SHARING ALONE?
THE INFLUENCE OF NEIGHBOURHOOD COHESION ON WILLINGNESS TO SHARE

A STUDY OF AIRBNB AND SNAPPCAR

MSc Thesis by

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Abstract

The aim of this study is to establish to what extent willingness to share is dependent on neighbourhood cohesion. On platforms that operate on a local level, neighbourhood cohesion is expected to increase willingness to share because neighbourhood cohesion has shown to increase trust, which is an important precedent of sharing. Because of the social norms that arise alongside neighbourhood cohesion, bringing people from outside the neighbourhood into the neighbourhood could be perceived as non-desirable. Consequently, neighbourhood cohesion is expected to decrease willingness to share on globally operating platforms. Data are gathered on shared houses and cars, in order to explain supply on a locally operating platform – Snappcar – and on a globally operating platform, namely Airbnb. All data were collected in the city of Amsterdam, The Netherlands, in 94 Amsterdam neighbourhoods. Because the dependent variables are count variables, a negative binomial regression was used.

The results suggest that there is no relationship between neighbourhood cohesion and supply on Airbnb or Snappcar. While it could still be that trust arises from neighbourhood cohesion, it might not be the type of trust that is a result of neighbourhood cohesion that facilitates sharing.

Keywords: sharing economy, willingness to share, Airbnb, Snappcar, neighbourhood cohesion

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1. Introduction

Whether it is because of the recent financial crisis, growing technological possibilities, the partial 'dismantling' of the Dutch welfare state, or a growing interest in sustainability; sharing is on the rise in The Netherlands. More and more people are temporarily lending out goods, such as cars, tools, or even their spare bedroom. A recent publication estimates 940 000 Dutch citizens have participated in the sharing economy in 2015, as opposed to 570 000 in 2014 (ING, 2015).

Bourdieu (1984) stated that car ownership is not merely a consumption act, but also a way to express identity, class and status. In line with this, Russell Belk (1988) stated that "you are what you own", referring to the phenomenon that people tend to derive their identify from items in their possession. However, in 2014, the same Belk published an article titled "you are what you can access". He stated that with the rise of the internet people had gained other channels for self-expression and that therewith the desire to express oneself through ownership, had declined. Instead, people started sharing items with each other (Belk, 2014; Lamberton & Rose, 2012; John, 2013), a phenomenon which is now known as the sharing economy.

What is the sharing economy? Following Frenken et al. (2015), we parse the sharing economy into three elements, namely that it concerns *1)* **consumer-to-consumer interactions**, who provide each other *2)* **temporary access** to a *3)* **physical good**. Next to this, we can distinguish for-profit versus non-profit platforms (Schor, 2014). In this paper, only for-profit platforms will be discussed, namely Snappcar and Airbnb. More specifically, we focus on the **suppliers** on these platforms, which we will refer to as **sharing supply**.

Compared to traditional forms of sharing - such as sharing among friends - the newness of many sharing economy practices lies in the fact that they concern interactions between strangers that are mediated by technology (Guttentag, 2013; Hamari et al., 2015). Individuals that might otherwise never have met, can now contact each other via technological platforms in order to share resources. In most cases, this means actors perform transactions without having had any previous personal interaction.

Secondly, when we compare sharing economy practices to technologically mediated 'second-hand economy' practices such as on Amazon, Craigslist or the Dutch 'Marktplaats', it's newness lies in the fact that the transfer of goods is not permanent but temporary. On these second-hand platforms, risk lies mainly with the buyer, who does a monetary transaction without even knowing if he will receive the product at all (Van Wilsem, 2011). In sharing practices, the supplier is mostly the one who bears most risk, because the good he transfers is temporary; meaning the supplier expects the other to return the good undamaged so they can use it again.

Consumers participating, thus, have to build trust in a stranger - via a technological medium - to take proper care of their items and return them safely. This issue re-occurs every time the supplier plans on a transaction. Throughout this study we will solely reason from the perspective of the supplier rather than the renter and thus only measure supply on sharing platforms.

While digital reputation systems can offer an actor a foundation for trust, these systems have often been said to overrate positive features and under-report bad experiences (Schor, 2014; Slee, 2013). Although some say these reputation systems are not working adequately (Freitag & Traunmüller, 2009), the number of people that makes use of digital sharing platforms is growing (ING, 2015). Some researchers suggest trust is a phenomenon too complex to be understood merely through review systems and that other sources of trust might be at hand (Pick, 2012). To consider other mechanisms through which one might trust a stranger, we turn to Putnam's theory on social capital. Putnam defines social capital as 'connections among individuals - social networks and the norms of reciprocity and trustworthiness that arise from them' (Putnam, 2000, p.19). Weak ties - such as neighbours - have shown to be an important resource for individuals, leading to 'thin trust', or, 'trust placed in the anonymous other' (Li et al., 2005). A specific type of weak ties, namely neighbourhood attachment, has been found to be an important determinant of social trust, more important than other forms of social capital (Li et al., 2005). Neighbourhood attachment thus increases trust, which has often been cited as an important precedent of sharing behaviour (Botsman & Rogers, 2010). Building on these results, we study this relationship between neighbourhood cohesion and the willingness to share on sharing economy platforms. We expect higher levels of social cohesion to increase the chance of sharing on local platforms (Snappcar) but not to increase the chance of sharing on platforms that operate on a global level (Airbnb).

Sharing economy initiatives have been referred to in the same breath as so-called 'deglobalizing initiatives', such as localized food initiatives (Starr, 2010). Many sharing economy platforms emphasize the local aspect (Botsman & Rogers, 2010), explicitly trying to appeal to a sense of neighbourhood community (Peerby.nl, Snappcar.nl). For these 'local' platforms, we would expect the argument of neighbourhood attachment increasing trust to uphold, and expect higher neighbourhood cohesion to result in higher levels of willingness to share on a 'local' platform.

Other initiatives do not operate on a local level; sharing 'giant' Airbnb mediates between people all over the world, thereby operating on a global level. Nevertheless, the houses on Airbnb are, of course, embedded in a neighbourhood. Local residents who live near Airbnb accommodations have been found to complain about noise issues, security concerns (Leland, 2012) and have reported to be worried about increasing rents because of the short-term rentals (Said, 2012). If renting out an apartment on Airbnb is perceived as 'bad behaviour', it might be the norm to not undertake such activities for as cohesion increases, so does the extent to which people adhere to certain norms (Knack & Keefer, 1997). In this case, neighbourhood cohesion might decrease willingness to share. As such, the following research question is posed: *to what extent does neighbourhood cohesion affect sharing supply on local and global platforms?*

Previous research on the relationship between trust and sharing behaviour was mostly focused on review systems (Slee, 2013; Nunes & Correia, 2013), therewith not taking other possible sources of trust - such as cohesion - into account. It would be useful to further substantiate this debate with empirical research and thereby contribute to the growing body of literature on explaining sharing behaviour. In addition, we do not study one platform but compare two - a local and a global platform - thereby gaining insight on the 'geography of sharing'.

Other researchers have already studied the relationship between neighbourhood attachment and willingness to participate in sharing economy initiatives (Meelen et al., 2016). This paper is unique in the sense that it uses measures of actual sharing supply instead of a hypothetical statement of being 'willing to share'. This is of importance, since there is often a gap between what people say they might or will do and that which they actually do (Carrington et al., 2010).

We make use of data from 94 neighbourhoods in the city of Amsterdam, The Netherlands, to explain supply on a globally operating platform - Airbnb - and a locally operating platform, namely Snappcar.

2. Theoretical Framework

2.1 The sharing economy: what's new?

In the traditional economy transactions are mostly of a business-to-consumer nature. Businesses tried to strengthen their brand name through marketing strategies in order to increase institutional trust. For consumers, this offered a line of approach in what to trust and what to buy, and consumers felt safe believing this. But nowadays we can observe another - decentralized - source of trust, namely in the form of social media and peer experiences (Botsman, 2015). A phenomenon that has been facilitated by the growth of 'web 2.0' and information technologies, by which we are users encouraged to share their content with other users (Hamari et al., 2015; John, 2013). These technology mediated networks have enabled users to share photos, files, stories, and now also products and services (John, 2013; Kim et al., 2005).

Building peer-to-peer trust seems especially important in these consumer-to-consumer interactions and has been cited as a key determinant of sharing behaviour (Botsman & Rogers, 2010). In this context, this means that when someone trusts another individual, he or she expects the other to refrain from abuse of overuse of the shared item (Lamberton & Rose, 2012; Kim et al., 2005).

Sharing economy platforms try to facilitate trust through all sorts of mechanisms, the most common being the formalized review systems, by which users can share their experience with another user (Guttentag, 2013). While these systems may facilitate trust and have been found to be a major influence on hosts' decisions accepting guests (Liu, 2012), they have also been said to overrate positive features and under-report bad experiences (Schor, 2014; Slee, 2013). Although some say these reputation systems are not working adequately (Freitag & Traunmüller, 2009), the number of people that makes use of digital sharing platforms is still growing (ING, 2015). Recently, platforms have begun to collaborate with insurance companies, offering users various forms of insurance (Snappcar.com; Airbnb.com) in order to overcome the barrier of trusting a stranger. But since trust is not only a result of personal or shared experiences with the specific peer, but also of prior personal experiences with other peers (Abdul-Rahman & Hailes, 2000), it might be another source of trust is at hand. In this paper we will not discuss trust generated through review systems or insurance, but only trust as a result of prior personal experiences with other peers.

2.2 Cohesion as a source of trust

The idea that social connections between individuals can be a source of trust and social norms has been around for a long time. Within this literature of social cohesion - and social capital - the conceptualization of social capital has shown some variation. Where Bourdieu (1984) conceptualized social capital as a pool to draw resources from, Durkheim explains cohesion as 'mechanical and organic solidarity' (Carpiano, 2006). Putnam's definition is not entirely consistent throughout his work, but in his later work he describes social capital as ‘connections among individuals - social networks and the norms of reciprocity and trustworthiness that arise from them’ (Putnam, 2000, p.19). In spite of this variety, common ground can be found in the fact that cohesion always comes down to patterns of social interaction (for example between neighbourhood residents) and the associated values that arise from them (such as trust and norms of reciprocity) (Carpiano, 2006). In this paper, we will focus on what Putnam calls ‘external returns’ of cohesion, which are feelings of trust and norms of reciprocity (Putnam, 2001).

When studying cohesion in social networks, we then have to distinguish between weak and strong network ties. Strong ties consist of an individual's’ intimate relationships, which are often built up over a long history of interaction and facilitate ‘thick trust’. Thick trust manifests for example in the form of asking for advice on personal problems, keeping each other’s secrets or lending money (Leonard & Onyx, 2003). Weak ties on the other hand could be described as ‘acquaintances’ rather than intimate relationships. These acquaintances - such as neighbours - have also shown to be an important resource for individuals, leading to ‘thin trust’, or, ‘trust placed in the anonymous other’ (Granovetter, 1973; Li et al., 2005). The latter type of trust is an important precedent for transactions on sharing economy platforms, since these are mostly transactions that are to be performed with strangers.

