Platform Strategy

How to monetize a market with network effects

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Tobias M. Posthumus

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Supervisors:

Dr. Enrico Pennings, Erasmus School of Economics

Jochem Pasman, KPMG

Ingrid Sloots, KPMG

1 .Introduction

In 2016, Peter Evans and Annabelle Gawer published "The Rise of the Platform Enterprise: A Global Survey". Through collaboration with scholars from Africa, China, Europe, India and the United States, they identified the world's leading platform companies. These firms have gathered a great deal of attention. Scholars, institutions and news outlets have widely acknowledged the impact of the platform model. Notable examples include Uber's disruption of the taxi industry or Facebook connecting a staggering ~1.9 billion active monthly users (Statista, 2017). eCommerce marketplace Amazon.com is responsible for an astonishing 27,4% of the 2016 growth of US total retail (Zaroban, 2017). Such numbers may not come as a surprise; platforms have moved away from the linear value chain and into operating a market on their own. Nonetheless, quantitative research regarding the platform economy is still extremely limited. The fields of management and public policy have been the first to extensively address the 'platform revolution'. The first by focusing on how to employ and make use of the platform business model. The second on discussing regulation of these new marketplaces. However, the quantitative analysis in the field of economics has been lagging behind. Even though economical models for two sided markets have been widely discussed, economic literature has not gone beyond theoretical models, case studies or quantitative analysis in regards to a single platform (e.g. "Estimating the Impact of Airbnb on the Hotel Industry" by Zervas et al., 2016). Though not without reason: researchers, although familiar with the flagships of the platform revolution, have been unable to identify what is to be considered the platform economy and the firms that operate within its boundaries. The survey by Evans and Gawer, however not exhaustive, provides a first systematic identification of leading platform companies. Thereby allowing for cross-industry and cross-regional economic analysis of these firms.

One of the key strategic challenges of platforms is monetizing their eco-system. From this perspective, many platforms and their unicorn valuations have been widely criticized. Not surprisingly when even 'success stories' such as that of Spotify are yet to claim any profitability. The criticism on loss-making unicorns can be partly refuted through the present investments in scaling with the prospect of future return after having sufficiently exploited the gains from network effects. In other words: to overcome the chicken-and egg problem of having to attract one side to a platform before the other will join. Only afterwards does focus shift to monetization. Other criticisms reflect skepticism of the potential revenue sources of a platform; the highest amount of users does not necessarily equate to high profits. Facebook was widely criticized in 2012 for buying the no-revenue generating Instagram for USD 1 billion to the extent that even comedians joined in on the ridicule. In 2016, Instagram has been estimated to have raked in USD 3.2 billion (Statista , 2017 ; Shah, 2016). Naturally, there is no one size fits all-solution to monetization of platforms (Sabourin., 2016). Furthermore, users often face low switching costs (Tan et al., 2015) and suppliers use multi-homing to mediate dependency on any single platform (Eisenmann, Parker and Alstyne, 2006). If users are upset with e.g. being (over)-charged or annoyed by the abundance of advertisements, they simple buy or sell through a different platform if possible. A platform should therefore only monetize where it is delivering sufficient value and where it causes the least friction to positive network effects. Even more, in some cases platforms gain from subsidizing one-side (supply/demand) to add more value to users on the other side of the platform (D. Evans, 2003; Weyl, 2009).

In this thesis, the monetization strategy of a platform is considered the choice of monetizing one or more sources of revenue. The platform may be monetized by either generating revenue from the supply side of the platform, the demand side, the successful transaction between the two sides or through the enhanced access to the whole community of users that the platform operator enjoys. The first three relate to the core interaction; the main interaction between parties that the platform facilitates. The fourth, monetizing the presence of the community, does not affect the core interaction.

The type(s) of monetization the firm is able to employ, may depend on the transaction costs the platform mediates i.e. where the platform adds value, as well as elasticities of demand and supply. The platform is in itself a market. Subsequently, an effective monetization strategy is limited to the boundaries of what the market allows. What enables Amazon to capture a margin on successful interactions, while Alibaba does not? What determines that Google's Youtube does not charge content creators, when Google Play Music does? This study expands on the database by Evans and Gawer. Building on existing economic, management and innovation literature, several hypotheses are determined. These hypotheses explore various aspects expected to influence the strategic choice of monetization: characteristics of the market facilitated by the platform, traditional competition within the industry, regional differences and firm characteristics of the platform operator.

A multivariate probit analysis, allowing for interdependency between monetization choices, is estimated under two distinct assumptions. The first assumes that transaction fees are ambiguously allocated to both parties that perform the transaction. The second assumes that transaction fees are either a charge to demand or supply, but cannot pass-through to the other. The results support an inverted U-curve relationship between the number of suppliers on a platform and the probability of monetizing suppliers. Another inverted U-curve relationship is found between the price level of payments and the probability of monetizing transactions. Furthermore, the estimations suggest that digital multi-sided platforms may have strategically eliminated charges to suppliers to outcompete traditional intermediaries in the industry. Followingly, we find that platforms operated by firms that operate multiple platforms are better able to monetize suppliers by generating additional surplus of being a one-stop shop of integrated platforms and being better able to employ price differentiations to capture this surplus. Lastly, Asian platforms, in comparison to platforms with headquarters in the rest of the world, are more likely to charge consumers while they are less likely to charge suppliers.

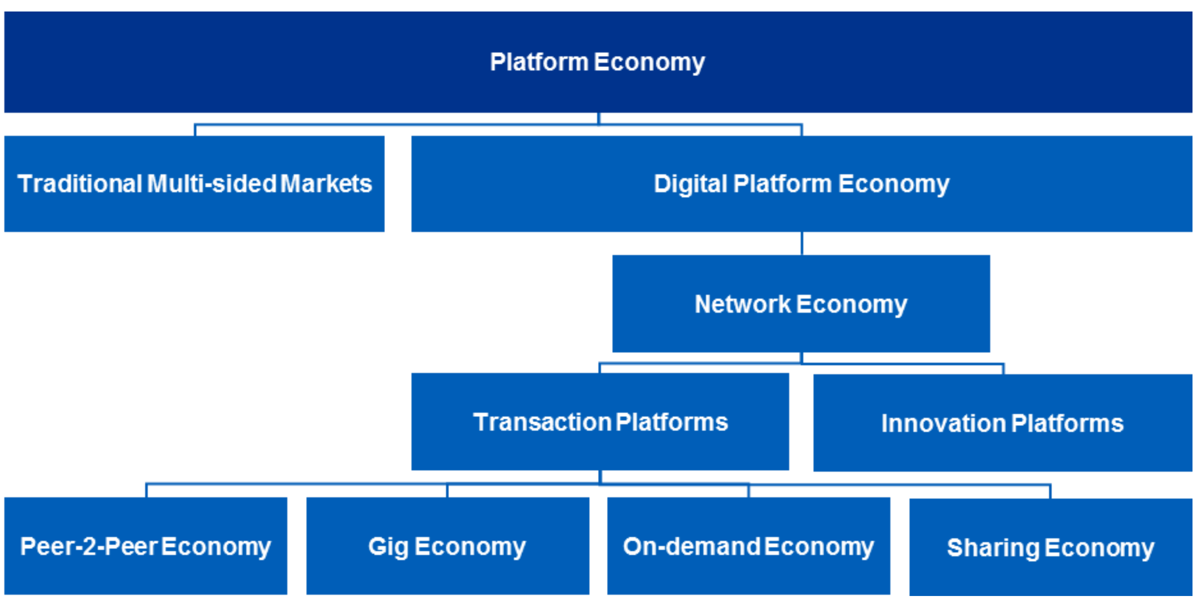
The main contribution of this thesis is threefold. Firstly, to the extensive case-based and qualitative research it adds a quantitative analysis of strategic firm behavior. Secondly, the results can provide useful insights in the field of finance as to more accurately assess the future value appropriation by new platform companies through the characteristics of the markets they operate. Thirdly, it provides direction for future research in the platform economy as an exploratory cross-industry and cross-regional economic analysis through a unique dataset.

The paper is structured as follows. Section 2 lays down the framework on which the research is based. The ensuing section 3 proposes several hypotheses. Section 4 elaborates on the dataset and section 5 on the methodology. Sections 6 and 7 present and discuss the insights and results from analyzing the data, as well as test robustness of the results. Lastly, limitations, conclusions and the subsequent implications of the study are discussed in sections 8 and 9.

2. Defining the platform economy

In a great amount of published literature, numerous terms interchangeably refer to firms operating digital platforms. These terms are however not perfect synonyms and sometimes misdirect the discussion away from meaningful content. E.g. recently, the Financieel Dagblad (dutch financial newspaper) published an article discussing why 'Sharing Economy' is an incorrect term because a platform such as Uber does not facilitate 'sharing', it is an 'on-demand economy' (15 April 2017, "Sharing zonder uitbuiting: het kan" –*sharing without extortion: it is possible*-). The article was however based on the wrongful assumption that these terms have to be mutually exclusive. Popular terms, including the Sharing Economy, On-Demand Economy and Network Economy, originate from several different aspects in which a platform model may prevail. This thesis is not meant to provide a definite definition of the terms used. Nonetheless, we shortly discuss several of these terms as a means of understanding the framework surrounding the subject of this study.

Figure 2.1: Frequently used terms within the Platform Economy



The broadest possible definition of the Platform Economy may include all products and services through which interaction between two parties is facilitated by a third party. Hence, a platform is by definition multi-sided. Subsequently, other than the recent rise of popular digital platforms, traditional marketplaces e.g. a shopping mall, are perfect examples of multi-sided platforms (MP) as well. A characteristic of multi-sided markets is network effects i.e. an increase in value of the network when more participants join the network. Taking this further, currency or even language may be viewed as a platform that facilitates transactions/interactions between two parties (multi-sided) that gains in value according to the amount of others that trade in the same currency or speak the same language (network effects). That aside, this thesis only covers digital multi-sided platforms (*DMP*). Separately stated in *Figure 2.1* but not necessarily a segment of the Digital Platform Economy, the term Network Economy gained traction as a classification of markets with large network opportunities due to digitalization around the start of this millennium. Digitalization and the internet enabled unprecedented scaling through network effects.

Furtermore, platforms may differ in output, mainly innovation or transactions (Evans & Gawer, 2016). For the purpose of analyzing monetization strategies, only the latter falls within the boundaries of this study, for the simple reason that innovation platforms do not focus on optimal revenue generation or profitability, but at improving or creating other business activities.

As will be elaborated upon in the next section, platforms mainly add value by diminishing transaction costs of interactions. Popular terms such as the Peer-2-Peer Economy (1), Gig Economy (2), On-demand Economy (3) and the Sharing Economy (4) hint towards market characteristics that follow due to lower transaction costs. Respectively,

(1) individuals are enabled to participate in markets (C2C / P2P) that traditionally demanded sufficient scale benefits to enter (B2C),
(2) firms tend towards hiring on a per project-basis in contrast to full-time employment,
(3) consumers prefer to rent access to an asset over owning it, and
(4) more efficient allocation of otherwise underutilized assets.

Although these terms may not be perfectly interchangeable, a single DMP is highly likely subject to more than one of these definitions. For instance ride-sharing platform BlaBlaCar enables individuals to participate in the transportation industry even with their supply only consisting of one single passenger-seat for only one route (Peer-2-Peer), allows consumers to access transportation without having to own a car (On-demand) and thereby more efficiently utilizes an otherwise less utilized car (Sharing). It should be noted as well that *Figure 2.1* is not all-inclusive. In the face of the ‘platform revolution’, numerous descriptive terms have been coined by all kinds of parties involved.

