Mobile Phone Usage in Complex Urban Systems: a space-time, aggregated human activity study

Tranos, Emmanouil; Nijkamp, Peter

DOI:
10.1007/s10109-015-0211-9

Mobile Phone Usage in Complex Urban Systems: a space-time, aggregated human activity study

Emmanouil Tranos
School of Geography, Earth and Environmental Sciences
University of Birmingham
e.tranos@bham.ac.uk

Peter Nijkamp
Dept. of Spatial Economics
VU University Amsterdam

Please cite as:

Tranos, E., & Nijkamp, P. (2015). Mobile Phone Usage in Complex Urban Systems: a space-time, aggregated human activity study. *Journal of Geographical Systems*, *17*, 157-185.

Abstract

The present study aims to demonstrate the importance of digital data for investigating space-time dynamics of aggregated human activity in urban systems. Such dynamics can be monitored and modelled using data from mobile phone operators regarding mobile telephone usage. Using such an extensive dataset from the city of Amsterdam, this paper introduces space-time explanatory models of aggregated human activity patterns. Various modelling experiments and results are presented, which demonstrate that mobile telephone data are a good proxy of the space-time dynamics of aggregated human activity in the city.

Keywords: Mobile phone, human activity, land use, urban dynamics
JEL: R14, R00, R15, O18

Acknowledgement

This research is funded by the Urban Regions in the Delta programme, Netherlands Organisation for Scientific Research (NWO) and by the Dutch Ministry of Infrastructure and the Environment (RWS). The authors would also like to acknowledge the support of John Steenbruggen for his help with data acquisition.

1. Introduction

The emergence of the 'digital age' has prompted over the years many scholarly and policy debates on its implications for cities and regions. Such debates are often centred on the question whether the seemingly footloose character of digital infrastructure would affect the material-geographic foundation of human settlements. There is indeed an intriguing relationship between Information and Communication Technologies (ICTs) and the morphology of cities. Surprisingly, the wealth of theoretical debates and conceptualizations was not paralleled by solidly tested empirical studies. Examples of influential studies include the seminal work of Graham and Marvin (1996; 2001) on 'Splintering Urbanism', Batty's (1997b) ideas on 'Virtual Geography' and Castells' (1996) 'Space of Flows'. Despite different starting points by various authors, the consensus on the above issues can be summarized in the following challenging proposition: "the city itself is turning into a constellation of computers" (Batty 1997a, p. 155). Indeed, it is widely accepted that more and more urban functions are heavily depending on ICTs nowadays. One of the outcomes of this transformation is that an intertwined constellation of computers – apart from supporting cities – can also generate an avalanche of data about cities that urban geographers and planners of the twentieth century have never dreamt of before. Such data, which is currently known as 'big data', can be used to model and monitor individual interactions in (almost) real time at a very detailed spatial resolution. Thus, this might be the turning point in orienting the discussion on cities and ICTs from a conceptual to a more empirical basis. The excess of new, detailed bottom-up data from digital sources enables the research community to study and model traditional geographic phenomena in an unprecedented fine-grained spatio-temporal resolution (for an extensive discussion see also Arribas-Bel 2014; Miller 2010; Tranos 2013; Tranos and Nijkamp 2014).

Clearly, the digital world comprises many types of data, such as GPS, Internet data and mobile telephony data. Nonetheless, the importance of urban analytics based on e.g. mobile phone data is not limited to revealing urban signatures at a very fine-grained scale. The usability of such data goes even further, as it can provide novel support tools to urban planning. At an aggregated level, the changes that mobile telephony introduced to cities can be illustrated as a new faster pace of urban life-style and, in general, as new and quicker urban systems metabolism. A *real-time city* acts and can be monitored instantaneously (Townsend 2000). This new characteristic of increased action in time and space from the urban user perspective and its response in terms of real-time monitoring creates a new exciting opportunity for urban planners and urban governance in general. In this context, Steve Graham (1997, p. 117) highlights this new real-time dimension as follows: "The traditional concepts of urban and regional planning are today outmoded. The harmonious development of areas towards equilibrium, the correct sharing out of resources, providing support to complementary developments within the city [...] these ideas have given way to the impression that spaces are fragmented, atomised and strongly competitive [and] the insertion of telecommunications into the city makes the development of spaces more complex and introduces today a third dimension into urban and regional planning [after space and time]: this is the factor of real-time" (ADUML 1991, p. 4).