Li and his colleagues (2005) studied the relationship between trust and a certain type of weak ties, namely neighbourhood attachment. They proposed to parse Putnam’s definition of social capital into three elements: formal civic engagement, informal personal networks and informal situational networks (i.e. neighbourhood attachment). Their research shows that neighbourhood attachment is the most important determinant of social trust. According to Putnam (2000), people in cohesive neighbourhoods learn to trust each other because they work together and make compromises for a common goal. The social support people then find in each other not only increases their trust in each other, but also reflects on their trust in others. Neighbourhood attachment thus increases trust, specifically ‘trust in the anonymous other’; an important precedent of sharing behaviour (Botsman & Rogers, 2010).

The concept of neighbourhood attachment is closely related to the concept of neighbourhood cohesion, as it is often considered part of cohesion. Neighbourhood cohesion can be said to consist of three elements, namely 1) neighbourhood attraction (or ‘attachment’), 2) neighbouring (e.g. visiting neighbours) and 3) psychological sense of community (Buckner, 1988).

2.3 Local versus global

The concept of a neighbourhood is especially relevant for many sharing economy initiatives, since often these platforms emphasize the local aspect (Botsman & Rogers, 2010), explicitly trying to provoke a sense of neighbourhood community (Peerby.nl, Snappcar.nl). The locality of the items is a key value of these platforms, for the nearness of these items increases user convenience. Such sharing economy initiatives have been referred to in the same breath as other so-called ‘deglobalizing initiatives’, such as local food initiatives (Starr, 2010). For these 'local' platforms, we would expect the argument of neighbourhood attachment increasing trust to uphold.

H1a: In neighbourhoods where cohesion is higher,
sharing supply on 'local' platforms is expected to increase.

Other initiatives do not operate on a local level at all. Sharing 'giant' Airbnb mediates between people all over the world, therewith operating on a global level. Nevertheless, the houses on Airbnb are embedded in a neighbourhood. Research has shown that Airbnb guests are inclined to spend less time in tourist areas than regular hotel guests and – instead - more in the area around their accommodation (Guttentag, 2013). Local residents who live near Airbnb accommodations have been found to complain about noise issues, security concerns and other conflicts concerning the accommodation (Leland, 2012; Said, 2012). Also, residents have reported to be worried about an increase of rents in the neighbourhood because of short-term rentals (Said, 2012). Thus in the case of Airbnb, the embeddedness of a potential 'sharer' in a neighbourhood, might put up an obstacle. As discussed earlier, higher levels of neighbourhood cohesion are associated with stricter 'norms' of how to behave and more pressure to adhere to these norms (the 'norms of reciprocity'). If renting out an apartment on Airbnb is perceived in a neighbourhood as 'bad behaviour', inhabitants might adapt their individual behaviour to these neighbourhood norms. Thus, although we expect neighbourhood cohesion in general to increase willingness to share because it produces higher levels of trust, in this case neighbourhood cohesion might decrease willingness to share because as cohesion increases, so does the extent to which people adhere to certain norms. The internal (e.g. guilt) and external (e.g. shame) sanctions associated with norms make it more likely for people to adhere to these norms and therewith contribute to the public good (Knack & Keefer, 1997).

H1b: In neighbourhoods where cohesion is higher,
sharing supply on 'global' platforms is expected to decrease.

It is this contrast of 'local' and 'global' platforms that is central in this research. Two underlying mechanisms can be identified, namely those of trust and norms of reciprocity. By studying one locally and one globally operating platform, we are able to assess whether the 'local community' – something that is often connected with the sharing economy (Botsman & Rogers, 2010; Agyeman, et al., 2013) – is indeed a precedent of local sharing, and that 'global' sharing is not.

Contrary to both hypotheses, one might also argue that neighbourhoods with high levels of social cohesion do not have a need for technologically mediated sharing platforms since sharing is already facilitated through higher levels of interpersonal contact, therewith resulting in less activity on sharing platforms. If this is the case, we can still observe less participation on Airbnb than on Snappcar in highly cohesive neighbourhoods, since house or room sharing is not facilitated by neighbourhood relationships, for people do not rent accommodations in their own neighbourhood.

2.4 Other explanations

Quite an amount of attention has been given to the reasons that motivate people to join sharing economy initiatives. This section discusses factors - besides neighbourhood cohesion - that could affect willingness to share on both platforms.

Share of privately owned houses

Renting out a house or apartment in Amsterdam is only permitted if one is the owner of the house. If the house is a rental, opportunities to sublet the house via for example Airbnb are very limited, especially for social rental accommodations. In most cases it is not permitted to sublet accommodation if the house if a rental of any kind, unless the owner and the tenant specifically agree this is allowed (amsterdam.nl).

H2: In neighbourhoods where the share of privately owned houses is larger,
Airbnb supply is expected to increase.

Total number of registered cars

The number of shared cars might well be dependent on the number of cars that is available for sharing. On the other hand, if there are many cars in a neighbourhood, it could be that everyone is already supplied with a car and subsequently there is no need for Snappcar cars. Consequently, supply might also be lower. A study by Meelen and his colleagues (2016) found that as the number of people that is in possession of a car increases, willingness to provide a shared car also increases. Building on these results, we formulate the following hypothesis:

H3: In neighbourhoods where the number of registered cars is higher,
Snappcar supply is expected to increase.

Distance to the city center

Several researchers have hypothesized that carsharing is more widespread in diverse areas that are close to transit facilities (Meelen, et al., 2016; Cervero & Kockelman, 1997; Coll et al., 2014). Empirical evidence, though, it not unambiguous. In the case of Airbnb, closeness to (tourist) facilities might make a location more attractive for tourists. Subsequently, sharing an apartment might be more attractive because either demand is higher or because one can heighten the asking price.

H4a: When the distance between a neighbourhood and Dam Square is smaller,
Airbnb supply is expected to increase.

As for Snappcar, we can expect the opposite effect. Citizens of Amsterdam have been known to experience difficulty parking their cars. Despite efforts by the municipality this problem has only been growing, especially in the city centre. The parking facilities in the city centre are under extra pressure since visitors also park their cars here, because of closeness to tourist, shopping and other recreational facilities. A 2012 survey indicates that almost 36% of Amsterdam citizens in the city centre often do not use their car because they fear there will not be a parking space available when they return. 20% of inhabitants of the 'old city' centre reported they had at some point in life even considered moving because of the parking issues in their residential area (Parkeerplan Amsterdam, 2012). When your car is borrowed and upon returning cannot be parked in the vicinity of your house, this is not very convenient. We hypothesize that inhabitants of neighbourhoods with parking problems are less inclined to borrow someone else's car, because of this reason.

Figure 1. Classification of Amsterdam areas: severity of parking problems. *Source*: Parkeerplan Amsterdam (2012).

H4b: When the distance between a neighbourhood and Dam Square is larger, Snappcar supply is expected to increase.

Progressive and 'green' electorate

Following Hansen and Coenen (2014), there can be place-specific norms and values that influence the landscape of sustainability transitions. A large share of 'green' people in an area can facilitate 'green' practices, cultures and institutions, which otherwise could have been considered strange (Longhurst, 2015). A recent study by Meelen et al. (2016) showed that environmentally conscious people are more inclined to participate in sharing practices, both as a user and a provider. Others suggest that the initial intrinsic motivations (e.g.: positive feelings towards sustainability) have been replaced by extrinsic (e.g.: economic) motivations (Hamari et al., 2015). There is, however, no clear empirical evidence for this claim.

In addition, younger people nowadays are said to show less interest in car ownership as being important to self-definition and to view car-ownership as more of a 'hassle' (Belk, 2014). It is the same – young – group of consumers that show a tendency to adopt new and digital innovations more rapidly, because they are more comfortable with digital platforms and at the same time more socially forward (Blackburn, 2011). Younger, often highly educated people are often categorized as ‘early adopters’ of innovations (Rogers, 2003). They are considered ‘digital natives’ and therefore are more inclined to participate on digitally mediated platforms (Blackburn, 2011), such as Airbnb and Snappcar. A recent survey in The Netherlands showed that while some people view new technologies as scary or even a threat, others consider them an opportunity. Specifically, voters for the Dutch political parties D66 and GroenLinks would consider technologies an opportunity (De Hond, 2016). People that vote for D66 or GroenLinks are relatively young, highly educated show a tendency towards ‘progressive’ and green values (Nationaal Kiezersonderzoek, 2012). We will categorize this group as potential ‘early adopters’ of digital sharing platforms. Hence:

H5: In neighbourhoods with a larger share of GroenLinks-D66 voters,
sharing supply is expected to increase.

Percentage of one-person households

Previous research has shown a positive correlation between the number of one-person households and the number of shared cars (Celsor & Millard-Ball, 2007), which could be explained by the fact that households with children are in need of cars with special features, such as children seats (Meelen et al., 2016). As for Airbnb, a study by Meelen et al. (2016) showed that the percentage of one-person households in a neighbourhood has a positive effect on the provision of shared accommodations (and not on the *use* of shared accommodations). Building on these results, we formulate the following hypothesis:

H6: In neighbourhoods with a higher percentage of one-person households,
sharing supply is expected to increase.

Income

Findings on the effect of income on carsharing are not unambiguous. Some research has shown high income to have a negative effect on participation in carsharing (Zhou & Kockelman, 2011; Coll et al., 2014), while a different research showed a positive effect of high income on carsharing (Burkhardt & Millard-Ball, 2006; Meelen et al., 2016). Opposing logics could be at work here. On the one hand, sharing might be more attractive to people with lower incomes, because this way they have access to goods or services they otherwise would not have been able to afford (Litman, 2000). Furthermore, they might be more inclined to supply goods because it can be a source of extra income (Fraiberger & Sundararajan, 2015). On the other hand, people with a higher income might have more items to share and can bear more financial risk (in case a good is damaged). Next to this, people with higher income have been known to experiment more with new practices (Rogers, 2010), such as sharing platforms. The ING Economic Bureau (2015) found that people with a high income are more inclined to share items in general. A recent study by Meelen et al. (2016), however, found that people with higher incomes are less inclined to provide a shared car.

3. Data and method

3.1 Research context

The data on cohesion were collected by the municipality of Amsterdam in all 94 neighbourhoods as defined by the municipality, and thereby generalizable to the population of Amsterdam. We cannot directly generalize the results to other cities, for Amsterdam is visited by a relatively large amount of tourists (ois.amsterdam.nl) and Airbnb regulations differ among countries and cities (Coldwell, 2014) as do rules concerning the use of passenger cars in city centres. Because of its high population density and well-developed digital infrastructure, Amsterdam has proven to be an attractive environment for sharing platforms. The city council has declared the ambition to become a ‘sharing city’ and actively promotes sharing, which makes the city an interesting research opportunity (sharenl.nl). For the purpose of this study, data on sharing behaviour in Amsterdam and the control variables were collected from various sources. These data were thereafter assigned to the 94 neighbourhoods as defined by the municipality. Thus, the units of analysis under study are neighbourhoods in the city of Amsterdam.

3.2 Data and measurement

3.2.1 Cohesion

The independent variable in both the Airbnb and the Snappcar model is neighbourhood cohesion, on which data were collected as a part of ‘Safety Monitor’ (Veiligheidsmonitor) 2014-2015 survey that is conducted by the municipality of Amsterdam every twelve months. The basis for this questionnaire is the national Safety Monitor as conducted by Statistics Netherlands (CBS), to which the municipality of Amsterdam adds some city specific questions for their own use. The resulting Safety Monitor dataset that was used contains data collected between September 2014 and August 2015. The initial survey was offered to 54000 people and the response rate was approximately 30%, resulting in a sample of 16248 people (Verantwoording Veiligheidsindex 2014, OIS Gemeente Amsterdam). In this research, 3180 observations were excluded because we only included respondents living in the city of Amsterdam. Our final sample contains 13068 observations.