3. Theory and hypotheses

The academic understanding of the platform model is supported by two main pillars of economic literature. These are the works by Ronald H. Coase (transaction costs) and Jean Tirole (double-sided markets).

The disruptive effect of the platform model, enabled by technological advancements, lies in the abolishment of transaction costs. Ronald Coase (1937) linked the theory of the firm to mediating these costs. According to this view, the theory of the firm is to integrate actors that frequently interact under one banner, removing the necessity of e.g. bargaining for every interaction between these actors or searching for the right person to interact with for every repetition of the interaction. The Coase theorem states that if property rights are clearly established and tradeable, and if there are no transaction costs nor asymmetric information, the outcome of negotiations will be Pareto efficient (Coase, 1960). In this scenario, there would be no necessity for firms of any kinds. Jean Tirole (2004) subsequently determines that the failure of Coase theorem is also necessary for the existence of a two-sided market. Mainly, the externalities that arise to one side (i.e. buyers/sellers) of the market because another side (i.e. sellers/buyers) is attracted to the platform cannot be perfectly internalized in negotiation between the end-users. Hence, the property rights of this added value is neither defined nor tradeable. In other words, when an user joins the platform the value of the platform to all other users increases. However, the joining user is not able to negotiate in order to receive a portion of this surplus he/she adds by joining. The surplus is simply too little and spread over too many other users to be tradeable. Yet, the platform is in a unique position to appropriate (part of) the added surpluses created by an increasing user-base. The platform operator can simply ‘negotiate’ for this value by setting the prices it charges its users for participation on the platform. In most instances, these prices are allocated to users in accordance to the elasticities of demand and supply and the marginal effects of supply and demand (Rochet & Tirole, 2004). The surplus created by a new user is a network effect that is either direct/same-side or indirect/cross-side. Consider a new supplier joining an online marketplace; the direct network effect may be of negative value as it increases the competitiveness between suppliers. However, the indirect network effect attracts more buyers to the network because they can choose from a larger and more diversified offering on the platform. In turn, the increase in the number of buyers provides a surplus to the suppliers because they can advertise to a larger user-base. The indirect or cross-side network effects are in most cases larger than the direct or same-side network effects. Subsequently, the surplus from network effects differs over who joins the platform. The surplus of a new supplier may be much larger than the surplus created by a new buyer. When a platform has an abundance of buyers and a little amount of suppliers, the positive network effects has been largely enjoyed by the supply-side. In this case, the platform operator may capture the surplus by allocating charges to suppliers because the charge is inelastic with the number of suppliers. For the buyers, the value created by the amount of participants in the network has been too small. If they are charged, they may simply leave the platform. Hence, the number of buyers is highly elastic with what they are charged. Furthermore, such a charge to buyers indirectly diminishes the surplus that may be captured from suppliers.

Rochet and Tirole (2001) discuss the lack of neutrality in allocation of charges by the platform. The end-users of a platform do not solely care for the total costs associated with the transaction but rather the allocation of these costs between them. If charges could simply pass-through to the other side, end-users would be neutral or indifferent towards any allocation of the costs they would incur during a transaction. This neutrality does not hold in many cases because charges to one side might be too small to justify the transaction costs of identifying, bargaining or writing them in a contract. Additionally, there might be a lack of low costs billing systems to even pass-through such a charge e.g. charging a Facebook-user for reading a post is more expensive to bill than the value created by the interaction. Neutrality also implies that all transactions/interactions can be monitored. This is especially an impossibility when the interaction between end-users is of a non-pecuniary nature and difficult to accurately measure e.g. attention given to advertisements or content. Rochet and Tirole (2004) further investigate pricing structure by distinguishing membership (transaction-insensitive) and usage (transaction-sensitive) fees. Usage fees limit the number of transactions, but are more conveniently redistributed between end-users as buyers/sellers may set a new price accordingly. Hence, such fees are able to pass-through to the point of optimal allocation regardless of them being charged to buyers or sellers (comparable to VAT). This pass-through assumption entails that the transaction fee T is allocated between the price for the consumer P^* and the income of the vendor I by setting the level of δ.

$$I = P - \delta * T$$

$$P^* = P + (1 - \delta) * T$$

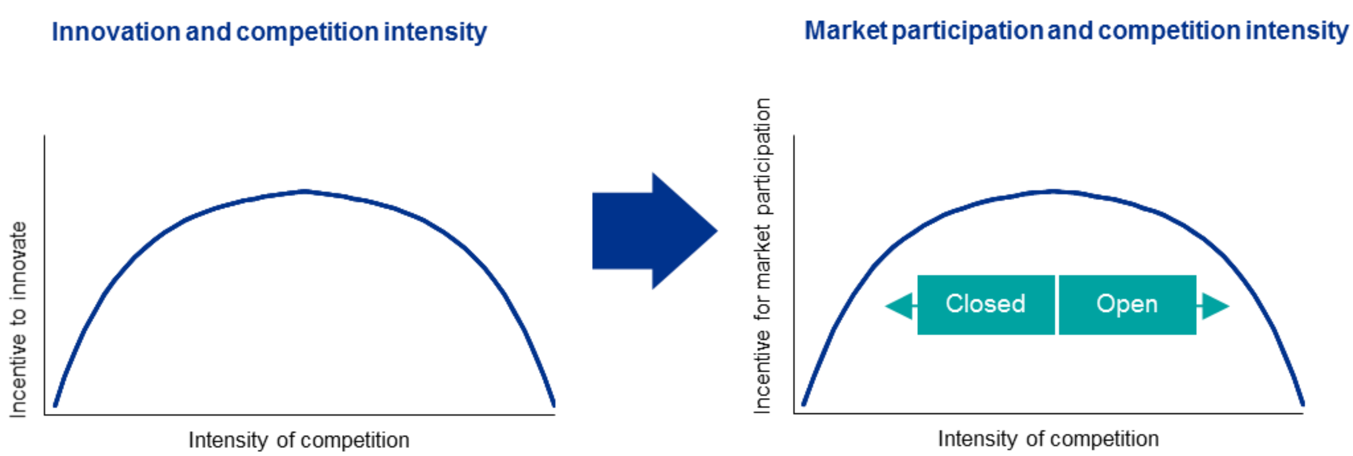
However, this re-allocation may be limited by platform regulation. Take for instance a seller participating in multiple online marketplaces. The rules of more than one platform may specify that the price set by the seller may not exceed the price set by the seller on any other platform. When one platform charges the seller a transaction fee and another charges the exact same fee to the buyer, the seller would set his price higher on the first platform relative to the second. With optimal pricing due to passing-through (part of) the charges to the other party, the seller and buyer would be indifferent on which platform they complete the transaction. The gains to both parties are equal on the two platforms. Now, when the first platform determines that sellers may not set their prices higher than on the second platform, the seller will have to set a sub-optimal price on at least one of the two platforms. Nonetheless, even in such cases the pass-through effect is at most restricted, not absent. Membership fees on the other hand, are considered sunk costs and are not included in negotiations –price setting– for a transaction. Subsequently, this thesis follows this reasoning in assuming that transaction fees are ambiguously allocated between the transacting parties, but membership fees are sunk costs incurred to either one or both sides without the possibility of passing through to the other. Later on, the assumption of pass-through of transaction fees is eliminated ($\delta = 1$).

Next, a platform may balance openness and curation in various ways. A definition provided by Thomas Eisenmann, Geoffrey G. Parker & Marshall Van Alstyne (2009):

> *"A platform is 'open' to the extent that (1) no restrictions are placed on participation in its development, commercialization, or use; or (2) any restrictions –for example, requirements to conform with technical standards or pay licensing fees– are reasonable and non-discriminatory, that is, they are applied uniformly to all potential platform participants"*

Relatively less suppliers may hint at a more curated and closed platform with selected and filtered participants whereas relatively more suppliers suggest an open platform. These concepts may refer to respective levels of low and high competition intensity. Relating this concept to the economics of innovation, the inverted U-curve relationship between competition intensity and investing in innovation by Aghion et al. (2005) can be applied. More specifically; at low levels of competition, an increase in the intensity of competition creates an 'escape competition effect' at which incentives to innovate increase. On the contrary, when there is high competition in a market, a further increase will decrease the incentives to innovate. This follows the reasoning that less of the value of innovation can be appropriated to the innovator. The theory may hold true for the willingness-to-pay charges for market participation on platforms as shown in *Figure 3.1*. Consequently, the marginal incentives for suppliers being charged for (increased) market participation is expected to differ between open and closed platforms. The willingness-to-pay is dependent on the surplus created by network effects. At high levels of competition (open) on the platform, the marginal supplier generates a lower positive indirect network effect i.e. attracts relatively less new buyers, than negative direct network effects i.e. more competition. At high levels, an investment in (enhanced) access may result in only more 'noise' and the marginal positive network effect of newly attracted buyers is spread over more suppliers. Hence, it is more difficult to appropriate the indirect network effects. At low levels of competition (closed), an increase in intensity will increase the willingness to 'escape competition'. Now, the positive indirect network effects of the marginal supplier will be relatively larger than the negative direct network effects. The surplus created by attracting new buyers may be appropriated through enhanced access. Additionally, low levels of competition intensity signal higher bargaining power for the supplier relative to the platform operator, resulting in a lower probability of the platform capturing value from the supplier.

Figure 3.1: Competition intensity and willingness to invest in (increased) market participation.



Consider the accommodation platform Airbnb in several hypothetical situations. When there is a small amount of accommodation providers in the area, there is little incentive to invest in a higher position in the search results. The user is likely to spot your listing nonetheless and the amount of Airbnb users that would visit the area is limited because they rather use a platform that offers more accommodation choices. Airbnb would also refrain from charging the accommodation provider because the potential loss in the number of providers reduces the value of the platform more than the potential revenue gains from charging them. Additionally, when there is a relatively large amount of accommodation providers in the area, the investment in a higher position in the search results is more likely to be followed by similar investments of competitors. There are a large amount of users looking for accommodation, but their business is heavily competed over. The result being a relatively quick return to a level playing field even after investing in (enhanced) access. However, somewhere between these extremes exists an optimal incentive. At this level of competition intensity, the sponsored listing allows a significant comparative advantage in a sizeable market that the accommodation provider is willing to invest in.

The competition intensity or openness of a platform can be proxied by the number of suppliers (to be elaborated upon in *Section 4.3*). Note that charges to users on the platform and the number of users on the platform are causally connected and results may be ambiguous either way. The necessary assumption that all platforms in the analysis are in a close-to steady state is a strong one. However, the strict requirements for sample selection, as will be elaborated upon in *Section 4.1*, allow for this assumption to be made; Platforms in the sample have already strongly positioned themselves on the open to closed-spectrum. Even more, in many cases, the platform has positioned itself on this spectrum before any attempt at monetization (users first, monetization second). Based on this discussion, we formulate:

> **Hypothesis 1:** The probability of a DMP charging suppliers has an inverted U-curve relationship with the number of suppliers.

Furthermore, Parker, Alstyne & Choudary (2016) discuss the benefits of charging the successful transactions on a platform, mainly due to the uniqueness of not negatively affecting network effects. The network effects are created when joining the network, while the first charges only arise during the completion of a transaction. Nonetheless, it may prove a difficult challenge to capture transactions on the platform. The authors discuss the example of service providing platforms. Transactions are high likely completed off-platform when a service provider and consumer discuss and agree upon the terms of service in person. Airbnb, Groupon and Fiverr combat this problem by temporarily preventing participants from connecting directly. However, this type of governance reduces in effectiveness when transactions involve more expansive search goods/services. When price levels increase to the level of a large home improvement or the purchase of a house or a car, a consumer will be more demanding in wanting to view the product or meeting the service provider in person before payment takes place. Therefore, when prices are sufficiently high, the platform may need to move from monetizing transactions to charging (enhanced) access fees to either supply and/or demand (Parker, Alstyne & Choudary; 2016).