The above mentioned evolution has also met severe criticism. Critical approaches on the merit of real-time urban analytics, such as these based on mobile phone data, can be found in the urban literature. The basis of such approaches is the often used argument that the pervasive character of ICTs across different economic sectors and urban environments supports the operation of the capitalist system at a global level (e.g. Sassen 1991). In such a framework, critical geography would argue that space has been de-humanized and objectified (Graham 1997). For example, Soja (1989) highlights how planning and geography have understood space as a dead, fixed, immobile and undialectic entity, which is based on passive measurements instead of actions and meanings. These ideas pass judgment on Newtonian-influenced approaches towards space and time. Massey (1992) has criticized the above strand of research by emphasizing that space and time are conceptualized in classical physics as independent objects. However, post-modern urban theory argues against the separation of space and time as in reality what exists in the joint effect of *space-time* (Thrift 1996). Thus, similarly to the non-linearity and multiplicity of time, places are divert, overlapping, non-contiguous and dynamic (Graham and Healey 1997; see also Steenbruggen et al. 2014).

Urban analytics based on mobile phone or other big data sources can offer a new departure for an answer to the above criticism on positivistic approaches to urban theory. The use of mobile phone based urban analytics enables the research community to analyse and model the *pulse of the city* (Batty 2010). Such measures do not focus on the physical form per se, but on human activity and its projection on cities. The use of such pervasive digital infrastructural systems results to large pools of human behavioural data, which can then be used as a means to understand the structure of cities (Louail et al. 2014). And most importantly, the underlying assumption is not a static canvas of urban zones, but instead a dynamic understanding of urban environment as illustrated by numerous and diverse individual urban life-styles. Space is not separated by time, as the domain of such urban analytics is the space-time nexus from an (almost) real-time perspective.

Despite the importance of the wealth of information generated by mobile telephony and other digital infrastructures, mobile phone based urban analytics is not an end in its own. The applicability of such analytics in supporting urban planning may reinforce the potential of the latter and provide new opportunities for urban management and development. For example, Ahas and Mark (2005) predict that geo-located data from mobile phone operators will be utilized in three areas in urban planning: (1) as a means to monitor the usage of transport infrastructure and especially that dedicated to commuting between city and suburban areas; (2) to study, understand

and quantify the temporal dimensions and the dynamics of urban space; (3) to model, plan and design transportation and transport infrastructure.

Much of the discussion on the digital world is focused on top-down approaches. Nonetheless, due to the pervasiveness of mobile telephony, urban planning can also benefit from bottom-up initiatives. Bisker et al. (2010) suggest that apart from the benefits arising from top-down urban computing and sensing, which is mostly the responsibility of urban planners, citizen-based initiatives can further reinforce developments in urban planning. For instance, advances in emergency situations management can be made utilizing the wide spread of mobile phone data, volunteer participation and existing technology. An often utilized example in the literature is hurricane Katrina and the heavily affected city of New Orleans (Evans-Cowley 2010). Citizens using their mobile phones created a detailed photographic record of their properties before they were demolished, a task which could not have been undertaken by the overwhelmed city authorities (ibid.). In a different example, the collective contribution of data from mobile phone users can be used as the basis for average speed maps and other traffic information that can influence travel choices (Evans-Cowley 2010). Clearly, such data can lead to the coordination of transportation in real time (Townsend 2000). In general, the data-rich nature of digital information systems provides a great opportunity of spatial complexity analysis. This forms also the background of the present study.