Neighbourhood cohesion was measured through 6 items on a 5-point Likert scale. The items are the following;

- 1 ‘People in the neighbourhood hardly know each other’
- 2 ‘People in the neighbourhood interact with each other in a pleasant way’
- 3 ‘I live in a sociable neighbourhood where people help each other and undertake activities together’
- 4 ‘I feel at home with the people in my neighbourhood’
- 5 ‘I have regular contact with people in my neighbourhood’
- 6 ‘I am satisfied with the population composition in my neighbourhood’

A low score (lowest: 1) implies the respondent agrees and a high score (highest: 5) implies a respondent disagrees. As a result, a low score implies a high rate of cohesion. The scores were reversed in order to make interpretation more intuitive.

These items represent different aspects of cohesion, namely both behavioural aspects (e.g. 'People in the neighbourhood hardly know each other') as well as attitudinal aspects (e.g. 'I live in a sociable neighbourhood … '). As stated by Buckner (1988), neighbourhood cohesion can be said to consist 1) attraction-to-neighbourhood, 2) neighbouring and 3) sense of community (Buckner, 1988). Li and his colleagues (2005) found items representing these three aspects to form one scale together, including both attitudinal and behavioural aspects. We believe the six items used in this research can be said to correspond fairly well with these three elements. A factor analysis of the items as they were collected in Amsterdam, showed that item 2, 3, 4 and 5 can be said to measure the same construct, while item 1 and 6 do not. Items 2-5 showed a factor loading of 0.87, 0.90, 0.911 and 0.79 respectively. For the purpose of this research, these four items will together form one scale, hereafter called 'neighbourhood cohesion'.

When discussing social networks, one ideally makes use of a population rather than a sample, mapping all networks ties in order to assess the strength of the ties. Unfortunately such data are not available to us. However, since all items focus clearly on neighbours, they refer to what is called a 'situational network', which is a typical example of a network consisting of 'weak ties' from which people can receive support in their daily activities. The opposite would be a network of strong ties, from which individuals can derive (deep) emotional support (Li et al., 2005).

For the purpose of this research it is important to stress the difference between individual perceptions or feelings of cohesion and neighbourhood cohesion. These perceptions and feelings are measured on the individual level, but thereafter aggregated to the neighbourhood level. The mean neighbourhood score resulting from this will form the measure of cohesion of residents of that neighbourhood. To make statements about group level behaviour based on individual attributes, could be an example of an 'exception fallacy' (Balram & Dragicevic, 2005). Since the Safety Monitor offers us 13068 completed surveys in 2014-2015, we believe there are sufficient observations in every neighbourhood aggregate the data to the level of neighbourhood (minimum: 10).

3.2.2 Airbnb and Snappcar

The dependent variables are the number of shared Snappcar cars and Airbnb houses per neighbourhood, for which two separate models will be applied. Since these listings provide information about supply and not about use, one registered car or house represents one individual who is willing to share.

The registered Airbnb houses were collected via the website 'Inside Airbnb' (Cox, 2016). The data file on this website contains all Airbnb houses that were listed in Amsterdam as available for 1 day of more between the 3rd of January 2016 and the 3rd of January 2017, which were 10970 houses in total after excluding houses that were not located in the city of Amsterdam. These (scraped) data are available under Creative Commons (Public Domain Dedication) and are anonymized. Anonymized - in this case - means that no first or last names are included and that the location is anonymized. In practice, this means the location of a listing will be within 150 meters from the actual address. Listings in the same apartment building will appear scattered around the building. Furthermore, it has to be noted the availability is a 'snapshot' at one point in time and that no distinction could be made between 'not available' and 'booked'. Therefore, if a house/room were fully booked, it would not appear in the list. Each house ID is accompanied by X Y coordinates as well as various other particulars such as price and year-round availability. Through the use of ArcMap, the X Y coordinates were assigned to an Amsterdam neighbourhood. The resulting data file contained a count of Airbnb houses per neighbourhood.

The Snappcar listings were manually scraped from the Snappcar website (www.snappcar.nl). The Snappcars used in this research are all cars that were listed in Amsterdam on the Snappcar website on the 2nd of February 2016, which were 534 cars in total. Each car that is shared on the Snappcar website contains the brand of the car, the name of the street in which it is located and the price at which one can rent the car. The street name that indicated each car's location was used to assign all 534 cars to a neighbourhood through the use of a street name book provided by the municipality of Amsterdam. In some of these cases, a street would fall in more than one neighbourhood. A car was then split up in two (or three) and assigned to several neighbourhoods, resulting in non-integer neighbourhood car counts such as 1.333 or 1.5.

3.2.3 Other variables

The socio-demographic and spatial factors that are also included in the models are partly collected by the municipality of Amsterdam, partly obtained from Statistics Netherlands (CBS) and through Google Maps. These variables are the following;

Airbnb	**Snappcar**
Number of houses privately owned	Number of registered cars
Distance to Dam Square	Distance to Dam Square
GroenLinks-D66 voters	GroenLinks-D66 voters
Household income	Household income
One-person households	One-person households

Airbnb: Privately owned houses

Privately owned, means that a house is in possession of the inhabitant and not rented. By using this variable, rented house in the private sector as well as social housing are excluded, because in both cases it is not allowed to sublet an apartment through Airbnb (unless this is explicitly agreed on by tenant and landlord) (www.amsterdam.nl). The number of privately owned houses is measured as a raw count on the neighbourhood level. Data are provided by the research department of the municipality of Amsterdam (OIS) and stem from 2015.

Snappcar: Total number of cars

The number of cars that is shared might well be dependent on the number of cars that is available for sharing. For this reason, the total number of registered cars per neighbourhood was obtained from CBS Statline (Kerncijfers Wijken en Buurten, 2015) and included in the Snappcar model. Though the CBS neighbourhoods follow a different coding system than the Amsterdam neighbourhoods, the actual neighbourhoods are the same. CBS and Amsterdam neighbourhoods were merged using Stata 14 with the use of a document provided by the municipality, in which CBS and Amsterdam neighbourhood codes were coupled.

Airbnb and Snappcar: Distance to the city centre

The city of Amsterdam has quite an apparent city centre - in terms of tourism as well as centrality – namely Dam Square. Dam Square is near the Central Station, the canals, as well as various museums and other tourist attractions. Accommodations that are close to Dam Square might be more attractive to tourists because of their closeness to these tourist attractions. The coordinates of Dam Square were obtained via Google Maps and thereafter the distance between each neighbourhood and Dam Square was calculated with ArcMap (a component of Esri ArcGIS). To compute this distance, the centroid of each neighbourhood shape was used. The distance between the centroid and Dam Square was thereafter calculated through Spatialite, a database management program with which one can edit spatially enabled SQLite databases. The resulting distance was then multiplied by 1.4. This multiplication is a theory by Hermann Minkowski and is also known as ‘taxicab geometry’. It is often used to measure ‘distance via roads’, which is a better approach in terms of ‘actual distance’ or put differently; the amount of time it will take to go from A to B (Krause, 1986).

Airbnb and Snappcar: Voting behaviour

The research department of the municipality of Amsterdam (OIS) provided data on voting behaviour in the elections of the Dutch Parliament (‘Tweede Kamerverkiezingen’) in 2012. In this research, votes for both the political parties GroenLinks and D66 were used because we believe these parties represent a relatively young, progressive and environmentally oriented electorate that is also more inclined to adopt new technologies, such as digital sharing platforms (Nationaal Kiezersonderzoek, 2012). These votes are expressed in percentages (of the total number of votes). The percentages of votes for D66 and GroenLinks were accumulated and together form a new variable, namely percentage of GroenLinks and/or D66 voters.

The share of GroenLinks-D66 voters serves as a proxy for young, highly educated people that have progressive and green values. One could argue these attributes should be considered separately, for when the share of GroenLinks-D66 has an impact on sharing supply, we would not know how much of the relationship is explained by age, values or education. Unfortunately, data on 'progressive' and 'green' values are not available for this neighbourhood classification, which led to the use of GroenLinks-D66 voters instead. Due to multicollinearity, age and education could not be included at the same time as GroenLinks-D66 voters. Though this is unfortunate, this does strengthen our believe that GroenLinks-D66 voters are indeed younger and highly educated[1].

Airbnb and Snappcar: Household income

The financial risk that is associated with sharing one's house or car, might be less of an issue for people with a higher income. On the other hand, supplying a shared car or house might be more attractive for people with a lower income, because it provides an extra source of income. Data on household income were provided by the research department of the municipality of Amsterdam (OIS) and stem from 2012. Social security and other premiums (such as alimony payment or income taxes) have already been subtracted from this amount. The resulting household income is expressed in Euros.

Airbnb and Snappcar: One-person households

Data on family composition were also provided by OIS and stem from 2015. The number of one-person households is measured as a raw count of one-person households.

Appendix A holds an overview of the mean of all variables per neighbourhood.

The level of analysis is the neighbourhood level. Our database contains cohesion measurements from 94 neighbourhoods and thus 94 cases. Due to missings on the main independent variable – cohesion – and control variables, several neighbourhoods had to be excluded from the analysis. Furthermore, two neighbourhoods were excluded after they appeared as outliers in the analysis. These neighbourhoods contained only one respondent who completed the Safety Monitor survey and were industrial areas were almost no one lives. The resulting sample contains 84 neighbourhoods. Analyses are performed in Stata 14.

[1] Correlation GroenLinks-D66 and high education: 0.90. Correlation GroenLinks-D66 and age category 18-45: 0.70.

Table 1. Unstandardized neighbourhood level variables

	Type	Obs.	Mean	Std. Dev.	Min.	Max.
Airbnb	Sharing supply	84	130.58	121.74	0	662 (5%[2])
Snappcar	Sharing supply	84	6.35	5.31	0	22.83 (0.5%[3])
Cohesion	Independent	84	3.20	.18	2.73	3.78
Houses privately owned	Control Airbnb	84	1418.96	811.57	128	3709 (31%[4])
Registered cars	Control Snappcar	84	2528.27	1492.64	480	7485
Distance to Dam	Control	84	5562.51	3484.99	399.25	15334.16
GroenLinks-D66 (%)	Control	84	19.95	7.92	4.6	31.5
Household income	Control	84	32520.18	8354.08	23310	64621
One-person households	Control	84	2744.14	1582.99	111	8531 (66%[5])

3.3 Research strategy

As outlined, this study aims to shed light on the relationship between neighbourhood cohesion and sharing supply. Because the dependent variables are count variables, namely the number of Snappcar cars and Airbnb houses, a Poisson regression model was used. When fitting these models, the data showed strong signs of overdispersion (i.e., the variance was much larger than the mean), which is often the case for count data applications that represent real-life situations. For this reason, a negative binomial model was used. The negative binomial distribution – a variation on the Poisson distribution - is equipped to handle overdispersed count data based on Poisson distributions, by adding a random component that reflects the uncertainty about the actual rates at which ‘success events’ occur (Gardner et al., 1995).