> **Hypothesis 2:** When the price level increases, the probability of charging transaction fees decreases while the probability of charging access fees increases.

The first 2 hypotheses have stated expected relationships between monetizing a certain revenue source and respectively the number of suppliers and the price level associated with transactions between end-users. Other than these characteristics of the platform itself, strategic behavior may be affected by characteristics that are exogenous to the platform: characteristics of the industry, the parent company and the domestic market. Due to the exploratory nature of this study and the limitations of the dataset, these relationships are not analyzed in detail. Nonetheless, for these three topics –the industry, the parent company and the domestic market– three respective hypotheses are formulated. These three are discussed in order.

Firstly, a simple characteristic of the industry in which the platform operates is defined: The presence of gatekeepers. Platforms expectedly attempt to weaken the market power of intermediaries that have been traditionally dominating the market. These intermediaries, frequently referred to as gatekeepers, already perform a matchmaking function in the industry. A clear example of this is the presence of travel agencies in the travel industry. New travel platforms do not only have to provide a platform where consumers, hotels and airlines can find and transact with each other, they have to attract these parties despite the existing relationships between these parties and the traditional travel agencies. These agencies are also platforms and in almost all cases they are digital platforms as well. Still, even though these gatekeepers only had to launch a website to become digital multi-sided platforms, something all of them did in the 90's, our dataset that includes the largest travel platforms in the world does not include any traditional travel agencies. It does include Agoda, Airbnb and Tujia that launched in respectively 2005, 2008 and 2011. In such industries, with the traditional presence of gatekeepers, the new DMP's have expectedly gained their comparative advantage by opening their platforms to a larger amount of offerings than their traditional counterparts. If this is the case, the DMP's that are active in these industries are more likely to have diminished or fully eliminated access charges in order to attract more suppliers to their platforms.

Hypothesis 3: The presence of traditional gatekeepers decreases the probability of a platform to charge suppliers.

Secondly, the type of parent company that is operating the DMP, the platform operator (PO), may act differently in accordance to their complete portfolio of DMP's. Rochet-Tirole (2004) argue that bundling may benefit platforms differently than firms operating in classical markets (e.g. price discrimination or entry deterrence). Bundling in the platform economy may refer to integration or dependency of one platform to another. When one platform enjoys a large user base, the PO may have these network effects spillover to another platform. It is not unusual to observe a large platform launching or integrating new platforms with different core interactions e.g. Google (Alphabet Inc.) expanding from search engine (Google Search) to social network (Google+), music platform (Google Play Music), software manufacturing (Android / Google Play Store), video sharing (Youtube) and much more. The spillover to Google+ from the existing Google user-base resulted in 10 million users signing up for Google+ within 2 weeks of launch (Goldman, 2011). Brand loyalty and convenience played a major part in these events; the Google brand has no lack of fans and Google+ was already integrated with various other Google platforms from the very start. The multi-platform operator (MPO) creates additional value by providing a 'one stop'-shop. Furthermore, MPO's, by definition, are capable of operating more than one platform. Additionally, these platforms all meet the requirements set for being included in the sample (annual revenue of at least USD 200 million or more than 10 million monthly active users). Hence, MPO's have expectedly more experience and capabilities than their single (large) platform operating competitors. Consequently, they may be better able to effectively employ price discrimination e.g. through different types of membership. In other words, a MPO can better adapt their platform's pricing structure to the willingness to pay of its many individual suppliers.

Combining the surplus in convenience and brand loyalty with the enhanced ability to capture such surpluses, we expect that MPO's are more likely to monetize access fees:

> **Hypothesis 4:** A DMP is more likely to charge its users, supply or demand, when its operator has a portfolio of more than one large platform in the sample.

Finally, digital platforms included in the sample are almost all internationally orientated. Even though domestic markets account for the most dominant source of revenue in nearly all instances, an even greater portion is appropriated in foreign markets. For instance, American platform eBay, even with 27 different country-specific web-addresses, had 42% of its 2016 revenue originate from the United States (eBay, 2017) and German platform Delivery Hero generated 48% of its 2016 revenue in the European market, despite operating in the Middle East, North Africa, Asia, Australia, Latin and North America as well (Delivery Hero, 2016). While collecting data in preparation of this study, little variation between regions was observed in regards to pricing structures besides the level of transaction fees. These transaction fees often deviated on the same platform between countries, which may be due to certain region-specific factors, such as a reallocation of the relevant VAT or price discrimination between different income levels. Still, one geographic divide in the sample became quite apparent. Namely, Asia and the rest of the world. Let alone generating revenue in other continents, many of the Chinese based platforms even limit their language settings to what is spoken in the Greater China Region. One of the most internationally known platforms from Chinese origin, Alibaba, makes close to 90% of its revenues from its domestic Chinese market (Statista, 2017). There may be numerous Asian platforms operating on a global level. Nonetheless, this divide in inter-continental expansion between non-Asian platforms and Asian platforms likely persists throughout the sample due to the high requirements for sample selection (*Section 4.1)*. An European or North American platform may simple not be able to meet these requirements without expansion to other markets. In regards to culture and language, expansion to respectively North America or Europe faces relatively less obstacles than expansion to Asia. On the other hand, China and India have a respective ~1,4 billion and ~1,3 billion inhabitants (World Population Review, 2017), which is sufficiently large to meet the sample requirements while focusing on the domestic market alone. If region-specific characteristics affect strategic choices by platforms, a difference should be identified between Asia and the rest of the world. Two notable characteristics of the Asian market are observed, which may have a significant effect on the monetization strategy of platforms.

Firstly, inter-platform competition is expectedly of a higher intensity in Asia than it is in the rest of the world. After extensive translation efforts, it is apparent that the Asian platforms in the sample are much more focused on the domestic market. Additionally, European and American platforms expanding to Asia, more specifically China and India, are numerous. With close-to half of DMP's in the sample being headquartered in China, and the remaining half not lacking DMP's with a foothold in China, DMP's will have to be more competitive to attract users i.e. decrease access fees.

Secondly, the Asian consumer is notably different in behavior. Especially in the case of social media, the Asian users seems much more willing to be charged for use of the platform. The largest Asian messaging platforms QQ and WeChat generate revenue by selling stickers and emoticons that users use to communicate with each other. On the other hand, there is not a single non-Asian messaging platform in the sample that monetizes users in a similar fashion. This difference may have resulted from path dependency due to users expectations; charging a European consumer to use emoticons will high likely generate substantial resistance because users have come to expect that such functionalities are free.

> **Hypothesis 5:** DMP's with headquarters in Asia are less likely to charge access fees to suppliers, but more likely to monetize demand in comparison to DMP's with headquarters in the rest of the world.

These five hypotheses will be tested in section 6. Before that, the following section 4 and 5 elaborate on the database and the methodology.

4. Data

A big part of this study involved the creation of the dataset. Therefore, before detailing the variables used, this section will firstly go through the sample selection process and how the dataset came to be.

4.1 Sample selection

The Global Platform Survey by Evans et al. (2016) includes 176 digital platform companies with a valuation greater than USD 1 billion with headquarters in 23 countries and 28 industries. Although far from an exhaustive or perfectly correct list of all platform businesses, these highly successful companies can be assumed to employ the most effective monetization strategies for their corresponding markets. Furthermore, the high valuation requirement makes the attempt at an (close to) exhaustive dataset of these firms plausible. The transformation of the dataset follows three phases.

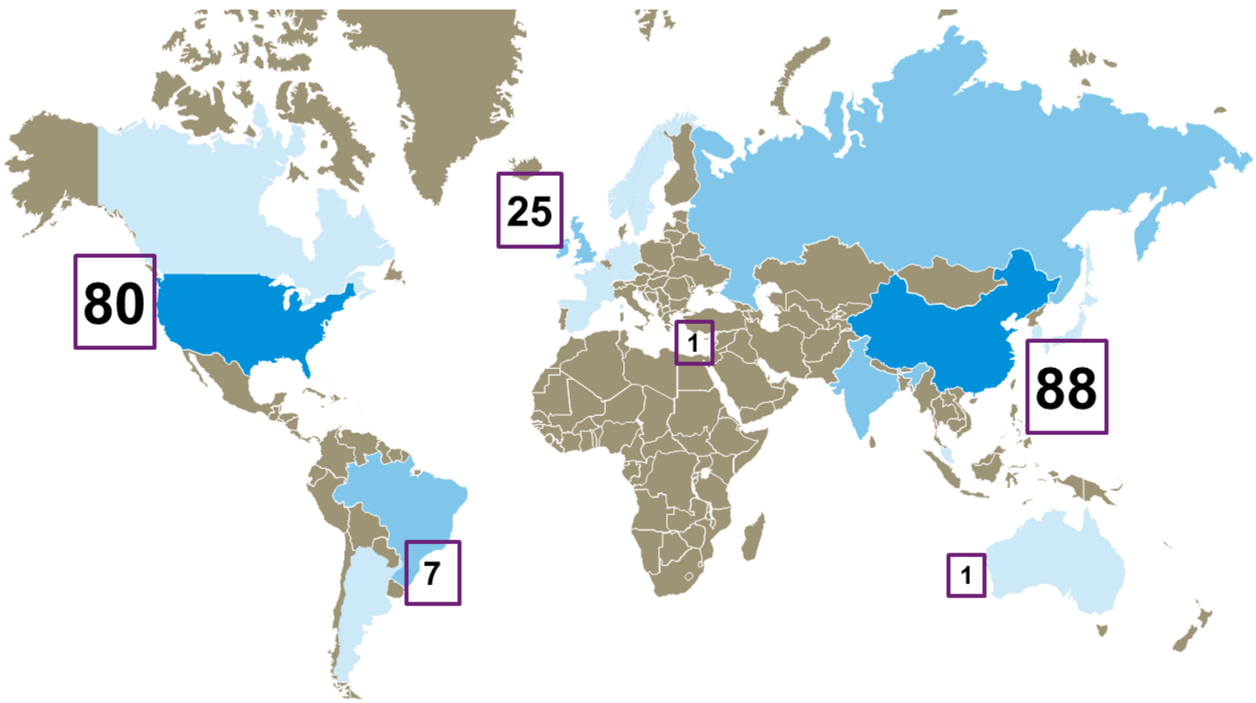
Firstly, the database is corrected and updated according to market developments and the scope of this study. The first referring to the correction of wrongfully included firms that are actually not multi-sided. These digital firms have been included in the survey while their core interaction is between the user and the platform as a service (6 firms e.g. Dropbox), the 'platform' actually employs a traditional merchant/producer model as an only supplier to a digital storefront (14 firms including Blue Apron and Wharby Parker) or the 'platform company' is an investment group with equity ownership in actual platform firms (5 firms). The alteration in data because of the scope of the study, i.e. platforms with successful monetization strategies, refers to the removal of platform company Powa Technologies that went bankrupt after the survey took place, the exclusion of (mainly) innovation platforms (6 firms e.g. Intel) as well as platforms Letgo and Nextdoor, who, despite their unicorn valuations, have not generated any revenue yet. Additionally, the industries are redefined at a less detailed level. For instance, 'messaging' and 'social' are now both considered social platforms.