The present study aims to investigate the potential of the wealth of data generated from mobile phone usage in modelling the aggregated human activity in space and time, taking Amsterdam as the point of reference. This study is situated within a fast developing research domain which aims to utilise (big) data from mobile phone operators in space- time urban analysis. As Calabrese et al. (2014, p. 25:4) highlight, data from mobile phone operators offers "the possibility to study micro- and macro-behaviors and truly reflect human behavior given the fact that data is becoming more and more available". In essence, such data reflect the collective behaviour of people (Calabrese et al. 2010). Examples include, among others, the work Ratti et al. (2006), who map the intensity of urban activities in Rome and Amsterdam, a paper from Reades, Calabrese and Ratti (2009), who identified a clear relationship between aggregated mobile phone usage and human activity using the city of Rome as a case study and the work of Sevtsuk and Ratti (2010), who used mobile phone usage as a proxy to model population distribution over time and space. More recently, Jacobs-Crisioni et al. (2014) employed data from a mobile phone operator to evaluate the impact of land-use density and mix on urban activity patterns and Calabrese et al. (2011) investigated the relationship between face to face and mobile phone based interactions. In a cognate research domain, data from mobile phone operators has been also utilized in mobility studies (e.g. Calabrese et al. 2013; Lambiotte et al. 2008; Licoppe et al. 2008). In complexity science such data has been utilised in exploring the statistical mechanisms governing the formation of human communication networks (e.g. Candia et al. 2008; Song et al. 2010a; Song et al. 2010b).

The point of departure here is the work of Toole et al. (2012), who analysed data from mobile phone operators using machine learning classification algorithms to identify land use types. In a similar vein, Reades, Calabrese and Ratti (2009, p. 835) highlighted the relationship between land use types and mobile phone usage, but they also stated that a "straightforward regression […] appears insufficient to account for the way that bandwidth usage changes in areas of intensive activity, such as the CBD [Central Business District]." Pei et al. (2014) employed aggregated mobile phone usage data to proxy resident activities and through them to define land use types. Based on the above developments in the literature, this paper aims to advance the urban analysis domain by: (a) providing a more in depth spatio-temporal analysis of mobile phone usage, which represents aggregated human activity; and (b) test the official delimitation of land use types against the aggregated human activity patterns depicted by mobile phone usage. We do the above by providing evidence derived from statistical modelling. Our analysis agrees with Reades, Calabrese and Ratti's (2009) remark about the complex relationship between land use type and mobile phone usage, but at the same time our analysis demonstrates that regression techniques can result to a good approximation of this relationship even after considering its dynamic nature.

The paper is organized as follows. Section 2, apart from presenting the data used in this paper, will be devoted to the description of space-time mobile phone usage patterns in Amsterdam, with particular emphasis on temporal variability. Next, Section 3 will analyse the centrality orientation of mobile phone usage, while land-use dimensions are modelled in Section 4. In Section 5 we will offer some concluding remarks.

2. Mobile phone usage over time and space: an aggregated human activity measure

This section aims to highlight the – largely unequal – distribution of mobile phone usage over time and space in Amsterdam. With the use of descriptive and spatial statistics, we will shed light on how mobile phone usage varies across space and time, and use this statistical knowledge in the next section to model such urban dynamics. Using as the main assumption the idea that mobile phone usage depicts human activity, the results of our analysis can be translated as an effort to project and model aggregated human activity at a very detailed spatial and temporal resolution within an urban environment. The underlying assumption is that mobile phone usage is a good proxy for population distribution at such resolution (e.g. Sevtsuk and Ratti 2010). Of course, this does not come without limitations. For instance, people who sleep do not use their phones and therefore their concentrations cannot be depicted by such data. Or, the whereabouts of people who have their phones turned off cannot be included in such data. Having said that, the size of the sample (almost everybody owns a mobile phone) enables us to consider data from mobile phone operators as a fairly good approximation of aggregated human activity (Sevtsuk and Ratti 2010).

