economy Firms Shape Their Institutional Environment to Gain Legitimacy. *Academy of Management Discoveries*, 4(3), 248–272. <https://doi.org/10.5465/amd.2016.0153>
- van Haaren, J., Vermeulen, S., Klijs, J., Koens, K., & Bijl, J. (2021). *Short-term accommodation rental in Amsterdam*. <https://doi.org/10.2873/111443>
- Vermeulen, P., & Raab, J. (2007). Innovations and Institutions. In *Innovations and Institutions* (pp. 12–36). Routledge. <https://doi.org/10.4324/9780203964057>
- Vuong, Q. H. (1989). Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses. *Econometrica*, 57(2), 307. <https://doi.org/10.2307/1912557>
- Wenting, R., & Frenken, K. (2011). Firm entry and institutional lock-in: An organizational ecology analysis of the global fashion design industry. *Industrial and Corporate Change*, 20(4), 1031–1048. <https://doi.org/10.1093/icc/dtr032>
- Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy. *Work, Employment and Society*, 33(1), 56–75. <https://doi.org/10.1177/0950017018785616>
- Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, 21(4), 724–735. <https://doi.org/10.1287/isre.1100.0322>
- Zeileis, A., Kleiber, C., & Jackman, S. (2008). Regression Models for Count Data in R. *Journal of Statistical Software*, 27(8), 1–25.

8. APPENDIX A - MARKETS

Table 18. Overview of all the gig markets that are analysed

Market category	Market name	Total platforms
<i>A - Agriculture</i>	A011 - Cultivation of annual crops	0
	A012 - Cultivation of perennial crops	0
	A013 - Cultivation of ornamental plants	0
	A014 - Breeding and keeping animals	2
	A016 - agricultural services; treatment of crops after harvest	2
	A017 - Hunting	0
	A024 - Forestry services	2
	A031 - Fisheries	0
	A032 - Fish and shellfish farming	0
<i>E - Extraction and distribution of water; waste and wastewater management and remediation</i>	E381 - Waste collection	0
	E390 - Remediation and other waste management	0
<i>F - Construction industry</i>	F431 - Demolition of buildings, earthmoving, and test drilling	14
	F432 - Building installation	18
	F433 - Finishing buildings	33
	F439 - Roof construction and other specialized construction work	10
<i>G - Wholesale and retail trade; repair of cars</i>	G451 - Trade in cars and trailers, possibly combined with repair	0
	G452 - Specialized repair of cars	2
	G479 - Retail trade not via shop or market	16
<i>H - Transport and storage</i>	H493 - Road passenger transport	9
	H494 - Freight transport by road	53
	H501 - Sea and coastal shipping (passenger shipping and ferry service)	1
	H502 - Sea and coastal shipping (freight, tank, and towage)	0
	H503 - Inland shipping (passenger shipping and ferry services)	1
	H504 - Inland shipping (freight, tank, and towage)	0
	H511 - Passenger transport by air	0
	H512 - Freight transport by air	0
	H522 - Transport services	18
	H532 - Post without universal service obligation and couriers	0
	<i>I - Lodging, meal, and beverage provision</i>	I562 - Canteens and catering
I563 - Restaurants, cafeterias, etc.		8
<i>J - Information and communication</i>	J591 - Production and distribution of films and television programs	2
	J592 - Making and publishing sound recordings	6
	J620 - Information technology service activities	38
	J631 - Data processing, web hosting and related activities; web portals	26
	J639 - Other information service activities	10
<i>K - Financial institutions</i>	K661 - Financial intermediation, advice etc. (not for insurance and pension funds)	2
	K662 - Insurance and pension fund services	0
	K663 - Wealth management	0
<i>M - Advice, research, and other specialist business services</i>	M691 - Legal services	13
	M692 - Accountancy, tax advice and administration	27
	M702 - Management and business consultancy	19
	M711 - Architects, engineers and technical design and consultancy	14
	M712 - Inspection and control	2