A side note is that caution is needed when using Poisson based models with small samples, although literature is not clear on what exactly is a small sample. Separate models with fewer variables were run to make sure not too many variables were included, which will be discussed in the next chapter.

Model 1

The first model contains only our dependent variable (Airbnb), independent variable (cohesion) and the main control variable for Airbnb, namely number of houses privately owned.

Model 2

The second model assesses whether neighbourhood cohesion is associated with Airbnb supply. In this model the dependent variable is the number of Airbnb houses in a neighbourhood, which is regressed on *neighbourhood cohesion* as well as the control variables *number of privately owned houses, distance to*

[2] 5.12% of all houses in this neighbourhood or 19.48% of all privately owned houses in this neighbourhood
[3] 0.5% of all registered cars in this neighbourhood
[4] 31% of all houses in this neighbourhood (social housing, rentals and privately owned)
[5] 66.45% of all households in this neighbourhood

Dam Square, percentage GroenLinks-D66 voters, household income and *number of one-person households.*

Model 3

The third model contains only our dependent variable (Snappcar), independent variable (cohesion) and the main control variable for Snappcar, namely number of registered cars.

Model 4

The fourth model assesses whether neighbourhood cohesion is associated with Snappcar supply. In this model the dependent variable is the number of Snappcar cars in a neighbourhood, which is regressed on *neighbourhood cohesion* as well as the control variables *total number of registered cars, distance to Dam Square, percentage GroenLinks-D66 voters, household income* and *number of one-person households.*

All the control variables as well as both dependent variables (Airbnb and Snappcar) are on the neighbourhood level, not on the individual level. To use data on the neighbourhood level to make statements about individual behaviour, could be an example of the 'ecological fallacy' (Balram & Dragicevic, 2005). In order to overcome this problem, heterogeneity analysis of these variables could be performed. The more homogeneous a neighbourhood is, the more acceptable it is to use neighbourhood data to make statements about individual behaviour. Since our variables are only available to us on a neighbourhood level, unfortunately, such analyses could not be performed.

4. Results

4.1 Airbnb

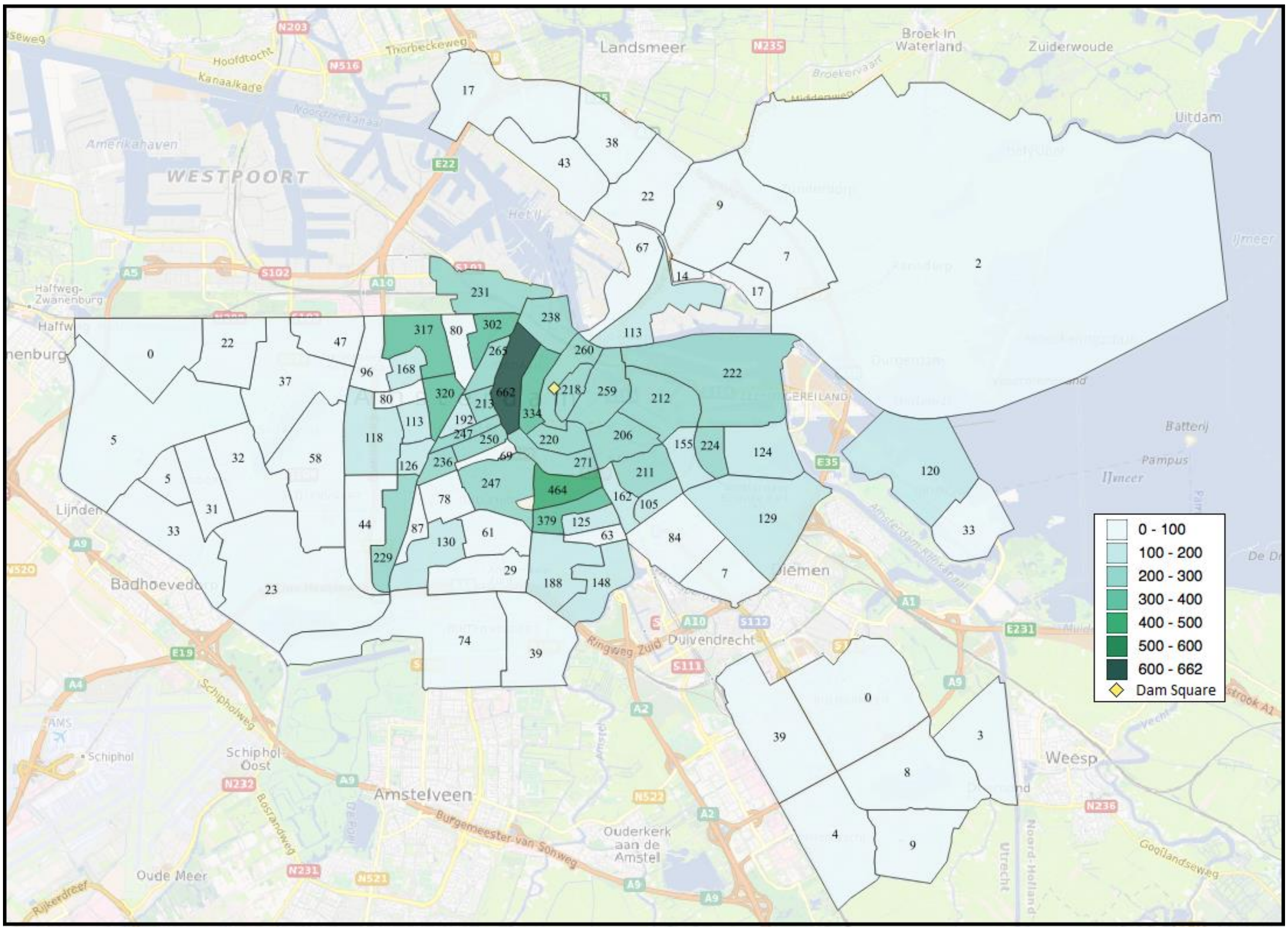
Table 2 presents the models with only our independent variable (cohesion) and dependent variable (Airbnb supply), controlled for the number of houses that is privately owned (Model 1). The results show that the number of privately owned houses has a positive effect on Airbnb supply ($\beta=0.35$, p-2s <0.05, IRR=1.415). Neighbourhood cohesion does not have a significant effect on Airbnb supply.

Table 3 presents the full model of Airbnb testing hypothesis H1b, H2, H4a and H5-H6 (Model 2). The model displays the standardized coefficients and the odds ratios (calculated over unstandardized coefficients) in order to ease interpretation. The data provide no confirmation for H1b, with insufficient evidence of a relationship between neighbourhood cohesion and Airbnb supply.

The findings do provide evidence for H2, H4a and H5. In neighbourhoods where there are more houses in private ownership, Airbnb supply is higher (H2). Findings suggest that in neighbourhoods where 31%[6] of the houses are privately owned, the predicted number of Airbnb listings is 268, whereas the predicted number of listings is 86 in neighbourhoods where 14%[7] of the houses are privately owned ($\beta=0.26$, p-2s <0.01, IRR=1). Second, there is evidence that in neighbourhoods that are further away from Dam Square, Airbnb supply is lower (H4a) ($\beta=-0.65$, p-2s <0.001, IRR=0.99). In neighbourhoods that are 10 kilometres away from Dam Square, the predicted count of Airbnb listings is 43, versus 225 listings in neighbourhoods that are 1 kilometre away from Dam Square. Third, in neighbourhoods with a higher percentage of GroenLinks-D66 voters, Airbnb supply is higher (H5). In neighbourhoods where 4.6% votes GroenLinks-D66 (the lowest percentage in this sample), the predicted number of Airbnb listings is 33, versus 229 listings in neighbourhoods where 31.5% votes GroenLinks-D66 (the highest percentage in this sample) ($\beta=0.52$, p-2s <0.001, IRR=1.07). Lastly, household income has a negative effect on Airbnb supply ($\beta=-0.17$, p-2s <0.05, IRR=0.99). In neighbourhoods with an average household income of 23310 Euros (the minimum average income in this sample), the predicted number of Airbnb listings is 166, whereas for neighbourhoods with an average household income of 64621 Euros (the maximum average income in this sample) the predicted number of Airbnb listings is 74.

[6] 31% of all houses in this neighbourhood (social housing, rentals and privately owned) (3709 out of 11954 houses)
[7] 14% of all houses in this neighbourhood (social housing, rentals and privately owned) (128 out of 912 houses)

Figure 2. Number of Airbnb houses per neighbourhood.



McFaddens' pseudo R^2 penalises models when adding more variables to the model. This type of adjusted R^2 is suitable for interpreting negative binomial regression models. Though it cannot be interpreted as the amount of explained variance, this measure does tell us something about the model fit (Hilbe, 2008). For the full Airbnb model McFaddens' pseudo R^2 is 0.133. A log-likelihood test shows that the full model (with cohesion) does not fit significantly better than the model with only control variables (LR chi(1)=0.02; Prob>chi 2=0.888). Next to this, AIC is lower in the model with only control variables than it is in the full model with cohesion (respectively 853.27 and 855.24) as is the BIC (respectively -124.58 and -120.17), indicating adding cohesion does not improve the model fit.

To see whether the residuals are more or less evenly distributed across Amsterdam and not clustered in a specific geographical area, the residuals were plotted on a Amsterdam neighbourhood map. The results can be found in *Appendix E.*