Before developing our analysis, a short description of the main dataset will be presented. This dataset has been provided by a major mobile phone operator in The Netherlands. It includes aggregated telecommunication counts at the level of the GSM (Global System for Mobile Communications) cell on an hourly basis for 2010. In total, 815 such urban zones are included in the analysis (see also Figure 3). These irregular zones vary in size, in such a way that smaller GSM zones are designed for busier areas. Although various telecommunications counts were initially included in the data, such as the number of new calls that took place in a specific zone during the course of an hour, the number of SMS (short message service) texts sent from a specific zone and the average call length, the main variable of interest is the number of Erlangs. This is an aggregation of all telecommunication activity: if 30 phone calls take place within one hour at a specific GSM cell and each of these calls has a duration of 5 minutes, then the total number of Erlangs will be 2.5 (30*5 = 150 minutes = 2.5hours). Erlang has appeared to be a better proxy for the total telecommunication activity and therefore is the preferred variable of interest here.

Figure 1 presents the first step in our effort to analyze the spatio-temporal variability of mobile phone usage within Amsterdam. This is a rank plot of all the GSM cells of the study area based on average Erlangs for each cell for the year 2010. The reader is reminded that the mobile phone usage is aggregated on an hourly basis, so that the average Erlangs for each cell is the average of 24(hours)*365(days)=8760 observations, except from any missing values. What becomes apparent from this plot is the inequality of the spatial distribution of mobile phone usage in the urban area of Amsterdam. Mobile phone usage drops exponentially indicating a form of spatial hierarchy of the GSM zones. The first five zones in terms of mobile phone usage represent in average 3 per cent of the total mobile phone traffic in the study area and only 0.23 per cent of the total area. This fairly unequal distribution results in a Gini coefficient of 0.37.

Going a step further in analysing the temporal variability of the mobile phone usage, Figure 2 presents the average hourly variation in terms of Erlangs across the study area. Not surprisingly, this figure presents the ‘pulse’ of the city of Amsterdam (Batty 2010), which reflects the daily life pattern, or, in other words, the aggregated human activity. Very limited mobile phone usage is observed during the night time, while this usage gradually increases from 7am onwards. After 9am it reaches a plateau, which peaks at 5pm when usually office work ends and then it gradually decreases. A potential caveat here is the observation that mobile phone usage during the morning peak is slightly lower than the one during the afternoon peak as this might be related with communication patterns instead of aggregated human behaviour (e.g. Becker et al. 2011; Caceres et al. 2008). However, motorway traffic in Amsterdam (see Appendix 1) during the same period also reveals a similar pattern according to which the evening peak car traffic in motorways is higher than the equivalent morning one advocating towards the ability of mobile phone data to capture human behaviour.

Although it is interesting to validate the human hourly patterns with mobile phone data, what is missing from Figure 2 is the spatiality of mobile phone usage and consequently the spatiality of the aggregated human activity within Amsterdam. In order to add this dimension in our analysis, Figure 3 presents the spatial distribution of mobile phone usage, in terms of average Erlangs, during different times of the day. The different maps are comparable, as Erlangs are expressed here as standard deviations from the average mobile phone usage at the reference time across the study area and in the year 2010. The highly polarized picture of 3am changes during the morning peak of 9am, when GSM zones with mobile phone usage higher than the average are more spread. Similar spatial distributions can be observed for the next two time slots (12pm and 5pm). The picture changes again to a more centralized distribution at 7pm and continues like this during the night. The above qualitative analysis is verified by the Gini coefficients, which are also presented in Figure 3. According to this measure, mobile phone activity is distributed more unequally in space during night, when mobile phone activity is concentrated in fewer GSM zones, while inequality decreases during the day. Although this comes as no surprise as most of the population sleeps during night, the Figure 3 depicts these areas in Amsterdam where human activity takes place during night hours from an aggregated perspective.