	M721 - Scientific Research and Development	3
	M722 - Research and development in the field of social sciences and humanities	1
	M731 - Advertising agencies and dealing in advertising space and time	19
	M732 - Market and Opinion Research Agencies	17
	M741 - Industrial Design	26
	M742 - Photography and developing photos and films	21
	M743 - Translators and interpreters	14
	M749 - Other specialist business services	15
	M750 - Veterinary Services	19
<i>N - Rental of movable property and other business services</i>	N781 - Job placement	3
	N782 - Employment Agencies, Lending Agencies and Job Pools	0
	N783 - Payrolling	0
	N791 - Travel agencies and tour operators	12
	N799 - Providing information in the field of tourism and reservation agencies	2
	N801 - Private Security	0
	N803 - Detection	0
	N811 - Facility management	5
	N812 - Cleaning	34
	N813 - Landscape care	29
	N821 - Broad administrative and secretarial services	20
	N822 - Call centres	17
	N823 - Organizing conferences and fairs	0
	N829 - Other business services (rest)	4
<i>P - Education</i>	P856 - Educational services	39
<i>Q - Health and welfare care</i>	Q871 - Nursing homes	11
	Q872 - Homes and day care centres for the mentally handicapped	11
	Q873 - Homes and day care centres for the non-mentally handicapped and care homes	9
	Q879 - Youth care and social care with overnight stay	11
	Q881 - Social services without overnight accommodation aimed at the elderly and the disabled	20
	Q889 - Social services without overnight accommodation not specifically aimed at the elderly and disabled	46
<i>R - Culture, sport, and recreation</i>	R900 - Art	4
	R931 - Sports	5
	R932 - Other recreation	0
<i>S - Other services</i>	S949 - Philosophical and political organisations, other interest and ideological organisations, hobby clubs	0
	S951 - Repair of computers and communication equipment	9
	S952 - Repair of consumer goods (excluding computers, communications equipment, automobiles, and motorcycles)	9
	S960 - Wellness and other services; funeral industry	1

Table 19. Overview of all the sharing markets that are analysed1

Market category	Market name	Total platforms	
<i>D - Production, distribution and trade in electricity, natural gas, steam and cooled air</i>	D35111 – Electricity production by thermal and nuclear installations	1	
	D35112 - Production of electricity by wind energy	1	
	D35113 -Production of electricity by solar cells, and hydropower	1	
	D3520 – Production of biogas	0	
	D3530 – Production and distribution of steam, hot water, and cooled air	0	
	<i>G - Wholesale and retail trade; repair of cars</i>	G4721 - Potato, vegetable, and fruit shops	5
G4722 - Shops selling meat and meat products, game, and poultry		4	
G4723 - Stores in fish		4	
G4724 - Bread, confectionery, chocolate, and confectionery shops		4	
G4725 - Beverage shops		4	
G4726 - Tobacco Shops		0	
G4729 - Specialized stores in other food and beverages		3	
G4741 - Computer, peripheral and software stores		6	
G4742 - Telecommunications equipment stores		6	
G47431 - Audio and video equipment stores		5	
G47432 - Stores in a general range of white and brown goods		0	
G4751 - Clothing fabrics, home textiles and haberdashery shops		3	
G4752 - Do-it-yourself stores		3	
G4753 - Carpet and curtain shops		3	
G4754 - Shops for electrical household equipment and parts therefor		4	
G4759 - Shops for furniture, lighting, and other household goods (residual)		4	
G4761 - Bookshops		6	
G4762 - Newspaper, magazine, and stationery shops		3	
G4763 - Audio and video recording stores		3	
G4764 - Shops selling bicycles and mopeds, sports and camping articles and boats		7	
G4765 - Toy stores		3	
G4771 - Stores of clothing and fashion articles; textile supermarkets		9	
G4772 - Shoes and leather goods stores		5	
G4773 - Pharmacies		0	
G4774 - Drugstore, medical and orthopaedic stores		0	
G4775 - Stores of perfumes and cosmetics		0	
G4776 - Flowers, plants, seeds, garden supplies, pets, and pet supplies		2	
G4777 - Jewellery and watch shops		2	
G4778 - Stores in other articles (rest)		2	
G4779 - Stores of antiques and second-hand goods		0	
<i>H – Transport and storage</i>		H4932 - Transport by taxi	7
		H4939 - Other road passenger transport	0
	H4941 - Freight transport by road (no removals)	2	
	H4942 - Moving Transport	1	
	H5030 - Inland shipping (passenger shipping and ferry services)	0	
	H5040 - Inland shipping (freight, tank, and towage)	0	
	H5110 - Passenger transport by air	0	
	H5121 - Freight transport by air	0	
	H52109 - Storage in distribution centres other and storage (not in tanks, cold stores, etc.)	4	
	H5221 - Land transport services	7	