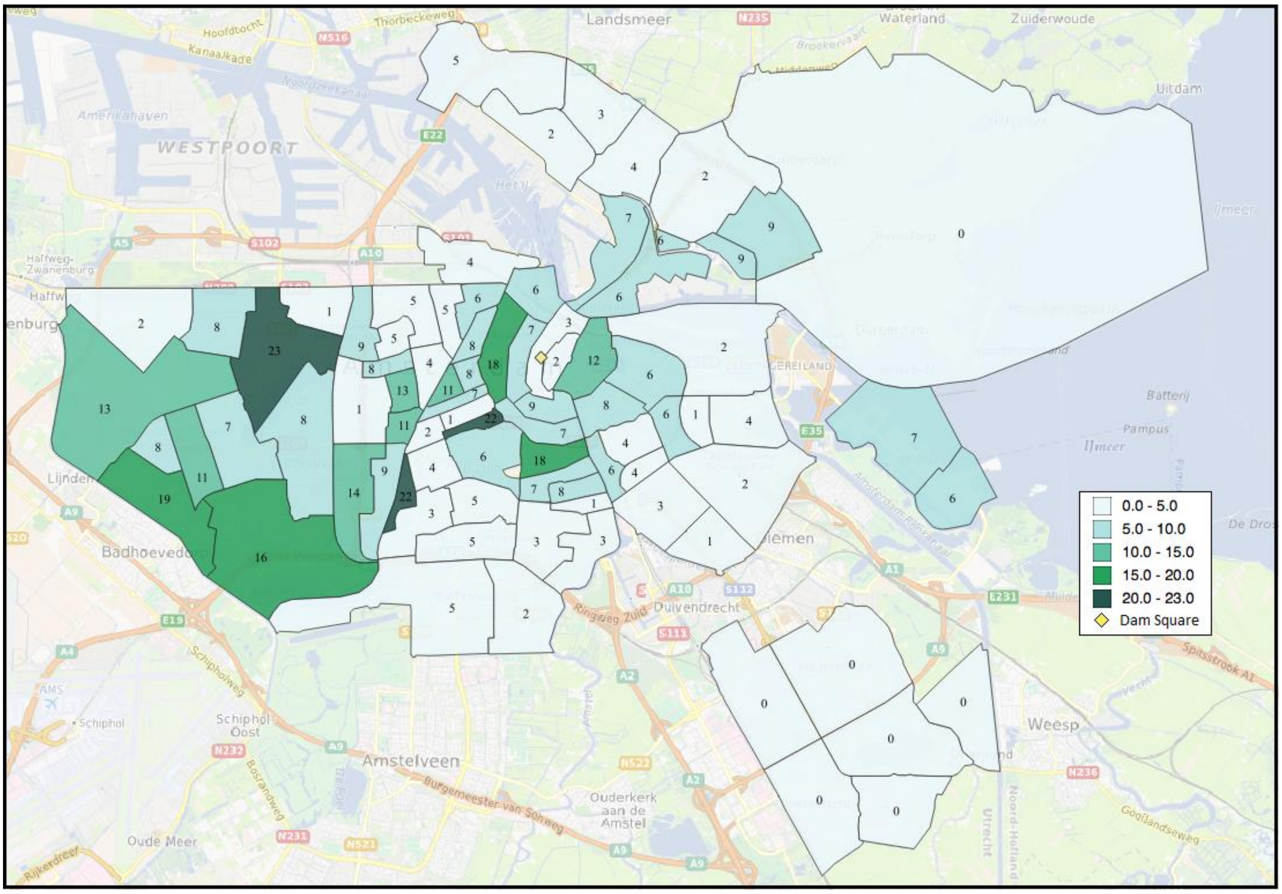
4.2 Snappcar

Table 4 presents the model with only our independent variable (cohesion) and dependent variable (Snappcar supply), controlled for the number of registered cars (Model 3). The results show no evidence for a relationship between Snappcar supply and cohesion or the number of registered cars.

Table 5 presents the full model of Snappcar testing hypothesis H1a, H3, H4b-H6 (Model 4). Again, the model displays the standardized coefficients and the odds ratios (calculated over unstandardized coefficients). The data provide no confirmation for H1a, with insufficient evidence for a relationship between neighbourhood cohesion and Snappcar supply.

None of the control variables show significance, expect for Distance to Dam Square. We conclude there is no support for H3 and H5-H6 (respectively number of registered cars, GroenLinks-D66 voters and one-person households). The variable average household income does also not show significance. As for distance to Dam Square, the direction of this effect is in contrast with our expectation, which was that in neighbourhoods closer to Dam Square, Snappcar supply would be lower (H4b). Evidence suggests that when a neighbourhood is closer to Dam Square, Snappcar supply is higher (β=-0.37, p-2s <0.05, IRR=0.99). In neighbourhoods that are 10 kilometres away from Dam Square, the predicted count of Snappcar listings is 4, versus 10 listings in neighbourhoods that are 1 kilometre away from Dam Square.

Figure 3. Number of Snappcar cars per neighbourhood.



AIC is somewhat higher in the model with only control variables than it is in the full model with cohesion (respectively 489.71 and 489.43). At the same time, BIC of the model with only control variables is lower than in the full model with cohesion (respectively 15.06 and 17.21). These statistics do not present us with sufficient evidence to conclude either the model with or without cohesion fits better. For the full model, McFaddens' pseudo *R^2* is -0.014. A negative adjusted R^2 is possible when the number of cases is small, but nevertheless it does not imply a good model fit. A log-likelihood test shows that the full Snappcar model (with cohesion) does not fit significantly better than the model with only control variables (LR chi(1)=2.28; Prob>chi2=0.1315).

To see whether the residuals are more or less evenly distributed across Amsterdam and not clustered in a specific geographical area, the residuals were plotted on a Amsterdam neighbourhood map. The results can be found in *Appendix E.*

4.3 Additional results

As mentioned earlier, caution is needed when performing Poisson based models with small samples. To account for this potential problem, both forward selection and backwise deletion stepwise regression were applied to make sure the results were not influenced by the combination of a substantive number of variables with a small sample size. Effects remain rather stable in the Airbnb models and we conclude the number of variables in our full model does not pose a problem. Several more restricted models were run in all of which the direction and significance of all effects remains the same. The only deviation is that household income only shows significance when GroenLinks-D66 voters is included. Models without GroenLinks-D66 voters are shown in *Appendix C.*

Further investigation of these models teaches us that when 'distance to Dam Square' is excluded from the Snappcar model, neighbourhood cohesion has a significant influence on Snappcar supply. The full model minus 'distance to Dam Square' is included in *Appendix D*. The direction of the effect, however, is the opposite of what we expected. In neighbourhoods where neighbourhood cohesion is higher, Snappcar supply is lower (β=-0.21, p-2s <0.05, IRR=0.35). The models in *Appendix D* show that with most combinations of our control variables, neighbourhood cohesion is significant, except for when distance to Dam Square is included. The direction of the effect (higher cohesion equals less Snappcar supply) is a rather puzzling finding. Cohesion dummies were created in order to test for a possible inverted U shape of the cohesion effect. No evidence for an inverted U shape was found.

Furthermore, models in which neighbourhoods with few or many inhabitants were excluded showed similar results, indicating robustness of our findings both for Airbnb and Snappcar. After multicollinearity checks, we feel safe to say multicollinearity is not a major concern in both models (Cohesion = 0.81, VIF = 1.23; Range of all the control variables = 0.27-0.48, VIF = 2.10-3.66). The Airbnb and Snappcar model hold different control variables and can therefore not be statistically compared in terms of model fit.

Table 2. **Airbnb**: Standardized results negative binomial regression (including odds ratios)

	β	SE	exp(B)
Cohesion	.0840836	.1543821	1.000423
Houses privately owned	.3470354*	.1341647	1.524779
N	84		
LR chi2(6)	8.40		
Prob > chi2	0.0150		
Pseudo R2	0.0085		
AIC	985.597		
BIC	0.459		

two-sided p<0.05, p<0.01**, p<0.001****

Table 3. **Airbnb**: Full Model. Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.0095419	.0678097	.9532557
Houses privately owned	.2606049**	.0984122	1.000317
Distance to Dam Square	-.6483024***	.0921673	.999815
GroenLinks-D66 voters	.5724584***	.0909975	1.074873
Household Income	-.1652868*	.074846	.9999805
One-person households[8]	.1360919	.103338	1.000085
N	84		
LR chi2(6)	146.75		
Prob > chi2	0.0000		
Pseudo R2	0.1488		
AIC	855.248		
BIC	-120.167		

two-sided p<0.05, p<0.01**, p<0.001****

Table 4. **Snappcar**: Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.1746249	.0995795	.4164045
Registered cars	-.0019123	.090191	.9999987
N	84		
LR chi2(6)	3.06		
Prob > chi2	0.2161		
Pseudo R2	0.0063		
AIC	487.741		
BIC	5.797		

two-sided p<0.05, p<0.01**, p<0.001****

[8] A dummy variable for having either children or no children was also created; this did not change the results substantially.

Table 5. **Snappcar**: Full Model. Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.1571113	.1039371	.4546478
Registered cars	.1021594	.1488382	1.000069
Distance to Dam Square	-.3714284*	.1766915	.999894
GroenLinks-D66 voters	-.1191003	.1643431	.9850805
Household Income	.0789981	.1298456	1.00009
One-person households	-.0561404	.1519609	.9999649
N	84		
LR chi2(6)	5.01		
Prob > chi2	0.4150		
Pseudo R2	0.0104		
AIC	489.431		
BIC	17.211		

two-sided p<0.05, p<0.01**, p<0.001****

5. Conclusion and discussion

Many new firms have joined the sharing trend, some of which have grown tremendously over the past few years, such as Airbnb. Despite this, quantitative research on the topic is still lacking. While previous research on trust focussed mostly on peer reviews, this study sought to explore a different possible source of trust, namely neighbourhood cohesion. The aim of this study was to shed light on the relationship between neighbourhood cohesion and willingness to share. Specifically, it sought to research to what extent supply on Airbnb and Snappcar in Amsterdam could be explained by neighbourhood cohesion. By focussing on supply, we addressed the 'trust' issue that is coupled with sharing one's car or house with a stranger. For this purpose, fresh data were collected from snappcar.nl and existing data on Amsterdam were gathered from various sources.

The results indicate there is no relationship between neighbourhood cohesion and Snappcar or Airbnb supply. Regarding Airbnb, a negative effect of cohesion on Airbnb supply was expected because of potential social norms that discourage people to sublet accommodation via Airbnb, which strengthen when neighbourhood cohesion is higher. The fact that there is no evidence for a relationship between neighbourhood cohesion and Airbnb supply does follow our logic that Airbnb involves 'global' sharing instead of 'local' sharing. Since neighbourhood cohesion is a local phenomenon, it makes sense this does not influence the extent to which we share with people from outside our neighbourhood, or even country.

As for the general lack of findings concerning cohesion, several conclusions are possible. Firstly, we could conclude there is no relationship between sharing supply and neighbourhood cohesion, and that sharing might be better explained by geographical or economic factors. Regarding Snappcar, it has to be noted that cohesion as well as the other factors did not explain much of the Snappcar supply. Based on the fact that only the distance to Dam Square showed to have an influence, we could hypothesize that Snappcar supply is better explained by geographical factors than it is by more 'social' concepts. Other geographical measures, such as population density or closeness to transit facilities, were unfortunately not available for this specific neighbourhoods classification. It could be these types of factors are more successful in explaining car sharing. Here lies an important opportunity for future research.

A second explanation could be that opposing logics are at work and that therefore no relationship was found. Contrary to our hypothesis, one might also argue that neighbourhoods with high levels of social cohesion do not have a need for technologically mediated sharing platforms since sharing is already facilitated through higher levels of interpersonal contact, therewith resulting in less activity on sharing platforms. If cohesion at the same time *does* increase sharing supply (as hypothesized), this could explain the lack of findings. When distance to Dam Square was not included in the Snappcar analysis, cohesion would even show to have a negative influence on Snappcar supply. Trying to explain the direction of this effect is problematic, but could follow this same logic. In highly cohesive neighbourhoods, people might not need an intervening platform to borrow a car because they feel they can simply ask their neighbours. To explore this mechanism further, future researchers could gather data on sharing practices that exist alongside digital sharing platforms.

A third possible explanation for a lack of findings, is the way neighbourhood cohesion is measured. Although we believe the items in the Safety Monitor are an appropriate representation of ‘neighbourhood cohesion’, perceived neighbourhood cohesion will always be something that is subjective and also, subject to expectations. It might well be that people select a neighbourhood to live in and that this decision is partly based on their views of how people should interact with each other. A high cohesion score is then more an indication of how well social interactions in a neighbourhood are aligned with the respondents’ norms, rather than a representation of overall cohesion. In addition, our cohesion measurement does not enable us to distinguish between the underlying mechanisms that were defined, namely trust and norms of reciprocity (both a consequence of neighbourhood cohesion). Ideally, one would be able to identify these mechanisms separately instead of measuring the covering construct (neighbourhood cohesion). Unfortunately, this type of data was not available to us.