Figure 3 provided a first picture of the change of aggregated mobile phone usage in time and space in Amsterdam. Given our main assumption that mobile phone usage reflects aggregated human activity and its dynamics, this analysis can provide valuable insights on where human activity is concentrated in Amsterdam and how this concentration changes over time. In order to do so, Local Indicators of Spatial Autocorrelation (LISA) are employed. The latter is a widely used spatial statistic which identifies hotspots and therefore, contributes significantly to our understanding of the global pattern of spatial autocorrelation (Anselin 1995).

Figure 4 documents the temporal variability of the Amsterdam central areas using the different LISA indicators of average Erlangs at different times of the day. These maps only include the high-high clusters derived by the LISA indicators using rook contiguity to build the spatial weight matrix. Moreover, the analysis here distinguishes between working and non-working days (left and right panel of Figure 4 respectively). The latter category includes weekends and public holidays in The Netherlands. Although Figure 4 includes the LISA high-high clusters only for 3 distinct time periods, the overall set of the 24 LISA maps for working and non-working days is available online as an animation[1]. Although most of the central cells are located around the geometric centre of the study area, central areas change over the course of the day depicting the

[1] https://dl.dropboxusercontent.com/u/5198653/Amsterdam_LISA_mobile_maps.zip

change of population presence and indicating the fast dynamics of the aggregated human activity. Moreover, changes can be observed between the same time periods between working and non-working days.

To better understand these changes, Figure 5 presents the spatial median of all the LISA high-high clusters at an hourly basis for working and non-working hours (Figure 5a and 5b respectively). For instance, the spatial medians of all the LISA high-high clusters fall outside the A10 motorway between 5.00-9.00am for working days. A10 is the ring road around Amsterdam's central area and is represented with bold black line in Figure 5. On the contrary, during non-working days the spatial medians of the LISA high-high clusters falls outside A10 only between 6.00-8.00am. The spatial medians of high-high clusters during non-working days tend to concentrate in only two locations: the first one is the south tip of the central area of Amsterdam (the Nine Streets area) and the second is the Schiphol Airport. In general, a more dispersed pattern is observed during working days, indicating the higher spatio-temporal variation of the aggregated human activity during these days in comparison to the most clustered pattern of the non-working days.

Finally, Figure 6 presents the distribution of the average distances of all the LISA high-high clusters from Amsterdam Central Station at an hourly basis. In order to construct this graph, we measured the distance between every LISA high-high cluster using the centroid of the relevant polygons and Amsterdam Central Station. This process was repeated 24 times for each hourly time period. Then, the mean of all the distances for every hour was calculated. The Amsterdam Central Station has been chosen as it represents a focal point of the structure and function of Amsterdam. The vertical axis of Figure 6 represents distance from Central station in meters and the horizontal the temporal dimension at an hourly basis. For instance, the average distance between all the LISA high-high clusters is maximised at 5am during working days and at 7am during non-working days. Again, we can observe that in average LISA high-high clusters are substantially further away from the city centre on working days (6151m) than on non-working (5006m). This finding validates that the aggregated human activity appears to be more spatially dispersed during working days.

3. Central locations of aggregated human activity in Amsterdam: official vs. empirical delimitations

The previous section explored the spatio-temporal variation of the aggregated human activity and based on this, identified the centres of human activity and mapped its dynamics. The next step, which is the focus of this section, is to juxtapose our bottom-up delimitations of Amsterdam's central areas with the official definitions of Amsterdam's centres using land-use data from CBS (2012). In order to test this research question, the below probit model is developed and estimated:

$$probit\{Pr(lisa_{it} = 1|x_{it})\} = b_1 citycenter_i + b_2 outercitycenter_i + b_3 localcenter_i + c_1 citycenter_i * H_t + c_2 outercitycenter_i * H_t + c_3 localcenter_i * H_t + a_0 + \varepsilon_{it} \quad (1)$$

The left hand-side variable of this model ($lisa_{it}$) is a binary variable indicating whether a GSM zone i is part of a high-high cluster according to the LISA indicator at time t. In order to distinguish between working and non-working hours, the model is estimated twice: the first time, $lisa_{it}$=1 only for working days while for second time $lisa_{it}$=1 for non-working days. The probability of a zone to be part of such a LISA cluster is regressed against three land-use types: city center locations ($citycenter_i$), outer city centre locations ($outercitycenter_i$) and local centre locations ($localcenter_i$). These variables are based on the official Amsterdam land use delamination (CBS 2012) and are illustrated in Figure 7. Moreover, in order to capture the temporal variability of the effect of the above land-use types on mobile phone usage, the three variables are interacted with dummies indicating the different hours of the day.