<i>I - Lodging, meal, and beverage provision</i>	I55101 - Hotel Restaurants	0	
	I55102 - Hotels (no hotel restaurants), guest houses and conference venues	0	
	I55201 - Rental of holiday homes and apartments	23	
	I55202 - Youth hostels and holiday camps	0	
	I5530 - Campgrounds	2	
	I56101 - Restaurants	1	
<i>L - Real estate rental and trade</i>	I56102 - Fast food restaurants, cafeterias, ice cream parlours, food stalls, etc.	1	
	L68203 - Rental of other living space	22	
<i>N - Rental of movable property and other business services</i>	L68204 - Rental of real estate (not residential)	18	
	N7711 - Rental and leasing of passenger cars and light commercial vehicles	14	
	N7712 - Rental and lease of trucks, buses, and motorhomes	9	
	N7721 - Rental of sports and recreational articles	16	
	N7722 - Video stores	10	
	N77291 - Rental of reading materials	15	
	N77292 - Rental of clothing and household items	20	
	N77299 - Rental of other consumer goods (rest)	17	
	N7731 - Rental and leasing of agricultural machinery and equipment	0	
	N7732 - Rental and leasing of construction machinery and installations	12	
	N7733 - Rental and leasing of computers and office equipment	15	
	N7734 - Rental and lease of ships	9	
	N7735 - Aircraft rental and lease	0	
	N7739 - Rental and lease of other machines and tools and of other goods	7	
	N78202 - Lending Agencies	2	
	<i>P - Education</i>	P85599 - Tutoring, training, and education (residual)	5
	<i>R - Culture, sport, and recreation</i>	R9311 - Sports accommodations	1
R9313 - Fitness Centres		0	
R9314 - Indoor Sports		0	
R9315 - Water sport		0	

Table 20. Categories for the skill of labour required in the gig markets.

Category	Explanation	Number	Markets
Unskilled labour	No education or experience required	1	E381 G479 I562 I563 N811 N812 N813 Q881 Q889 R900 R931 R932
Semi-skilled labour	Certain abilities or training is required beforehand, but not advanced education or specialized skills	2	A011 A012 A013 A014 A016 A017 A024 A031 A032 E390 F431 F433 G451 H493 H494 H501 H502 H503 H504 H511 H512 H522 H532 N781 N782 N783 N791 N799 N801 N803 N821 N822 N823 N829 S949 S960
Skilled labour	Requires advanced education or specialized skills	3	F432 F439 G452 J591 J592 J620 J631 J639 K661 K662 K663 M691 M692 M702 M711 M712 M721 M722 M731 M732

M741
M742
M743
M749
M750
P856
Q871
Q872
Q873
Q879
S951
S952

Table 21. Categories for the type of sharing markets.

Category	Number	Markets
Moveable property	1	G4721 G4722 G4723 G4724 G4725 G4726 G4729 G4741 G4742 G47431 G47432 G4751 G4752 G4753 G4754 G4759 G4761 G4762 G4763 G4764 G4765 G4771 G4772 G4773 G4774 G4775 G4776 G4777 G4778 G4779 N7711 N7712 N7721 N7722 N77291 N77292 N77299 N7731 N7732 N7733 N7734 N7735 N7739
Immovable property	2	H52109 H5221 I55101 I55102 I55201 I55202 I5530 I56101 I56102 L68203 L68204

Other

0

R9311
R9313
D35111
D35112
D35113
D3520
D3530
H4910
H4941
H4942
H4030
H5040
H5110
H5121
N78202
P85599
R9314
R9315

9. APPENDIX B – DATA COLLECTION OF EUROPEAN PLATFORMS

An additional sample for all European (EU27) platforms was constructed, excluding those platforms that are or have been active in the Netherlands. This extra sample was assembled to control the sample of Dutch platforms for international legitimacy spillovers on a European level. The database of the CEPS report was complemented through consulting official platform information websites of every EU27-member. To provide an example, the largest consumers association of Spain offers information concerning almost 400 platforms that are active in Spain (OCU, 2021). The total population of non-Dutch European platforms consists of 386 gig platforms, of which fifty-eight are dissolved, and 161 sharing platforms, of which thirty-three are dissolved. The main sources of data collection for the construction of the European sample are listed in **Table 22**. The market entry and market exit dates for European platforms was retrieved from information on the respective platforms' social media accounts. In particular, the date at which a social media account was created provides a good indication of when a platform has launched. Moreover, tracking down the exact starting date is not of essence since this study focuses on quarterly data.

Table 22. Sources of data collection for the construction of the European gig and sharing platform samples.