Lastly, we build on the study of Li et al. (2005), which concluded neighbourhood attachment was an important precedent of social trust. Since trust is often said to be an important precedent of sharing (Botsman & Rogers, 2010), we hypothesized neighbourhood cohesion could be a source of trust, eventually leading to more sharing supply. While it could still be that social trust indeed arises from neighbourhood cohesion (or attachment), it might be a different type of trust that facilitates sharing supply, for instance trust in the platform itself. Sharing platforms themselves actively promote a sense of community and trustworthiness, also minimizing perceived risks by offering insurance or taking part of the responsibility when a transaction goes sideways (Snappcar.nl; Airbnb.com).

Next to neighbourhood cohesion, other explanations for the amount of sharing supply were considered. In line with expectations, a larger number of houses privately owned has a positive effect on Airbnb supply, as does the share of GroenLinks-D66 voters and closeness to the city centre. Neighbourhoods closer to the city centre, with more privately owned houses and a larger progressive-green electorate show more Airbnb supply than other neighbourhoods. Airbnb supply decreases as average neighbourhood income increases. While richer people do not really need the extra source of income Airbnb can provide, it might be a welcome extra for people financially less well off (Litman, 2000).

None of the explanations under consideration showed to affect Snappcar supply, except for the distance to Dam Square. While we expected that neighbourhoods closer to Dam Square would show less Snappcar supply because of parking problems, instead these neighborhoods showed *more* Snappcar supply. An explanation could be that people in more central neighbourhoods are less likely to own cars (see *Appendix B: Correlation Matrices*) *because* of these parking problems and therefore make more use of shared cars. As a consequence of higher demand, supply could then also be higher. The number of registered cars in a neighbourhood, however, did not show to be of influence. In addition, the costs of owning a car in the city center are higher because of higher parking costs, which could also make it more attractive to share a car (for extra income).

This brings us to an important limitation of this study, namely the fact that the subject under study is only supply, not demand. Supply and demand are undeniably connected to each other, but at this point it is unknown whether Snappcar demand mostly follows Snappcar supply, or the other way around. This issue does not only affect the results regarding closeness to the city center, but for instance also the number of registered cars. We expected that if the number of cars in a neighbourhood was higher, the number of shared cars would also be higher, but no relationship was found. The fact that the number of registered cars does not have an effect, could be explained by the fact that when there are more cars to share, there is also less need for shared cars, because most people already have one or more cars. The effect of the number of cars, thus, might work both ways. Future research would ideally be based on both supply and demand data that are measured over time. Such diffusion data could teach us a lot about whether Snappcar is more supply or demand driven and which neighbourhood characteristics might lie behind this.

Another important limitation of both the Snappcar and Airbnb analysis is that we did not control for the presence of other car- or home-sharing platforms or initiatives. If other car- or home-sharing platforms are available in a neighbourhood, this could influence the demand as well as the supply on Snappcar and Airbnb. Next to this, the data on supply was a 'snapshot' from the website. It would be better to scrape the data over a period of time, therewith correcting for a possible bias due to the day the snapshot was taken, or the time. Ideally, one would obtain data from the Snappcar or Airbnb database itself.

This study poses some further limitations. First, to use data on the neighbourhood level to make statements about individual behaviour, could be an example of the 'ecological fallacy' (Balram & Dragicevic, 2005). This potential issue applies to all of our control variables, as well as both dependent variables; Airbnb and Snappcar. In order to overcome this problem, heterogeneity analysis of these variables could be performed. If a neighbourhood is rather homogeneous, it is acceptable for that neighbourhood to use data on the neighbourhood level to make statements about individual behaviour. Since these variables are only available to us on a neighbourhood level, unfortunately, such analyses could not be performed.

Second, social network analysis ideally depends on data collected on whole populations, not samples, therewith mapping all network ties (Li et al., 2005). Such data were unfortunately not available to us. Since all questions respondents answered were clearly about their neighbours, we do feel comfortable to say the answers describe what is called a 'situational network'; a type of network consisting of ‘weak ties’ (Li et al., 2005). Still, a complete network or neighbourhood analysis would ideally contain all residents in a neighbourhood.

Nonetheless, this study made an important contribution to the research field of sharing behavior. Previous research on the relationship between trust and sharing behaviour was mostly focused on the individual level, therewith not taking other possible sources of trust - such as neighbourhood cohesion - into account (Pick, 2012; Corten et al., 2015). In addition, our data on sharing do not consist of ‘stated preferences’ but of actual sharing supply, which might come closer to actual sharing behaviour than ‘willingness to share’ as it is measured in surveys.

Building on Putnam (2001) and Li and his colleagues (2005) - who both concluded the external returns of neighbourhood cohesion are feelings of trust and norms of reciprocity - we hypothesized this would facilitate sharing behaviour. While it could still be that trust arises from neighbourhood cohesion, it might not be this type of trust that facilitates sharing. Consequently, policy makers who are interested in encouraging sharing would not have to consider neighbourhood cohesion as a source of trust in sharing platforms, but turn to other potential sources of trust. Further research, though, is necessary. We encourage other researchers to look further into these other sources of trust, such as reviews, local institutions and trust through the platform itself. For Snappcar specifically, an interesting research opportunity would be to further investigate the influence of spatial neighbourhood characteristics. To do so, we recommend to make use of longitudinal supply as well as demand data in order to measure sharing diffusion over time.

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Summary

Many new firms have joined the sharing trend, some of which have grown tremendously over the past few years, such as Airbnb. Despite this, quantitative research on the topic is still lacking. While previous research on trust focussed mostly on peer reviews, this study sought to explore a different possible source of trust, namely neighbourhood cohesion. The aim of this study was to shed light on the relationship between neighbourhood cohesion and willingness to share. Specifically, it sought to research to what extent supply on Airbnb and Snappcar in Amsterdam could be explained by neighbourhood cohesion. By focussing on supply, we addressed the 'trust' issue that is coupled with sharing one's car or house with a stranger. To understand the process of trusting a stranger, we turned to Putnam's theory on social capital. Putnam defines social capital as 'connections among individuals - social networks and the norms of reciprocity and trustworthiness that arise from them' (Putnam, 2000, p.19). Weak ties - such as neighbours - have shown to be an important resource for individuals, leading to 'thin trust', or, 'trust placed in the anonymous other' (Li et al., 2005).

Sharing economy initiatives have been referred to in the same breath as other so-called 'deglobalizing initiatives', such as local food initiatives (Starr, 2010). For these 'local' platforms, we would expect the argument of neighbourhood attachment increasing trust to uphold. Other initiatives do not operate on a local level at all. Sharing 'giant' Airbnb mediates between people all over the world, therewith operating on a global level. Nevertheless, the houses on Airbnb are embedded in a neighbourhood. Residents have reported to be worried about an increase of rents in the neighbourhood because of short-term rentals (Said, 2012). Thus in the case of Airbnb, the embeddedness of a potential 'sharer' in a neighbourhood, might put up an obstacle.

For this purpose, fresh data were collected from snappcar.nl and existing data on Amsterdam were gathered from various sources. We made use of data from 94 neighbourhoods in the city of Amsterdam, The Netherlands, to explain supply on a globally operating platform - Airbnb - and a locally operating platform, namely Snappcar. The results indicate there is no relationship between neighbourhood cohesion and Snappcar or Airbnb supply. Based on the fact that for Snappcar only the distance to Dam Square showed to have an influence, we could hypothesize that Snappcar supply is better explained by geographical factors than it is by more 'social' concepts. Other geographical measures, such as population density or closeness to transit facilities, were unfortunately not available for this specific neighbourhood classification. It could be these types of factors are more successful in explaining car sharing. Here lies an important opportunity for future research.

While it could still be that trust arises from neighbourhood cohesion, it might not be the type of trust that is a result of neighbourhood cohesion that facilitates sharing. Further research is necessary. We encourage other researchers to look further into these other sources of trust, such as reviews, local institutions and trust through the platform itself. For Snappcar specifically, an interesting research

opportunity would be to further investigate the influence of spatial neighbourhood characteristics. To do so, we recommend to make use of longitudinal supply as well as demand data in order to measure sharing diffusion over time.

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Appendices

Appendix A. Unstandardized neighbourhood characteristics

Table 6.

	bc10	Air bnb	Snapp car	Cohesion	Inhbi tants	Reg. cars	Privately owned houses	GL-D66	Household income	Distance to Dam Square	1p households
Burgwallen-Oude Zijde	A00	218	2	3.23	4250	705	527	31	27550	455.15	1834
Burgwallen-Nieuwe Zijde	A01	260	2.5	3.00	4535	875	591	31.5	28067	399.24	1971
Grachtengordel-West	A02	334	7	3.12	7060	2235	1861	29.5	47900	529.17	2688
Grachtengordel-Zuid	A03	220	8.5	3.21	4400	1405	1117	31.3	50652	1350.51	1571
Nieuwmarkt/Lastage	A04	259	11.5	3.37	9530	1950	1641	28.9	32483	1282.05	4022
Haarlemmerbuurt	A05	238	5.5	3.35	9290	2240	1496	26.7	33775	1756.09	3387
Jordaan	A06	662	18	3.32	19390	4020	3398	27	30175	1141.06	8531
De Weteringschans	A07	271	6.67	3.33	7350	1840	1741	31.3	37948	1844.38	2740
Weesperbuurt/Plantage	A08	206	8.17	3.14	7600	1625	1270	29.2	32970	2223.92	3078
Oostelijke Eilanden/Kadijken	A09	212	6.17	3.47	12945	3025	1982	24.7	31083	2836.11	4542
Spaarndammer- en Zeeheldenbuurt	E13	231	3.5	3.17	10755	2235	1219	22.3	26358	3223.38	3671
Staatsliedenbuurt	E14	302	5.5	3.29	13050	2650	2360	25.4	27860	2264.93	4847
Centrale Markt	E15	80	4.83	3.55	2535	645	445	19.6	32963	2755.44	621
Frederik Hendrikbuurt	E16	265	8.17	3.16	8370	1760	1443	27.6	28480	1848.34	3245
Da Costabuurt	E17	213	7.67	3.32	4655	1030	847	25.9	31268	1981.01	1668
Kinkerbuurt	E18	192	10.5	3.24	6195	1090	823	25.8	27613	2658.89	2801
Van Lennepbuurt	E19	247	7.17	3.22	7130	1300	988	21.8	25885	2639.20	3010
Helmersbuurt	E20	250	1	3.23	7520	1750	1434	28.3	35377	2458.49	2561
Overtoomse Sluis	E21	236	2.33	3.34	7740	1670	1585	29	32991	3701.53	2593
Vondelbuurt	E22	69	22.17	2.73	1895	545	371	26.8	47218	2471.34	578
Landlust	E37	317	4.5	2.94	18735	3945	2350	22.6	26258	3792.99	5259
Erasmuspark	E38	168	5	3.23	5895	1270	1311	25.5	28259	3962.80	1679
De Kolenkit	E39	96	9.33	3.13	9215	1800	708	15.6	25070	4903.38	2237
De Krommert	E40	320	4.33	3.22	12980	2720	2043	28.4	29388	3019.90	3806
Van Galenbuurt	E41	80	8.33	3.14	6720	1210	731	25.6	24615	4106.81	2956
Hoofdweg e.o.	E42	113	13.33	3.12	10435	2120	1283	23.7	25340	3803.97	3514
Westindische Buurt	E43	126	11.33	3.36	6785	1515	1099	28.5	31007	4149.38	2037
Slotermeer-Noordoost	F76	47	1	3.10	9455	2370	1123	9.2	25289	6102.24	2190
Slotermeer-Zuidwest	F77	37	22.83	2.97	17000	4375	1714	9.8	25426	7070.52	4105
Geuzenveld	F78	22	7.83	2.94	15030	4025	1172	8	27128	8671.18	2637
Eendracht	F79	0	1.5	3.21	2325	940	421	6	36406	10892.28	318
Lutkemeer/Ookmeer	F80	5	13.83	3.38	845	480	177	4.6	39640	11198.46	111
Osdorp-Oost	F81	32	6.83	3.14	15740	4885	2187	8.3	27460	8448.72	4409
Osdorp-Midden	F82	31	11.33	2.97	15735	4385	1788	7.8	27973	9640.56	3141
De Punt	F83	5	7.5	2.86	5485	1700	1007	7.8	26976	10521.57	1300
Middelveldsche Akerpolder/Sloten	F84	33	18.5	3.16	15090	5835	3163	10.7	39533	10804.23	1905
Slotervaart	F85	58	8	3.13	17585	4605	1972	13.3	29243	6709.35	3961
Overtoomse Veld	F86	118	1	2.88	11670	2540	824	16.5	28674	5038.84	2682
Westlandgracht	F87	44	14.17	2.86	7440	2020	931	20	33235	6205.02	2059
Sloter-/Riekerpolder	F88	23	15.5	3.23	13140	4990	2707	13	38873	8724.19	1877
Oude Pijp	K24	464	18	3.18	14975	2805	2403	27.1	29477	2652.76	6118
Nieuwe Pijp	K25	379	7	3.08	12240	2740	2074	27.4	28975	3305.38	4850
Diamantbuurt	K26	125	8	3.22	8230	1565	637	22.1	25924	3634.91	2773
Hoofddorppleinbuurt	K44	229	9	3.34	11535	3300	2425	26.7	33578	5700.15	3781
Schinkelbuurt	K45	87	22.33	3.17	3800	965	662	24.8	30014	5228.34	1429
Willemspark	K46	78	4	3.20	5690	2020	1188	23.6	58408	4114.64	1182
Museumkwartier	K47	247	6	3.43	11515	4070	2236	27.3	57193	2948.80	2901
Stadionbuurt	K48	130	3.33	3.017	11570	3150	1039	20.3	32818	5529.9	3758
Apollobuurt	K49	61	4.5	3.26	8645	3355	1940	24.2	64621	4.195.33	1681
Scheldebuurt	K52	188	3	3.36	14710	3885	2008	24.7	38269	4786.36	4010
IJselbuurt	K53	63	1	3.15	5205	1200	470	23.6	28703	4095.31	1744
Rijnbuurt	K54	148	3	3.32	9055	2255	989	22.4	28999	5315.788	3307