Secondly, I distinguish between the various platforms that are operated by the same platform company. 'Integrated' and 'investment' platforms, as defined by Evans and Gawer (2016), refer to firms that operate or own equity in one or multiple platforms. For instance, integrated platform company Amazon operates Amazon Appstore, Amazon Prime and Amazon Pay. All of which are multi-sided platforms that facilitate a different core interaction. A subsidiary platform is only included in the sample if it has at least USD 200 million in revenue or 10 million monthly active users, and was launched ≥ 2 years ago (≤ 2015). Only the African platform company Jumia is eliminated from the sample because of, although having unicorn valuation, not operating a single subsidiary platform that can be confirmed to meet the requirements with the information publicly available. The database now consists of 202 platforms by 168 firms over 16 industries (*Appendix Table 11.1*).

Thirdly, certain platforms that fit the aforementioned criteria but were yet to be included in the survey are added to the database. These platforms have been identified by existing literature, consulting industry experts and by analyzing unicorn listings. It should be noted that one industry is in its entirety excluded from both the survey and this study. This refers to platforms for erotic content.

The geographical spread of the sample is rather limited to three regions: Europe, North America and Asia (*Figure 4.1*). Noticeable is the high amount of platforms operating within clusters: 81 out of 202 platforms are operated from headquarters in either San Francisco or Beijing. This is partly due to the larger firms (Google, Apple and Baidu) establishing themselves in those cities, but even controlling for the multi-platform operating firms, these cities still house one third of all platform companies in the sample. Other than those two clusters, only Shanghai gathers more than 10 platform firms. All other cities within the sample house less than 5.

Figure 4.1: Geographic distribution of sample.

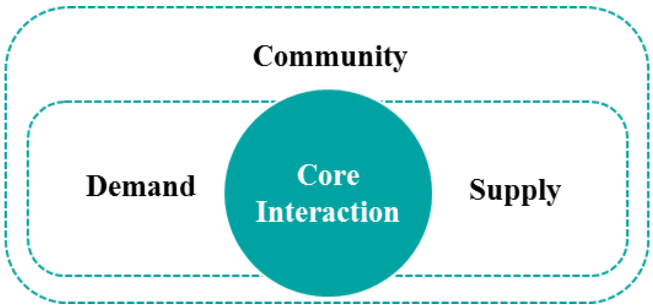


Lastly, the average age of platforms in the sample is quite young. The average platform is launched in 2006. Even more, the industry averages do not deviate more than one year from this average.

4.2 Monetization Strategies

A monetization strategy is in the context of this study the combination of choosing to monetize one or more of four possibly revenue sources (*Figure 4.2)*. None of these sources are mutually exclusive. Moreover, demand and supply in a multi-sided market may be completely different agents (e.g. a professional brand acting as a vendor on Amazon and a single individual acting as consumer) or the same agent that can either take the role of supply, demand or even both in any interaction (e.g. an user on dating platform OkCupid).

Figure 4.2: Monetization strategy is the decision of monetizing any single or combination of four revenue sources.



4.2.1 The core interaction

A DMP operates around its core interaction. If the core interaction includes a monetary transfer and the platform can service this transfer on-platform, the facilitator of the platform is in a position to monetize on these successful transactions. This refers to transaction, service and/or commission fees as well as any fees that are variable to the amount of successful transactions. This type of monetization may lead to friction in the amount of transactions between users or incentivize them to conclude the transaction off-platform. In markets with high competition between platforms, high transaction costs might deter suppliers in fear of lower profit margins. The obvious advantage lies in the guarantee to users, both demand and supply, that the platform will only profit if it can provide them successful transactions. The allocation of a transaction fee to either demand or supply is considered ambiguous at first, as the fee may pass-through by use of price setting (Rochet & Tirole, 2004). In a later part of the study, the transaction fee will be considered to be a charge to either supply or demand. If the DMP monetizes the interaction between its users, the dummy variable *Transaction* takes 1, 0 otherwise.

Example: Groupon enables suppliers to advertise their limited-time deals and charges a 25% commission fee once the buyer purchases the coupon.

4.2.2 Access of supply

Secondly, the value of a DMP might be greatly enjoyed by the supplying party in the core interaction. In these cases, the access by a supplier or content provider to a large user base that may be interested in their product, service or content may be monetized. This type of strategy is characterized by membership or listing fees that are invariable to the number of successful transactions. This includes all types of monetization to enhance access of supply to demand in relation to the core interaction. Examples include sponsored listings that increase the chances of being found by potential customers or premium memberships that allow for more listings. Note that all these types of charges are considered invariable to the number of completed transactions. Nonetheless, there is a single exception to this rule that is still defined as a charge to supply. Namely, on some eCommerce marketplaces, the vendor is charged for every recurring transaction it lists on the platform. When the transaction is completed, the vendor is charged the same fee to 'repost' the listing for the chance of another repetition of the transaction. These charges are variable to the number of transactions; the more transactions occur, the more the charge will be repeated. However the charge occurs before supply and demand may interact and successfully complete the transaction. Therefore, we include these types of charges as an access fee to suppliers. If the DMP monetizes the accessibility to the demand side of the interaction, the dummy variable *Supply* takes 1, 0 otherwise.

Example: Video sharing platform Vimeo offers 4 increasingly costly types of membership that enable the content provider to respectively upload 500MB, 5GB, 200GB or limitless uploading of videos.

4.2.3 Access of demand

Thirdly, a mirror image of the previous strategy, the added value of a DMP may originate from the potential in which users can connect to agents able to supply the products, services or content they are looking for. Hence, the (enhanced) access of the demand side to potential suppliers may be monetized. If the DMP monetizes the accessibility to the supply side of the interaction, the dummy variable *Demand* takes 1, 0 otherwise.

Example: Amazon Prime membership offers, among other things, early access to deals on Amazon.

4.2.4 Presence of community

Lastly, a DMP may find other ways to generate revenue than through the core interaction. Where the first strategy monetizes the interaction itself and the second and third the access of agents to the core interaction, the fourth monetizes the overall presence of the users. This can be done through two ways. Firstly, the DMP might monetize the traffic on its website(s) by e.g. selling advertisement or data products to agents outside of the participants in the core interaction. In this instance, the company operating the platform offers its premium access to its user-base. Secondly, the DMP can enjoy its premium access and offer the user-base products and services complementary or even unrelated to the core interaction. If the DMP monetizes the presence of the community, the dummy variable *Community* takes 1, 0 otherwise.

Example: Social platform Babytree facilitates (soon to be-)parents in sharing experience and advise. Complementary to the social interaction, Babytree offers products and services tailored to their demand.

The four defined forms of monetization or pricing structures are identified by scanning the respective websites, annual reports and financial statements of the platforms as well as third party sources e.g. case studies, business profiles and market analyses. Overall, more than 200 sources and multiple publications per source have been used to create the dataset. All sources are listed in *Table 11.2* of the appendix.

The share of firms using a certain monetization strategy are rather varied over industries (*Appendix: Table 11.1*). Access by demand is the least monetized source of revenue, being employed by only 16% of DMP's in the sample. Transactions are the most commonly monetized source of revenue with 61,9% of the sample monetizing transactions. Access by supply and the presence of the community are monetized by respectively 49,5% and 51% of platforms in the sample. The average monetization strategy is a combination of monetizing 1,8 out of the 4 revenue sources. Moreover, the sample does not deviate much from this average with 87,5% of the sample monetizing on only 1 or 2 possible revenue sources. As shown by the correlations in *Table 4.1*, there are no obvious parings of monetizing any two revenue sources. However, transaction fees and charging the access of demand are negatively and rather highly correlated. This may be because of transaction fees and access are two ways in which the same party can be charged. Keep in mind that transaction fees charge both sides ambiguously when the pass-through assumption holds. The negative correlation may hint at these pricing structures being partly interchangeable. In the cases that both are charged, the access fee is often in the shape of a premium membership that provides a reduction on costs per transaction, allowing for the consumer to choose their preferred payment structure to a certain extent. Even more, the correlation is expectedly driven by the media industry. In the case of platforms for video and music streaming (e.g. Apple Music, Spotify) the subscription model is often used to replace the necessity of individual payments for every transaction.

Table 4.1: Correlation table of the monetization of revenue sources.

	(1)	(2)	(3)	(4)
(1) Transaction	-	-0,09	-0,40	-0,34
(2) Supply	-0,09	-	-0,13	0,03
(3) Demand	-0,40	-0,13	-	0,01
(4) Community	-0,34	0,03	0,01	-

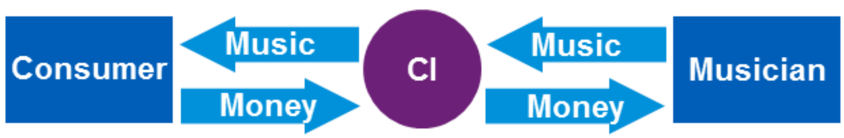
Furthermore, there is only a single platform in the sample monetizing on all 4 options: the Chinese real-estate platform SouFun (搜房网房天下). However, not too many conclusions should be drawn from these means as they are greatly influenced by the relatively large presence of eCommerce platforms in the sample (53). These platforms much more frequently monetize on transactions and suppliers than the average of all other industries. In practice, this takes the shape of commission fees and charging a vendor to (more prominently) showcase their products on the online marketplace.

4.3 Main variables

The market is facilitated by the DMP. Nonetheless, after a core interaction is established with a sufficiently large user-base, the DMP cannot easily alter the characteristics of the type of market they operate. These characteristics include the type of good or service that is offered. Specifically, if it is a search good of higher costs and a lower frequency of being bought by a consumer, or if it is not. Other market characteristics are the number of users on the demand and the supply side. Because of the extreme range in these numbers, from dozens to billions, the number of users are transformed to logarithms. It is the logarithm of the number of suppliers that is used to proxy the competition intensity. Traditionally, the Herfindahl-Hirschman Index is a popular measure for the competition intensity of a market. Unfortunately, this index is near impossible to apply in markets where there is little data on individual suppliers and their market shares, which is often the case when it considers the market on a digital multi-sided platform with millions of suppliers. The number of suppliers is in this case a viable alternative.

In regards of the second hypothesis, the pecuniary value of the core interaction is defined. Two challenges arise in this process. Firstly, the average value per transaction is only published by a handful of platforms. Secondly, the pecuniary value or price level of the core interaction is not always expressed as a transfer of money between supply and demand e.g. Spotify facilitates no direct transfer of money between the consumer and the producer of an album. The consumer pays the platform a monthly fee, but the consumer does not directly pay the musician or producer. Nonetheless, the album is still of monetary value. When analyzing the core interaction of Spotify (*Figure 4.3*) it is clear that the core interaction, even though there is a lack of direct payments, involves a transfer of money.

Figure 4.3: The core interaction of Spotify.



These cases, such as Spotify, make it difficult to appropriate pecuniary value to the core interaction. Therefore a categorical variable is created for the average price level (*Mean Price*). This may take the values 1 through 5 with the categories reflecting average pecuniary transactions in the core interaction of respectively less than 1 USD (*Mean price* = 1), 10 USD (= 2), 100 USD (= 3), 1000 USD (= 4) and more than 1000 USD (= 5). The platforms for which the average value is not publicly available, we turn to similar platforms that did make the information public and scan the listings on the platform for an accurate estimate of the price level. Returning to the example of Spotify, the price level is set as the same category as the price level of iTunes. The simplicity in the ranges of the price categories may limit the bias from incorrect estimations while providing a control for differences in time and effort the demand-side user might invest in the transaction. Because the dataset includes platforms whose interactions are of intangible, non-pecuniary value i.e. attention, a dummy variable *Pay* controls for the presence of pecuniary gains within the core interaction.