Data from	Countries	Types of platforms	Source
CEPS	EU27	Gig and sharing	(European Commission, 2021b)
PwC	Finland	Gig and sharing	(PwC, 2017)
Haavind	Norway	Gig and sharing	(Gimmingsrud & Bernt, 2017)
Näringspolitiskt Forum	Sweden	Gig and sharing	(Felländer et al., 2015)
Sharing city magazine	Denmark	Gig and sharing	(Rinne et al., 2017)
Dice Consult	Germany	Gig and sharing	(Busch et al., 2018)
Key-to-office	Austria	Gig and sharing	(Höflehner, 2015)
Ps2Share	Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Poland, Portugal, Russia, Spain, Sweden, Switzerland, UK	Gig and sharing	(Stanoevska-Slabeva et al., 2017)
Utopia	Germany	Sharing	(Utopia.de, n.d.)
InsuranceUp	Italy	Gig and sharing	(InsuranceUp, 2018)
FIN	Belgium	Gig and sharing	(Federale Overheidsdienst Financien, 2022)
Sharing economy UK	UK	Gig and sharing	(Sharing economy UK, n.d.)
Deleportalen	Denmark	Gig and sharing	(Deleportalen, n.d.)
OCU	Spain	Gig and sharing	(OCU, 2021)
Collaboriamo	Italy	Gig and sharing	(Maineri, 2016)

10. APPENDIX C – ROBUSTNESS CHECKS

Table 23. Gig platforms - Poisson regression models without the empty markets.

Variable	G0 P1	G0 P2	G0 P3	G0 P4	G0 P5	G0 P6	G0 P7	G0 P8
<u>Ecological model</u>								
Local density	0.182*** (0.013)	0.192*** (0.014)	0.183*** (0.013)	0.192*** (0.014)	0.180*** (0.015)	0.190*** (0.016)	0.189*** (0.015)	0.190*** (0.015)
(Local density ²)/100	-0.245*** (0.034)	-0.275*** (0.040)	-0.238*** (0.035)	-0.264*** (0.041)	-0.238*** (0.038)	-0.265*** (0.041)	-0.266*** (0.039)	-0.266*** (0.038)
Global density s1	-0.007*** (0.001)				-0.008*** (0.001)			
(Global density s1 ²)/100	0.001*** (0.0001)				0.001*** (0.0001)			
Global density s2		-0.007*** (0.001)				-0.007*** (0.001)	-0.005*** (0.002)	-0.005*** (0.002)
(Global density s2 ²)/100		0.001*** (0.0001)				0.001*** (0.0001)	0.0003* (0.0002)	0.0003* (0.0002)
Related density		-0.007*** (0.003)		-0.005** (0.003)				
(Related density ²)/100		0.002* (0.002)		0.002 (0.001)				
EU density s1			-0.001*** (0.0004)					
(EU density s1 ²)/100			0.00002 (0.00002)					
EU density s2				-0.001*** (0.0004)				
(EU density s2 ²)/100				0.00003* (0.00002)				
<u>Market control variables</u>								
Market size/1000					-0.003* (0.002)	-0.004* (0.002)	-0.003* (0.002)	-0.003* (0.002)
Semi-skilled markets					-0.206** (0.111)	-0.188* (0.111)	-0.191* (0.111)	-0.190* (0.110)
Skilled markets					-0.601*** (0.115)	-0.649*** (0.119)	-0.606*** (0.118)	-0.604*** (0.118)
Service type					0.555*** (0.158)	0.550*** (0.161)	0.535*** (0.159)	0.517** (0.161)
<u>Institutional shock dummies</u>								
COVID-19 lockdown							-0.174 (0.220)	-0.110 (0.229)
Policy WAB							0.602*** (0.245)	0.496** (0.269)
Exit of UberPOP								-0.176 (0.155)

Intercept	-0.624** (0.276)	-0.856*** (0.252)	-1.456*** (0.228)	-1.373*** (0.226)	-0.475 (0.279)	-0.847** (0.272)	-0.944*** (0.324)	-1.004*** (0.325)
Observations (<i>N</i>)	2,508	2,508	2,508	2,508	2,508	2,508	2,508	2,508
Log Likelihood	-1,620.217***	-1,619.166	-1,615.996**	-1,613.526*	-1,609.982***	-1,607.027*	-1,601.620***	-1,600.575
AIC	3,250.434	3,252.333	3,241.992	3,241.051	3,235.964	3,234.055	3,227.241	3,227.150

Notes:

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$ (all two-tailed); Standard errors shown in parentheses are robust standard errors clustered by quarter and Market (SBI 2008)