Station Zuid/WTC e.o.	K59	29	4.5	3.08	1400	780	522	28.6	50937	5325.85	414
Buitenveldert-West	K90	74	4.5	2.96	13650	7485	2997	18.7	36760	7454.99	4493
Buitenveldert-Oost	K91	39	2	3.01	7785	2760	1491	13.7	34305	6763.20	2694
Weesperzijde	M27	162	6	3.32	4980	1160	1055	29.9	34828	3391.24	1651
Oosterparkbuurt	M28	211	4	3.11	10790	1980	1464	26.2	27876	3256.08	3688
Dapperbuurt	M29	155	6	3.27	8935	1670	1070	22.1	25846	3954.10	2952
Transvaalbuurt	M30	105	3.5	3.20	9105	1615	959	22.6	26392	4014.80	2644
Indische Buurt West	M31	224	1	3.11	12655	2260	1722	24.8	25718	4471.11	3889
Indische Buurt Oost	M32	124	3.5	3.03	10150	1940	1017	18.7	25775	5740.01	2819
Oostelijk Havengebied	M33	222	2	3.32	18355	5410	3350	27.6	41796	4505.17	3956
IJburg West	M35	120	7	3.46	14235	3900	2596	24.4	43612	9751.03	1667
IJburg Zuid	M51	33	6	3.44	6750	1795	1040	20.1	38135	11628.9	948
Frankendael	M55	84	3.33	3.44	10415	2850	917	20.7	29822	5121.21	3694
Middenmeer	M56	129	2.33	3.55	15200	4100	2751	29.7	41389	6385.21	3631
Betondorp	M57	7	1.33	3.17	3175	1030	239	10.7	23729	6740.17	1194
Volewijck	N60	67	7.33	2.10	9670	2445	509	13.9	23570	3630.04	2618
IJplein/Vogelbuurt	N61	113	6	3.12	8215	1930	760	13.3	24313	3463.94	2355
Tuindorp Nieuwendam	N62	17	8.5	3.54	3495	1290	288	13.1	27166	5783.74	876
Tuindorp Buiksloot	N63	14	6.33	2.87	1850	615	128	13.4	27209	4619.26	377
Tuindorp Oostzaan	N65	43	1.5	3.29	10870	3655	1389	8.1	27372	5877.74	2281
Oostzanerwerf	N66	17	4.5	3.06	8740	3170	1606	9	33037	7747.67	1497
Kadoelen	N67	38	3	3.30	2840	1180	661	13.1	38323	6838.73	344
Nieuwendam-Noord	N68	7	9	3.01	13050	3585	1661	8	27498	7000.86	2469
Buikslotermeer	N69	9	2	3.22	13175	3690	1924	11.1	28214	6420.44	3379
Banne Buiksloot	N70	22	4	3.13	13840	3960	1553	6.9	27942	5843.33	2660
Waterland	N73	2	0	3.78	2160	1075	651	21.3	46631	11983.22	295
Bijlmer Centrum (D,F,H)	T93	39	0	3.05	23130	4775	2285	8.2	23310	10766.41	6809
Bijlmer Oost (E,G,K)	T94	0	0	3.19	26755	6575	3709	8.4	25559	11540.65	6870
Nellestein	T95	8	0	3.19	3000	1085	672	14.5	28475	14010.86	978
Holendrecht/Reigersbos	T96	4	0	3.15	18250	4660	1995	12.7	27169	14037.97	4208
Gein	T97	9	0	3.26	11550	3640	1966	8.6	30109	15334.16	2296
Driemond	T98	3	0	3.42	1485	675	325	10.8	37490	14754.75	186

Appendix B. Correlation matrices

Table 7. Correlation matrix: Airbnb.

	Airbnb	**Cohesion**	**Houses privately owned**	**Distance Dam Square**	**GL-D66**	**Household income**	**One-person households**
Airbnb							
Cohesion	0.1274						
Houses privately owned	0.3385	0.0768					
Distance Dam Square	-0.6852	0.0402	0.0782				
GL-D66	0.7107	0.2519	0.0640	-0.7172			
Household income	0.003	0.2798	0.1251	-0.0163	0.3037		
One-person households	0.5467	-0.0929	0.6012	-0.1933	0.1383	-0.3340	

Figure 4. Correlation matrix Airbnb.

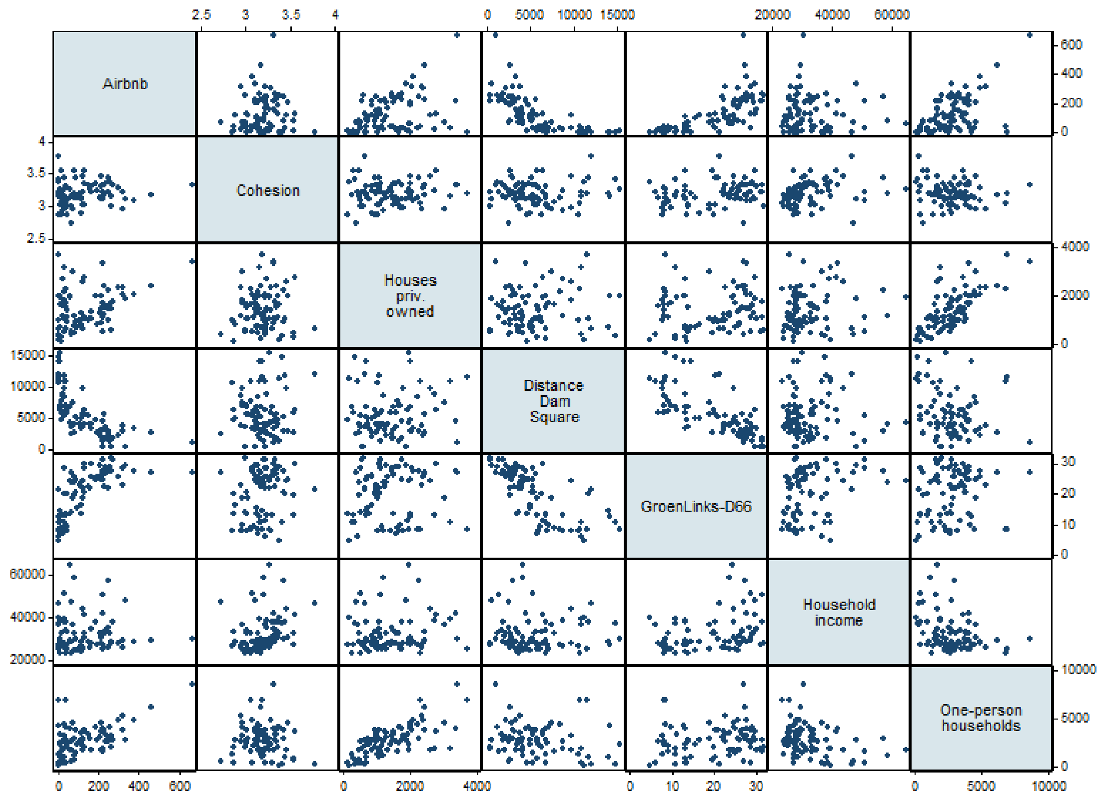
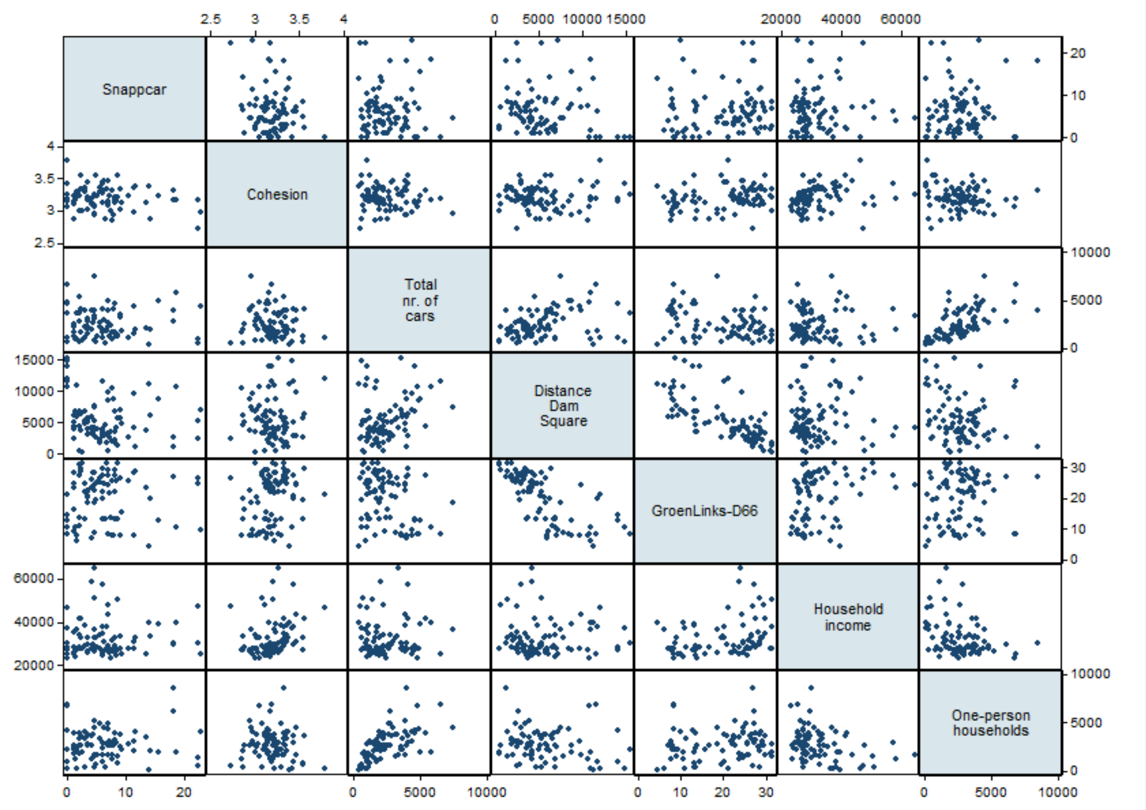


Table 8. Correlation matrix: Snappcar.