In a similar fashion as *Mean price*, the frequency of transactions is estimated as categorical variable. The categorical variable *Frequency* may take the values of 1, 12, 52 and 365 as a very crude representation of the times per year a consumer is expected to purchase a product or service in the relevant industry.

Table 4.2: Descriptive statistics.

Variable	Mean	Standard deviation	Min	Max
Transaction	0.63	0.49	0	1
Supply	0.50	0.50	0	1
Community	0.52	0.50	0	1
Demand	0.16	0.37	0	1
Ln #suppliers	13.67	4.78	3.40	24.57
Ln #demand	17.92	2.32	8.16	21.39
Pay	0.69	0.46	0	1
Mean price	2.29	1.33	0	5
Frequency	127.37	154.76	1	365
Gatekeepers	0.29	0.45	0	1
MPO	0.29	0.45	0	1
Asia	0.44	0.50	0	1

Lastly, to test the three hypotheses regarding the presence of traditional gatekeepers, differences between MPO's and SPO's and between regions, we define three dummy variables. Firstly, the dummy variable *Gatekeepers* takes the value of 1 if the industry is traditionally dominated by intermediaries that facilitate the same interaction as the DMP. Secondly, the dummy variable *MPO* takes the value of 1 if the platform is operated by a company that operates more than 1 platform in the sample. Lastly, the dummy variable *Asia* takes the value of 1 if the platform operator has its headquarter in Asia, 0 if the DMP is headquartered elsewhere.

5. Methodology

This thesis argues that characteristics regarding the eco-system and characteristics of the platform pose a strategic choice on how to monetize the platform. In turn, a platform's (i) monetization choice (M_i) can take four different values ($M_i \in t, s, c, d$). These relate to the four potential sources of revenue as discussed in the previous section. Subsequently, a multinomial logit model (MNL) might seem appropriate. However, the MNL model demands outcomes to be mutually exclusive, which is not a viable option in this setting. An outcome may be a combination of two or more choices. The same circumstances that allow for a revenue source to be monetized may very well increase the probability of monetizing any other revenue source as well. For this reason, the model is estimated as four separate univariate probit models of the form:

$$\Pr(Y_{m,i}) = \sum_1^k (\beta_{i,k} x_{i,k}) + \varepsilon_m$$

$$Y_m = 1(Y_m^* > 0)$$

Where the choice of monetization (Y_m) is employing any of the four defined revenue sources ($m \in t, s, c, d$). Secondly, we expect that monetizing one of the four sources of revenue may affect the probability of monetizing any of the other four. To account for this, we include correlations between the four monetization choices and estimate the four univariate probit models as a single multivariate probit model (MVP) with:

$$\varepsilon_m = \begin{bmatrix} \varepsilon_t \\ \varepsilon_s \\ \varepsilon_c \\ \varepsilon_d \end{bmatrix} \sim N_m \left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \begin{pmatrix} {\sigma_t}^2 & \rho_{st}\sigma_s\sigma_t & \rho_{ct}\sigma_c\sigma_t & \rho_{dt}\sigma_d\sigma_t \\ \rho_{ts}\sigma_t\sigma_s & {\sigma_s}^2 & \rho_{cs}\sigma_c\sigma_s & \rho_{ds}\sigma_d\sigma_s \\ \rho_{tc}\sigma_t\sigma_c & \rho_{sc}\sigma_s\sigma_c & {\sigma_c}^2 & \rho_{dc}\sigma_d\sigma_c \\ \rho_{td}\sigma_t\sigma_d & \rho_{sd}\sigma_s\sigma_d & \rho_{cd}\sigma_c\sigma_d & {\sigma_d}^2 \end{pmatrix} \right]$$

The advantage of the MVP over the univariate probit model is precisely these correlations. In other words, the choice of monetizing a revenue source is now interdependent with the decision of monetizing any other of the three revenue sources. To capture this interdependency, the MVP estimates all four probit models simultaneously. On the other hand, there is a disadvantage to this model as well. The MVP, compared to the four separate univariate probit models, has a lower degree of freedom because of inclusion of these correlations. Additionally, both probit models have a disadvantage over the multinomial logit model. This disadvantage is the number of observations that are included in the estimation. Despite the extensive data-collection, the sample does not lack in missing values. The multinomial logit model would still use observations with missing values, while the multi-and univariate probit model do not. This lowers the number of observations (N) used to estimate the coefficients to only 128 or 112 (depending on the inclusion of the variable *Gatekeepers*) from the total of 202 platforms included in the sample. For this reason, the dataset is transformed to enable a multinomial logit model in the robustness test (Section 8). Another impact of this problem is that any probit model accounting for industry fixed effects will be estimated over less than half of the total sample size. Hence, the models presented in the following section exclude industry fixed effects.

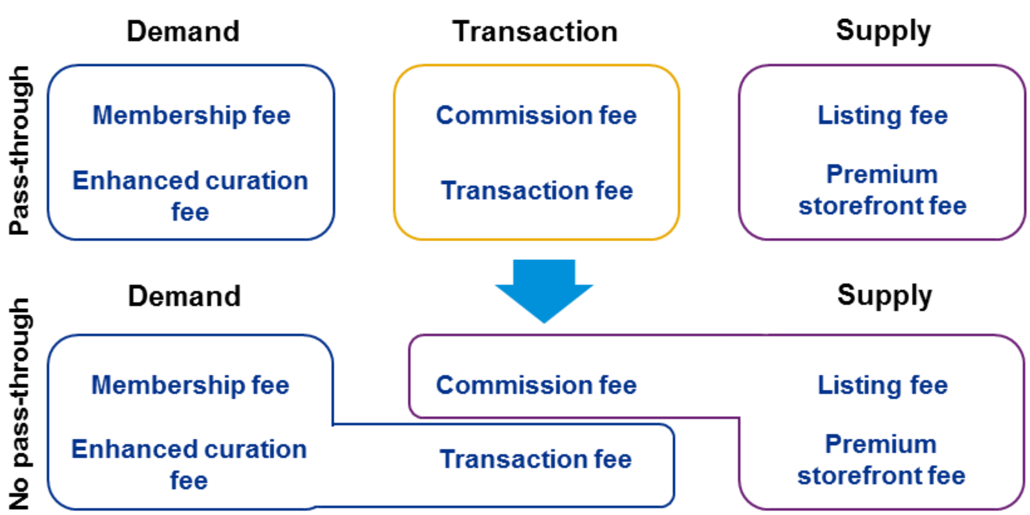
To test the inverted-U relationship of suppliers and the probability of charging the access of suppliers to the platform we include the log of number of suppliers (*Ln #suppliers*) and the quadratic function of this variable (*Ln #suppliers sq*). We expect a positive sign on the coefficient of *Ln #suppliers* and a negative sign on the coefficient of *Ln #suppliers sq* on the probability of monetizing suppliers. These signs would suggest the hypothesized inverted-U curve.

The relationship between price level and the probability to monetize transactions is tested by using an interaction term. A quadratic function of the price level (*Mean price)*, similar to the *Ln #suppliers*, is not valid because the *Mean price* for interactions between end-users includes platforms with interactions of no pecuniary value (e.g. Social platforms) in its first category (*Mean price = 1*). Furthermore, price levels and the presence of payments (*Pay*) between end-users are highly correlated. *Mean price* is therefore only included as an interaction with *Pay*. Now, the coefficient of *Pay* estimates the effect of having a core interaction with pecuniary value and the interaction *Pay x mean price* estimates how this effect changes when the pecuniary value increases to a higher price level category. *Pay* is expected to have a positive relationship with the probability of monetizing transaction, while this relationship is expected to be negative as the price level increases (*Pay x mean price).*

The last three hypotheses are tested by the respective dummy variables *Gatekeepers*, *MPO* and *Asia*. In line with hypothesis 3, we expect the coefficient of *Gatekeepers* to be negative in relation to the probability of monetizing access of supply. The 4th and 5th hypotheses are both in relation to the estimate of charging suppliers or demand. For the 4th hypothesis, we expect a significant and positive coefficient for *MPO* in both estimations on access fees (to supply and demand). The 5th hypothesis expects a positive and significant coefficient for *Asia* in determining the probability of charging demand, but we expect a negative and significant coefficient for charging supply.

The relationships we have now discussed are expectedly influenced by the pass-through assumption. The assumption defines that commission fees charged to suppliers, which are the most observed type of transaction fees, are inherently different than charging suppliers a membership fee. Recall that the membership fee is a sunk cost for the supplier but the transaction fee may be passed through to the consumer by simply setting a higher price. This may not necessarily be the case. A transaction fee, although variable to the number of transactions, may still be considered a fee to the supplier or to the demand side that is not able to pass-through. Imagine a vendor accepting payments via transfer through a payment platform. The vendor sets a price and a buyer decides to purchase it. It is high likely that only after this bargaining takes place, the buyer chooses the payment platform as the means for money transfer. The buyer is not in a position to renegotiate the transaction fee of the payment platform. In this case, the transaction fee can be considered a fee charged to buyers.

Figure 5.1: Redefining transaction fees as charges to demand or supply that are not able to pass-through.



Moreover, in every case that the transaction fee is not completely passed-through to the other side, the transaction fee to a supplier remains a charge to the supplier and the transaction fee to the buyer remains a charge to the buyer. Eliminating the ambiguity of monetizing transactions provides a more accurate estimation of the determinants of the probability to monetize supply or demand.

Hence, the MVP is estimated under this assumption of no pass-through as well. This entails that all observations that monetize transactions are now defined as either charging supply or demand. This process is visualized in *Figure 5.1* with several examples of fees that have been identified to belong to certain revenue sources in the data-collection process. In this transformation, the number of platforms that are considered to monetize their suppliers has increased by 44 to 140 and the number of platforms that monetize demand has increased by 25 to 60 platforms. Both of the estimations, with the pass-through assumption and with the assumption of no pass-through, will be discussed.

6. Empirical Results

Following the discussion in the last section, the results are firstly estimated by the separate univariate probit models (*Table 6.1*). Secondly, the results are estimated within a MVP model (*Table 6.2)* and thirdly, we repeat the MVP estimation with the assumption of no pass-through. The discussion of the results follows the same order, starting with the estimation of the univariate probit model in *Table 6.1* and its implications for the hypotheses.

Regarding the first hypothesis, which expects an inverted U-curve relationship between the number of suppliers and the probability of charging suppliers, *Table 6.1 Column 2* estimates a positive coefficient on *Ln #suppliers* and a negative coefficient on *Ln #suppliers sq*. This does indeed suggest the inverted U-curve; the relationship between the number of suppliers and the probability of charging suppliers is positive at first but becomes less and even negative as the number of suppliers increases, ceteris paribus. Nonetheless, both coefficients are insignificant at a 10% level. There is therefore no support for the 1st hypothesis. Still, in regards to this hypothesis, the assumption of pass-through states that commission fees are not considered charges to the supplier. Relaxing this assumption would allow for a more realistic result that will be discussed later on.

The first part of hypothesis 2 states that capturing transactions on-platform, and thereby potential monetization of transactions, becomes increasingly difficult when the transaction involves search goods. The reasoning also suggests that the presence of a pecuniary transaction between end-users allows for the capture, and thereby monetization, of transactions in the first place. This relates to a positive coefficient for the presence of payments (*Pay*) and a negative coefficient on the interaction term of *Pay* and the average price level of transactions (*Pay x mean price*). *Table 6.1 Column 1* is in line with these expectations with the coefficients of *Pay* and *Pay x mean price* being respectively positive and significant at a 1% level and negative and significant at a 5% level, ceteris paribus. This confirms the first part of hypothesis 2. The second part of the hypothesis states that when the price levels increase, the platform would become more likely to charge access fees. In other words, the DMP would shift to charging the access of either supply, demand or both because they less able to monetize the transactions between these parties.