	Snappcar	Cohesion	Registered cars	Distance Dam Square	GL-D66	Household income	One-person households
Snappcar							
Cohesion	-0.1961						
Registered cars	0.0089	-0.1116					
Distance Dam Square	-0.1927	0.0402	0.3013				
GL-D66	0.0835	0.2519	-0.3020	-0.7172			
Household income	0.0399	0.2798	0.0127	-0.0163	0.3037		
One-person households	0.0578	-0.0929	0.6129	-0.1933	0.1383	-0.3340	

Figure 5. Correlation matrix Snappcar.



Appendix C. Airbnb: additional results.

Table 9. **Airbnb** – **GroenLinks-D66 excluded**: Standardized results negative binomial regression (including odds ratios)

	β	SE	exp(B)
Cohesion	.1434306	.0784541	1.154227
Houses privately owned	.3156194**	.1212707	1.371108
Distance to Dam Square	-1.051425***	.0785115	.3494394
Household Income	-.0438113	.0938247	.9571345
One-person households[9]	.1537929	.1311021	1.166249
N	84		
LR chi2(6)	115.7		
Prob > chi2	0.0000		
Pseudo R2	0.1173		
AIC	884.299		
BIC	-93.547		

two-sided p<0.05, p<0.01**, p<0.001****

Table 10. **Airbnb** – **only Houses privately owned and Income included**: Standardized results negative binomial regression (including odds ratios)

	β	SE	exp(B)
Cohesion	.097938	.1539135	1.103839
Houses privately owned	.3608735**	.1364676	1.434582
Household Income	-.0827069	.119299	.920621
N	84		
LR chi2(6)	8.86		
Prob > chi2	0.0312		
Pseudo R2	0.0090		
AIC	987.140		
BIC	4.432		

two-sided p<0.05, p<0.01**, p<0.001****

[9] A dummy variable for having either children or no children was also created, this did not change the results substantially.

Appendix D. Snappcar: additional results

Table 11. **Snappcar – Only number of cars and GroenLinks-D66 included**: Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.204258*	.0995795	.815252
Registered cars	.0382128	.0939613	1.038952
GL-D66	.1275433	.0970578	1.136034
N	84		
LR chi2(6)	4.75		
Prob > chi2	0.1907		
Pseudo R2	0.0098		
AIC	488.050		
BIC	8.538		

two-sided p<0.05, p<0.01**, p<0.001****

Table 12. **Snappcar – Only number of cars and Income included:** Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.1848702	.1015008	.8312121
Registered cars	-.0046672	.0904941	.9953437
Household income	.0612769	.0981372	1.063193
N	84		
LR chi2(6)	3.46		
Prob > chi2	0.3259		
Pseudo R2	0.0072		
AIC	489.344		
BIC	9.832		

two-sided p<0.05, p<0.01**, p<0.001****

Table 13. **Snappcar – Only number of cars and One-person Households included**: Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.1798198	.099045	.8354207
Registered cars	-.0369583	.1023198	.9637163
One-person households	.0677243	.098564	1.07007
N	84		
LR chi2(6)	3.54		
Prob > chi2	0.3155		
Pseudo R2	0.0073		
AIC	489.264		
BIC	9.752		

two-sided p<0.05, p<0.01**, p<0.001****

Table 14. **Snappcar – Only number of cars and Distance to Dam Square included**: Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.1744009	.0963628	.8300601
Registered cars	.0705249	.0924935	1.073071
Distance Dam Square	-.237464*	.1034802	0.7923545
N	84		
LR chi2(6)	7,93		
Prob > chi2	0.0474		
Pseudo R2	0.0164		
AIC	484.872		
BIC	5.359		

two-sided p<0.05, p<0.01**, p<0.001****

Table 15. **Snappcar**: Full Model – **Distance to Dam Square excluded**. Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.2100336*	.1023629	.3486297
Registered cars	-.0053226	.143694	.9999964
GroenLinks-D66 voters	.0864237	.1352523	1.01096
Household Income	.0643875	.129776	1.000008
One-person households	.0533484	.1462567	1.000033
N	84		
LR chi2(6)	5.01		
Prob > chi2	0.4150		
Pseudo R2	0.0104		
AIC	491.798		
BIC	17.147		

two-sided p<0.05, p<0.01**, p<0.001****

Table 16. **Snappcar**: Full Model **– Distance Dam Square and GroenLinks-D66 excluded:** Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.202104*	.101882	.81701
Registered cars	-.0672424	.0939613	.9349685
Househ. income	.1106334	.0970578	.116985
1-p. households	.1161328	.1094168	.123145
N	84		
LR chi2(6)	4.60		
Prob > chi2	0.3306		
Pseudo R2	0.0095		
AIC	490.202		
BIC	13.121		

two-sided p<0.05, p<0.01**, p<0.001****

Table 17. **Snappcar**: Full Model **– Distance Dam Square and Income excluded**: Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.2039458*	.1011438	.8155065
Registered cars	.0334738	.1206634	1.03404
1-p. households	.0070012	.1121055	1.007026
GL-D66	.1240735	.1118056	1.132099
N	84		
LR chi2(6)	4.76		
Prob > chi2	0.3130		
Pseudo R2	0.0099		
AIC	490.047		
BIC	12.965		

two-sided p<0.05, p<0.01**, p<0.001****

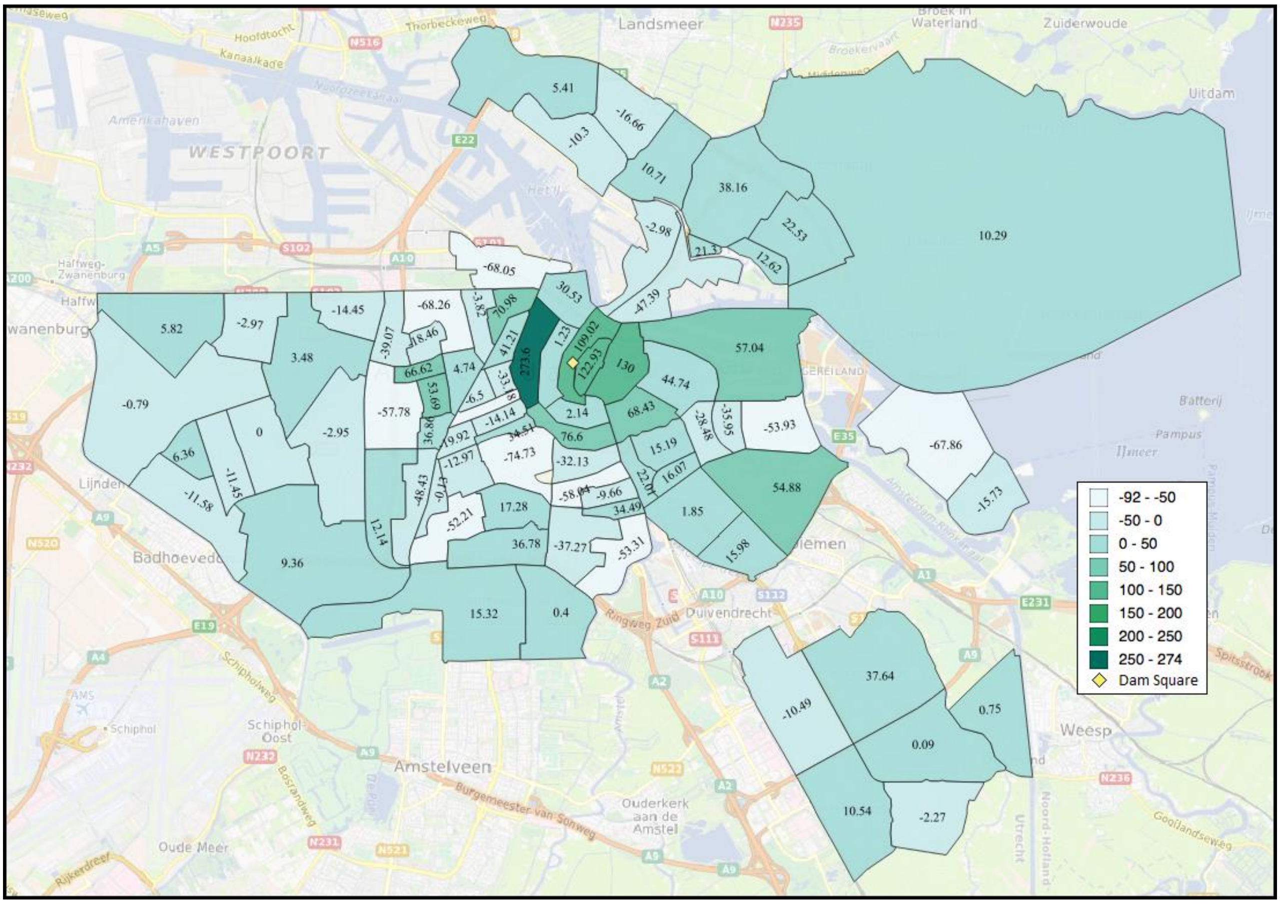
Table 18. **Snappcar**: Full model **– Income excluded**: Standardized results negative binomial regression (including odds ratios).

	β	SE	exp(B)
Cohesion	-.1614435	.1031851	.8509146
Registered cars	.0594739	.0932308	1.061278
1-p. households	.106513	.1066175	1.112392
GL-D66	-.1368955	.1569293	.8720613
Distance Dam Sq.	-.3490867*	.165651	.705332
N	84		
LR chi2(6)	9.24		
Prob > chi2	0.0999		
Pseudo R2	0.0191		
AIC	487806		
BIC	13.155		

two-sided p<0.05, p<0.01**, p<0.001****

Appendix E. Residuals per neighbourhood.

Airbnb



Snappcar