Table 6.1: Separate univariate probit regressions.

VARIABLES	Probit Transactions	Probit Supply	Probit Community	Probit Demand
Ln #suppliers	0.54**	0.23	0.02	0.03
	(0.25)	(0.18)	(0.03)	(0.05)
Ln #suppliers sq	-0.03**	-0.01		
	(0.01)	(0.01)		
Ln #demand	-0.15*	0.05	0.04	-0.17*
	(0.09)	(0.06)	(0.06)	(0.09)
Pay	3.42***	-0.62	-2.41***	-0.94
	(0.79)	(0.68)	(0.73)	(0.87)
Pay x mean price	-0.48**	0.20	0.57***	-0.66***
	(0.21)	(0.19)	(0.22)	(0.25)
Frequency	0.00	-0.00	0.00	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Gatekeepers		-0.32		1.59***
		(0.31)		(0.48)
MPO	-0.12	0.63**	0.07	0.44
	(0.35)	(0.30)	(0.28)	(0.42)
Asia	0.49	-0.41	0.44*	0.50
	(0.37)	(0.26)	(0.26)	(0.40)
Constant	-0.87	-2.07	-0.96	3.11*
	(2.05)	(1.52)	(1.01)	(1.60)
Observations	128	112	128	112

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

However, the coefficients of *Pay* and *Pay x mean price* on the probability of charging supply (*Table 6.1 Column 2*) are insignificant and on the probability of charging demand (*Table 6.1*

Column 4) these variables are respectively insignificant, and negative and significant at a 1% level. These results show that when the average price level of the transaction increases to a sufficiently high level the probability of monetizing demand decreases, ceteris paribus. This is contrary to the expectation that the probability of monetizing demand and/or supply would increase when price levels increase. Hence, the second part of hypothesis 2 is rejected.

Unexpectedly, the presence of payments decreases the probability of monetizing the presence of the community (*Table 6,1 Column 3*), ceteris paribus, at a 1% significance level while a subsequent increase in the average price level decreases this negative relationship and even makes it positive as price levels increase to a certain extent, ceteris paribus, at a 1% significance level. These coefficients strongly suggest the substitution from monetizing transactions to monetizing the presence of the community when it is difficult to capture transactions on-platform. The presence of *Gatekeepers* has, as expected, a negative, but insignificant at a 10% level, relationship with the probability of charging suppliers, ceteris paribus. These results cannot confirm the 3rd hypothesis stating that platforms which compete against traditional gatekeepers are less likely to charge suppliers.

The 4th hypothesis, on the difference between MPO's and SPO's, expects a positive coefficient of the variable *MPO* on the probability of monetizing suppliers. The estimation in *Table 6.1 Column 2* is perfectly in line with these expectations at a 5% significance level. This supports the 4th hypothesis.

Furthermore, the variable *Asia* is expected to have a negative coefficient on the probability to monetize suppliers and a positive coefficient on the probability to monetize demand. *Table 6.1 Column 2* and *4* suggest these relationships, but insignificant at a 10% level.

As mentioned before, the estimation of the univariate probit models is restricted because it does not allow for the interdependent relationships between the four monetization choices. The estimation is specified to allow for these interdependencies, which results in the MVP estimation in *Table 6.2*. The correlations, $\rho(Y_m, Y_m)$ with $m \in t, s, c, d$, are presented in the lower section of *Table 6.2*. The correlation between monetizing transactions and monetizing demand, $\rho(Y_t, Y_d)$, is negative and significant at a 1% level, ceteris paribus. Note that a correlation should be in the range of -1 to 1, but the estimated correlation is -1,07. This is still reasonable due to the large standard deviation of 0,35. The implication of this significant coefficient is twofold. Firstly, in circumstances that allow both the monetization of demand as well as the monetization of transactions, these two options may be considered substitutes. Secondly, the significance of the interdependent relationship suggests that the MVP is in this case more efficient than the univariate probit models.

Table 6.2: Multivariate probit regression with pass-through assumption.

VARIABLES	MVP Transactions	MVP Supply	MVP Community	MVP Demand
Ln #suppliers	0.54**	0.23	0.02	0.05
	(0.25)	(0.18)	(0.04)	(0.04)
Ln #suppliers sq	-0.02**	-0.01		
	(0.01)	(0.01)		
Ln #demand	-0.28**	0.06	0.05	-0.06
	(0.09)	(0.06)	(0.06)	(0.08)
Pay	3.40***	-0.69	-2.16***	-1.19
	(0.83)	(0.69)	(0.77)	(0.83)
Pay x mean price	-0.48**	0.23	0.53**	-0.54**
	(0.22)	(0.19)	(0.22)	(0.25)
Frequency	0.00	-0.00	0.00	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Gatekeepers		-0.30		1.79***
		(0.31)		(0.45)
MPO	-0.11	0.63**	0.14	0.59
	(0.36)	(0.30)	(0.30)	(0.39)
Asia	0.62*	-0.42	0.44	0.32
	(0.38)	(0.27)	(0.28)	(0.37)
Constant	1.30	-2.21	-1.10	0.87
	(2.38)	(1.54)	(1.11)	(1.56)
$\rho(Y_m, Y_t)$		-0.17	-0.12	-1.07***
		(0.20)	(0.19)	(0.35)
$\rho(Y_m, Y_s)$	-0.17		-0.17	0.07
	(0.20)		(0.15)	(0.20)
$\rho(Y_m, Y_c)$	0.12	-0.17		-0.47
	(0.19)	(0.15)		(0.31)
$\rho(Y_m, Y_d)$	-1.07***	0.07	-0.47	
	(0.35)	(0.20)	(0.31)	
Observations	112	112	112	112

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Taking this into account, the coefficients of interest have not changed in sign or significance when comparing the univariate probit models and the multivariate estimation.

Lastly, we re-estimate the MVP under the assumption that transaction fees may not pass-through (*Figure 6.1*). Any charges to suppliers –sunk costs to suppliers or costs variable to the number of transactions– are now considered costs incurred by suppliers. The same principle applies to charges to demand. Consequently, all observations that monetize transactions are allocated to either supply or demand, resulting in the MVP only estimating three models simultaneously instead of four. Naturally, this model is incapable of testing the second hypothesis regarding the monetization of transactions. The coefficients of this estimation are presented in *Table 6.3*.

First to be noticed is that the coefficients on *Ln #suppliers* and *Ln #suppliers sq* are now significant at a respective 5% and 1% level. An increase in the number of suppliers increases the probability of charging suppliers when there are relatively less suppliers on the platform, ceteris paribus. However, an increase in the number of suppliers decreases the probability of charging suppliers when there is a relatively high number of suppliers on the platform, ceteris paribus. The MVP suggests this inverted U-curve relationship under both assumptions.

As discussed in the previous section, even when the pass-through of transaction fees by the supplier to the buyer occurs, the supplier would almost always incur at least a part of the transaction fee. Consequently, the supplier can be considered to be charged even when the charge is variable to the number of transactions. Hence, for analyzing the probability of charging suppliers the estimation in *Table 6.3 Column 1* provides a more accurate estimation than *Table 6.2*. Therefore, hypothesis 1 is confirmed. The predicted relationship between the number of suppliers and the probability of monetizing supply is visualized under both assumptions in *Figure 6.1* and *Figure 6.2*. The two figures and their respective assumptions may be interpreted by *Figure 6.1* visualizing the predicted probability of charging suppliers a fixed fee, invariant to the number of transactions, and *Figure 6.2* expanding this to the predicted probability of either charging a fixed fee or a fee variable to the number of transactions to suppliers.

The second hypothesis cannot be tested by the estimation in *Table 6.3* because this specification of the model does not allow an estimation on the probability of monetizing transactions.

Figure 6.1: Predicted values of the probability to monetize suppliers' (enhanced) access.

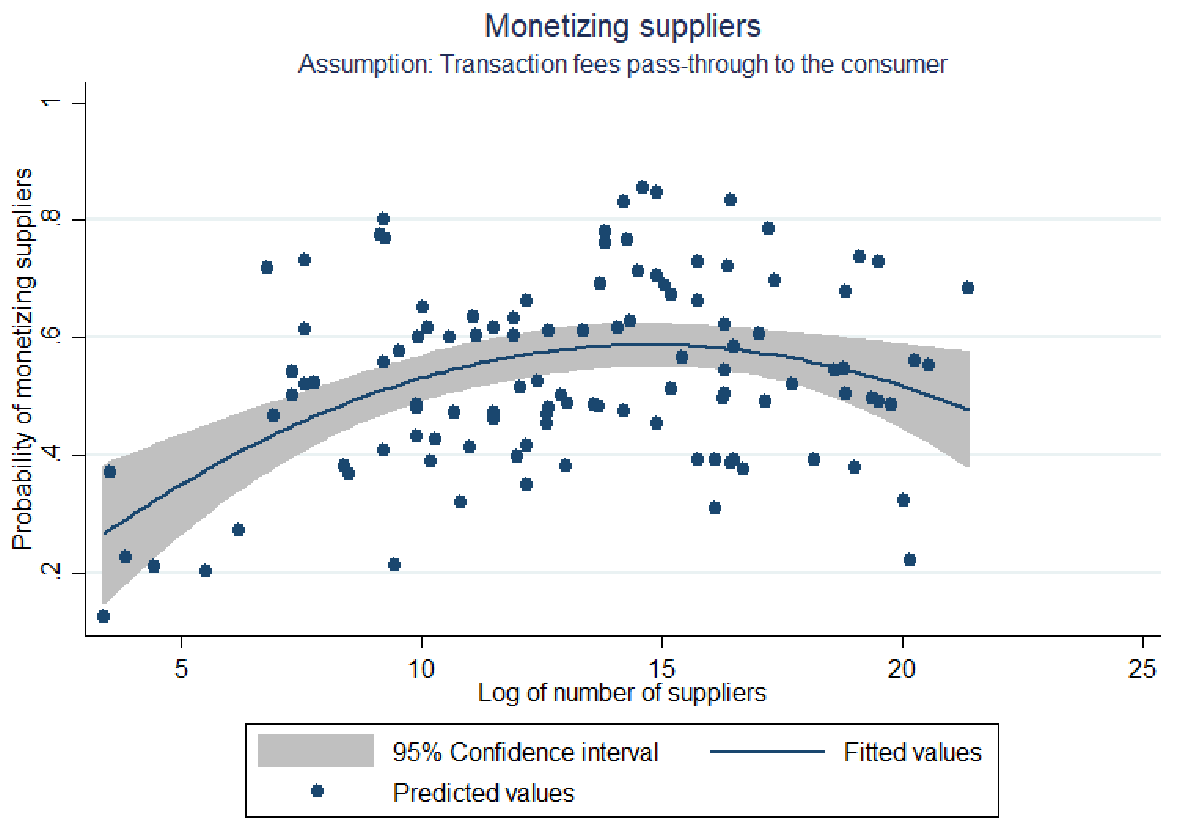


Figure 6.2: Predicted values of the probability to monetize suppliers through access or transaction.

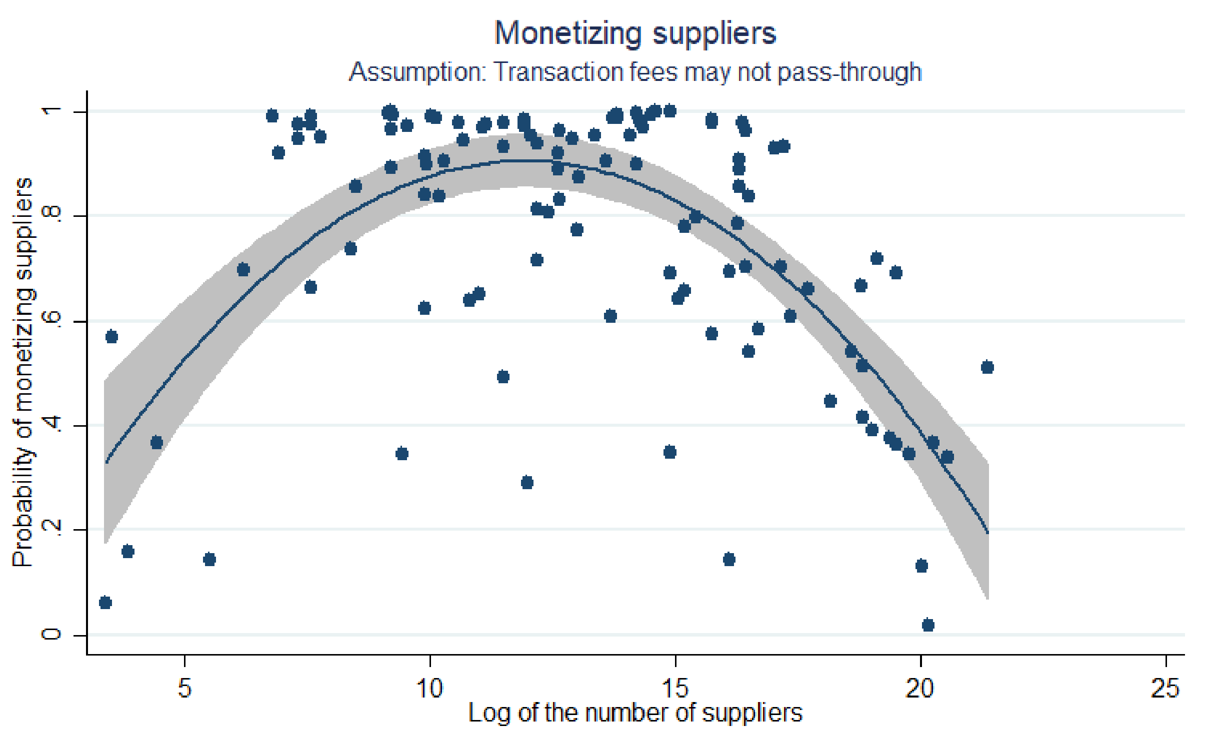


Table 6.3: Multivariate probit regression with no pass-through assumption.

VARIABLES	MVP Supply	MVP Community	MVP Demand
Ln #suppliers	0.51**	0.02	0.08**
	(0.20)	(0.04)	(0.04)
Ln #suppliers sq	-0.02***		
	(0.01)		
Ln #demand	0.19**	0.06	-0.27***
	(0.08)	(0.06)	(0.07)
Pay	-1.41*	-2.06***	1.57**
	(0.79)	(0.75)	(0.69)
Pay x mean price	0.61***	0.52**	-0.65***
	(0.24)	(0.22)	(0.20)
Frequency	-0.00*	0.00	0.00
	(0.00)	(0.00)	(0.00)
Gatekeepers	-0.96**		1.02***
	(0.41)		(0.34)
MPO	0.84**	0.10	-0.22
	(0.40)	(0.30)	(0.33)
Asia	-0.67**	0.41	0.50*
	(0.33)	(0.28)	(0.30)
Constant	-4.42**	-1.36	2.88**
	(1.84)	(1.08)	(1.17)
$\rho(Y_m, Y_s)$		-0.04	-0.74***
		(0.19)	(0.25)
$\rho(Y_m, Y_c)$	-0.04		0.17
	(0.19)		(0.18)
$\rho(Y_m, Y_d)$	-0.74***	0.17	
	(0.25)	(0.18)	
Observations	112	112	112

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Lastly, we review hypothesis 3, 4 and 5. Contrary to the first hypothesis, there is no support that the estimation in *Table 6.3* is more or less accurate in testing these hypotheses than the previous estimation in *Table 6.2*. Hence, we'll discuss how these estimations remain consistent or not over both assumption.

Firstly, in regards to hypothesis 3 –the effect of gatekeepers on charges to supply– we again notice a decrease in the probability of monetizing supply, *Table 6.3 Column 1*, due to the presence of gatekeepers (*Gatekeepers*), ceteris paribus, but now significant at a 5% level. This is in line with expectations. Nonetheless, because of the high insignificance of this coefficient in the previous estimation, there should remain some level of nuance with regard to the interpretation of the results for this hypothesis.

Unrelated to the hypothesis, the presence of gatekeepers has a notable relationship with the probability of monetizing demand *(Table 6.3 Column 3*). The presence of gatekeepers increases the probability of charging demand, ceteris paribus, at a 1% significance level. A qualitative analysis of the platforms that charge demand and operate in an industry with traditional gatekeepers provides insight that may explain this finding. Namely, these platforms are mostly media platforms. Contrary to what may be wrongfully interpreted from the results, these platforms have actually lowered the charges to users significantly e.g. Spotify offers unlimited listening for USD 9.99, which potentially brings down the average price per song or album extremely close to zero and definitely much lower than the prices traditionally set by record companies. However, this reduction is not captured by the analysis. The model only estimates the probability of charging demand with any charge being larger than zero. While in these cases the access by demand is charged, the charge is a substitution of what would otherwise be a (larger) charge per transaction. Another explanation does not lie in the limitation of the dataset, but in the benefit of not charging suppliers. A platform may indeed lower or even diminish costs to the supplier to attract a higher number of suppliers despite the presence of gatekeepers, and will thereby generate sufficient indirect network effects that demand can effectively be monetized.

Secondly, *Table 6.3 Column 1* shows a platform being operated by a MPO has an increased probability of monetizing supply, ceteris paribus, at a 5% level of significance. This result has remained consistent over both assumptions. Hence there is evidence to support the first part of hypothesis 4, stating that MPO’s are more likely to monetize suppliers.

Thirdly, we review hypothesis 5 stating that Asian platforms are less likely to charge suppliers and more likely to charge demand than their competitors in the rest of the world. The first MVP estimation, *Table 6.2*, was in line with these expectations but insignificant. The second MVP estimation with no pass-through assumption, *Table 6.3*, provides more support for this hypothesis. Specifically, being headquartered in Asia decreases the probability of monetizing suppliers, ceteris paribus, at a 5% significance level and increases the probability of monetizing demand, ceteris paribus, at a 10% significance level.

On overall, we find evidence for hypothesis 1, 4 and 5. These relate to respectively the inverted U-curve between the number of suppliers and the probability of charging suppliers, a difference in monetizing behavior between MPO's and SPO's, and regional differences in monetizing behavior between Asia and the rest of the world.

Additionally, hypothesis 2 is partly confirmed, while there is only little support for hypothesis 3. For hypothesis 2, we reject that a sufficiently high average price level would increase the probability of a platform to charge supply or demand for access to the platform, ceteris paribus. More specifically, we find evidence that this substitution from monetizing transactions to charging access of supply or demand, is more likely a substitution towards monetizing the presence of the community. In regards to hypothesis 3, the presence of gatekeepers in the industry only significantly decreases the probability to monetize suppliers, ceteris paribus, when assuming no pass-through of transaction fees. It can therefore be stated that the relationship holds for charging suppliers, but it does not hold for charging suppliers fees that are invariant to the number of transactions.

7. Robustness

The dataset, although able to provide various insights, is limited in its number of observations, restricting the degrees of freedom. Even though this issue has been partly addressed in specifying the multivariate probit estimation, an adaptation of the dataset can allow a higher number of observations by use of a MNL.

Taking into account that this thesis aims to identify market characteristics as determinants for a strategic choice, it can be argued that when multiple potential revenue sources are monetized, both revenue sources are valid monetization strategies. Moreover, there is no monetization strategy that is only valid when it is combined with another. Hence, disallowing any situation in which determinants allow for a strategy that is qualified in combination with another, but would not be valid on itself. Following this reasoning, the data may be transcribed to allow the multinomial logit regression. In cases in which e.g. both transactions and the presence of the community are monetized, the observation is duplicated with one observation of transactions being monetized, the other the presence of the community (*Figure 7.1*).

Figure 7.1: Transforming the dataset to allow a multinomial logit regression.

Platform	Transactions	Community
X	Yes	Yes

Platform	Monetizes
X	Community
X	Transactions

The transformation does not allow for interdependent relationships between the monetization choices and assumes mutual exclusivity i.e. any observation may only choose to monetize one source of revenue. For this reason, the multinomial logit estimation is far from perfect.

Table 7.1: Multinomial logit regression on expanded data.

VARIABLES	MNL Transactions	MNL Supply	MNL Community	MNL Demand
Ln #suppliers	0.61*	0.12		0.06
	(0.33)	(0.27)		(0.37)
Ln #suppliers sq	-0.03**	-0.01		-0.00
	(0.01)	(0.01)		(0.02)
Ln #demand	-0.11	-0.00		-0.16
	(0.10)	(0.10)		(0.16)
Pay	3.51***	0.67		0.21
	(1.18)	(1.13)		(1.81)
Pay x mean price	-0.64**	-0.09		-1.05*
	(0.32)	(0.32)		(0.56)
Gatekeepers	-0.35	-0.62		1.58**
	(0.49)	(0.48)		(0.79)
Frequency	-0.00	-0.00		-0.01**
	(0.00)	(0.00)		(0.00)
MPO	-1.28**	1.05		1.06
	(0.61)	(0.74)		(1.19)
Asia	-0.28	-0.69		0.49
	(0.44)	(0.44)		(0.67)
Constant	-0.33	-1.06		1.83
	(2.55)	(2.49)		(3.79)
Observations	206	206	206	206

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Withstanding these shortcomings, the results as shown in *Table 7.1* do not deviate in sign from the previous results. The coefficients only lose in level of significance. Yet, this is within expectations.

The duplication of observations diminishes the variation in determinants for the observed monetization choice. To tackle this issue; the same MNL model is re-estimated over a sample of platforms that did only monetize one of the four revenue sources (N=63). The distribution of this sample of platforms that have employed only a single monetization strategy is highly skewed towards platforms that monetize transactions (N=32). Still, the results only change in level of significance but not in sign. Hence, the results discussed in the previous section prove to be rather robust.

8. Limitations

Even though the results may prove robust, the analysis is not without limitations. Especially because of the exploratory nature of the study, the findings remain rather superficial. This section discusses the most notable limitations and their implications.

An obvious limitation within the observation of platforms is the bias towards noticing high tech platform businesses. Although this thesis was an attempt at collecting an exhaustive sample within the strict requirements set, it is high likely that this goal was not reached. Gawer and Evans (2016) distinguish three types of platform enterprises; the first being asset light enterprises with the dominant part of the business being operated within a platform ecosystem. The second is asset heavy enterprises with a hierarchal organization and ownership of physical assets (e.g. stores, manufacturing plants) and the third being a mix of the two. The platforms fitting the requirements, but not included in the sample, are expected to more likely be operated by asset heavy and, to a lesser extent, mixed enterprises i.e. incumbents with a platform complementary to their existing (more prominent) activities. Overall, these platforms simply gain less attention from media and academics than unicorns that have solely focused on the platform model. This may have a multitude of reasons e.g. incumbents may be less inclined to share information on their platform related ‘side’ activities. An example of such a platform is Moovel operated by Daimler AG, which is expected to fit the requirements set for the sample, but cannot be confirmed to do so by any source available at the time. Only two (relatively) asset heavy enterprises are included in the data: Sears and Walmart. Still, platforms by asset heavy enterprises are not expected to behave much different but to more actively monetize the presence of the community. Note that, even though Sears and Walmart opened up their digital platforms to other suppliers, creating a larger user-base through network effects, they benefit greatly through their own premium access to the whole user-base. Still, the findings of this study should not be applied to asset heavy enterprises without sufficient nuance.

Similarly to the lack of a certain type of enterprise, the lack of publicized data on educational and health care platforms has led to the complete exclusion of these industries in the empirical analysis. These two industries are quite unique due to their semi-public character. It is an extremely strong assumption, that should not be made, that strategic behavior of online marketplaces equates the strategic behavior of health care platforms. This poses quite a limitation on the study as health care and education, although hardly present in the sample, are considered high potential industries for the platform model. Moreover, the eco-system operated by the platform in such an industry is expectedly much more complex than a core interaction of only suppliers and consumers/users, with additionally complex strategic behavior. Future research on health care platforms might provide insights of high societal value.

Furthermore, there is some ambiguity in distinguishing transaction fees and charging access. Charging membership fees to the demand side by several media streaming platforms has substituted the need of direct interaction between supply and demand. Hence there exists high uncertainty on the specifics of the core interaction. Fortunately, these platforms are small in number and not likely to affect any conclusions drawn from this study. One way to address the ambiguity of transaction fees and charges to demand and/or supply has been the assumption of pass-through and the assumption of no pass-through. In reality, to what extent pass-through actually takes place may be a topic for future research on itself. Even in cases where platform regulation disallows a vendor to set a price higher than the price chosen by the vendor on other platforms, diminishing the ability to pass-through the transaction fee to the consumer by increasing the price, the vendor would still be able to fully pass-through the costs of the transaction fee if the vendor is only selling through a single platform.

Finally, the cross-sectional analysis fails to notice changes in strategy or market characteristics over time. The assumption of steady-state i.e. platforms in the sample have reached a form of maturity, remains reasonable. Yet, path dependency may have restricted evolution in monetization strategy. Platforms can be locked-in at sub-optimal pricing structures they previously employed to enjoy greater network effects. Such a case would definitely not be unique. Most platforms transition from optimizing network effects to optimizing monetization at some point of maturity. Panel data would provide more trustworthy results by enabling analysis of these changes in monetization strategy.

9. Conclusion

The Platform Economy and the platform business model have gathered large amounts of attention from academics, media outlets, businesses and policy makers. As platform companies have displaced the oil titans as the highest valued firms, it is not an understatement to call the phenomenon a ‘Platform Revolution’. A systematic identification of platform companies by Evans and Gawer (2016) has provided a basis from which a sample of digital multi-sided platforms could be derived. Their Global Enterprise Survey served as a foundation for this thesis.

Through extensive data collection, an unique dataset is formed, which allows a quantitative analysis of strategic behavior in monetization of DMPs. A multivariate probit analysis has provided several key insights. Withstanding possible biases from subjective interpretation of available data, results remain robust over various specifications and different assumptions.

We find an inverted-U curve relationship between the number of suppliers and the monetization of suppliers. When there is a relatively low number of suppliers on a platform, the platform can capture a greater surplus from suppliers when the competition on the platform increases. In these circumstances, the marginal supplier generates a surplus to all other suppliers through indirect network effects i.e. attracts buyers to the platform, that are larger than the negative direct network effect of increasing the competition between suppliers. At higher levels of competition, i.e. relatively high number of suppliers, the effect reverses and the supplier’s likelihood to be charged decreases while their number grows. As the number of suppliers grows, the surplus generated by the marginal supplier decreases and eventually becomes negative once the positive indirect network effects fall below the level of negative direct network effects.

Furthermore, the potential of a platform to monetize transactions is partly determined by their ability to capture the transfer of payments. One determinant is the presence of pecuniary value in the core interaction. Another is that the average value does not exceed the level at which consumers would rather complete the transaction off-platform i.e. in person. When transactions are of no or high pecuniary value, the ability to capture transactions on-platform is diminished.

Hence, platforms move towards monetizing the overall presence of the community by offering goods and services relevant to the needs of the user-base or allowing third parties to offer such goods and services.

Moreover, we find several differences in monetization behavior in regards to firm and regional characteristics. Firstly, platforms operated by firms with a portfolio consisting of multiple platforms are more likely to monetize the supply side of the platform. This can be explained due to their enhanced capability of offering price discriminating membership programs that better fit the individual supplier’s needs or the added value of providing a one-stop shop of integrated platforms. Secondly, Asian platforms operate in a more competitive market, especially in China. This results in Asian platforms being less likely to monetize their suppliers in comparison to their counterparts in the rest of the world. On the contrary, the Asian platform is more likely to charge users on the demand side.

Another difference in monetization behavior is observed from firms operating in an industry that is traditionally dominated by gatekeepers / intermediaries. These digital multi-sided platforms seem to eliminate their charges to suppliers in order to outcompete their traditional competitors. However, the evidence to support this particular relationship is fairly weak.

The implications of this thesis are threefold. Firstly, the valuation of platforms may increase in accuracy because of a better understanding of their future potential to generate revenue in accordance to measurable determinants. In the introduction, we posed the question ‘what could determine that Google’s Youtube does not charge content creators, while Google Play Music does?’. Such monetization behavior may be explained by our findings. Specifically, the content creators, or suppliers, are much greater in number at the highly open platform Youtube, which generates a highly competitive environment not suitable for charging the access of suppliers. The surplus of indirect network effects from the marginal user is extremely small and difficult to appropriate. Additionally, the core interaction of Youtube, in contrast to Google Play Music, does not involve a pecuniary transfer between users and content creators. Instead of money, the user provides attention to the content creator. This diminishes Youtube’s ability to monetize transactions. Consequently, Youtube has monetized the presence of the community, namely through selling advertisements. This too, is perfectly in line with the monetization behavior expected from the analysis.

Secondly, platforms are found to suffer, at least to a certain extent, from path dependency. The main choices involved in designing the platform, namely the core interaction and positioning on the open-to-closed spectrum, have great influence on the monetization strategy it may employ in the future. Still, platforms in their early stages should remain focused on gaining sufficient network effects before shifting their focus towards monetization. However, changing these characteristics later on means friction with, or even the forfeiting of these gained network effects. In practice, when the core interaction does not allow for optimal revenue generation, platforms often have to design a completely new interaction that does allow for revenue generation. This emphasizes that platform managers and eco-system architects should consider future monetization from the very start of designing the platform.

Thirdly and above all, the Platform Economy should be considered to be a separate industry in its own right. Platforms are matchmakers. Their function or strategic behavior differs little or not at all over industries, at least when it comes to monetization. This insight results not only from the quantitative analysis, but the extensive research in creation of the dataset as well. Platform companies easily diversify to completely different industries not because of their capabilities or skills in the new industry, but because of their capabilities and skills in regard to creating digital multi-sided platforms. For incumbents this implicates that platform companies may be disruptors, but not necessarily competitors. Similar to how logit has embedded itself in the value chain of other industries, the platform simulates an identical role: a complementary industry that connects and empowers the network.

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11. Appendix

Table 11.1: Industry averages of revenue sources and number of observations.

Industry	Average employment of monetization..				N
	..transactions	**..supply**	**..community**	**..demand**	
Adtech	100,0%	66,7%	16,7%	0,0%	6
Booking	75,0%	75,0%	25,0%	0,0%	4
eCommerce/ Marketplace	84,0%	60,0%	52,0%	2,0%	53
Education	0,0%	0,0%	100,0%	100,0%	1
Fintech -banking	87,5%	12,5%	75,0%	12,5%	8
Fintech -pay	90,9%	36,4%	27,3%	0,0%	11
Food	100,0%	42,9%	0,0%	0,0%	7
Healthcare	-	-	-	-	5
Internet Software & Manufacturing	87,5%	62,5%	0,0%	25,0%	8
Internet Software & Services	25,0%	62,5%	75,0%	37,5%	8
Media	33,3%	33,3%	70,8%	50,0%	24
Office community	62,5%	62,5%	12,5%	37,5%	8
Real Estate	42,9%	71,4%	85,7%	14,3%	7
Search	0,0%	100,0%	100,0%	0,0%	6
Social	7,1%	50,0%	64,3%	25,0%	28
Transportation	100,0%	0,0%	25,0%	0,0%	8
Travel	100,0%	30,0%	50,0%	0,0%	10
Average / Total	61,9%	49,5%	51,0%	16,0%	202

Table 11.2: Database source list.

Company profiles / analyses, case studies & statistics by third parties		
Bloomberg	Financial Times	Recode
Business Insider	Forbes	Sramanamitra
CapitalIQ	Investopedia	Statista
Crunchbase	Marketplacepulse	Techcrunch
Deal.co	Motley Fool	Unicornomy
Expandedramblings	Onlinepaymentsystems.info	
Press releases, blogs & publications by first parties		
9fbank	IWJW	Shanghai Han Tao
Adyen	Jawbone	Shanghai Zhong Yan Information Technology
Agoda	JD.com	Sina
Airbnb	Jia	Slack Technologies
Alibaba	Jiuxian	Snapchat
Amazon	JUST EAT	Snapdeal
Apple	Klarna	Sony Entertainment Network
ASOS	Koudai Gouwu	SouFun
Atlassian	Kuaidi Dache	Spotify
Automattic	lamabang	Square
Avito.ru	Lazada	Steam
B2W digital	Leshi	Stripe
Babytree	Letgo	SurveyMonkey
Baidu	LinkedIN	Suzhou Tongcheng Travel
BeiBei	Live Nation	TangoMe
Beijing Downjoy Information Tech Co.	Loji	Tencent
Beijing Feixiangren	Lufax	Thumbtack
Bitauto	Lyft	To8to
BlaBlaCar	MakeMyTrip	TransferWise
Booking.com	Match Group	Trip Advisor
BuzzFeed	Meilishuo	TrueCar
Cheyipai.com	Meituan Dianping	Tujia
CNOVA	Mercadolibre	Tuniu
Cornerstone OnDemand	Microsoft	Twilio
Craigslist	Mogujie	Twitter
Credit Karma	Momo	Uber
Crfchina	Moxian China	UberEats
Criteo	MuleSoft	Udacity
CTrip	NantHealth	Uplay
Delivery Hero	NAVER	VANCL
DocuSign	NETFLIX	Vice Media

eBay	Newcapec Electronics	Vipshop
Edaijia	Newegg	VKontakte
Elance-oDesk	Nextdoor	Walmart
Ele	Olacabs	Wandoujia
Etsy	One97 Communications	We Doctor Group
Eventbrite	OpenTable	Wish
Everyday Network	Pandora Media	YAHOO! Japan
Expedia	PayPal	YAHOO!
Facebook	PaySafe	Yandex
Farfetch	Pea pod	Yello Mobile
Flipkart	People.cn	YELP
Focus Technology	Pinterest	ymatou.com
Funding Circle	PPdai	Youku Tudou
Global Fashion Group	Privia Health	Youxin Hulian
Google	Prosper Marketplace	YY Inc.
GrabTaxi	Proteus Digital Health	Zalando
		Zhejiang Panshi Information &
Gree	Visa	Technology Co.,
Groupon	Quikr	Zhubajie Network
Hootsuite	Qunar	Zillow
Houzz	Rakuten	Zomato Media
IAC Interactive	Renrendai	Zoopla
InMobi	RightMove	
Instacart	Schibsted Classified Media	
IronSource	Sears	