Table 1 presents the estimation results of the probit model (1). City centre and outer city centre locations are positively related, while local centres are negatively related with the central areas delimitation based on mobile phone usage. In other words, the aggregated human activity is clustered in city centre and outer city centre locations and not in local centres. Moreover, what is interesting in the below analysis is the differences between working and non-working days. As indicated in columns (1) and (3), coefficients are higher for non-working days especially for city centre locations. This means that the chances that the official city centre locations correspond to the delimitation based on the aggregated human activity measured by mobile phone usage are higher for non-working days. Moreover, the fit of the model is better during non-working days.

Columns (2) and (4) also include the interaction terms with dummy variables indicating the different hours of the day. Apart from the increase in model's fit which is not surprising, we can also observe a significant increase in the outer city centres coefficients. It seems that after addressing the temporal variability of the central locations as reflected in the clustered aggregated human activity, the correspondence between official and the empirical delimitation of the outer city central location increases with only marginal differences being observed for the city central locations.

In a nutshell, the correspondence between the official and the empirical delimitations of central locations is usually higher on non-working. This finding fits well with the outcome of the previous section, which indicated that central locations based on the mobile phone usage, are more concentrated on non-working days and are more dispersed on working ones.

Table 1: Mobile phone usage based central location delimitation against official central areas definitions

Dep. Var.:	(1)	(2)	(3)	(4)
	***LISA$_i$* for working days**		***LISA$_i$* for non-working days**	
citycenter	0.672***	0.599*	1.161***	1.181***
	(0.0738)	(0.323)	(0.0640)	(0.265)
outercitycenter	1.497***	2.144***	1.715***	2.099***
	(0.0549)	(0.173)	(0.0525)	(0.173)
localcenter	-2.432***	-3.564	-2.775***	-3.570
	(0.496)	(3.032)	(0.514)	(3.018)
hourly interactions	NO	YES	NO	YES
constant	-1.990***	-1.958***	-1.969***	-1.950***
	(0.0254)	(0.0257)	(0.0246)	(0.0249)
Observations	19,560	18,611	19,560	18,582
Pseudo R-squared	0.117	0.166	0.151	0.181

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

Finally, in order to better understand the characteristics of the areas where aggregated human activity, as reflected in mobile phone usage, is clustered, we create a new variable:

$$lisa\_sum_i = \sum_{t=0}^{23} lisa_{it} \qquad (2)$$

In plain English, this variable is simple summation of all the $lisa_i$ dummy variables and indicates how many time each GSM cell i is part of LISA high-high cluster. This variable is calculated twice, once for working and once for non-working days. Then, the new variable $lisa\_sum_i$ is regressed against the different land-use types for the city of Amsterdam (CBS 2012): (a) residential areas as depicted by the natural logarithm of the number of inhabitants per postal code[2] (*hab_pc_ln*); rail networks as the share of a GSM zone's area covered by rail network land-use type (*rail*); motorway networks as above (*motorway*); the share of retail land-use type (*retail*); the share of industrial land-use type (*industrial*); the share of business land-use type (*business*); the share of central location (*citycenter*); the share of outer city centre location (*outercitycenter*); and finally the variable *localcenter* illustrates local center locations. This model also controls for the natural logarithm of the area of the GSM cells (*area_ln*).The mathematical formation for this model, which is run separately for working and non-working days is presented below:

$$lisa\_sum_i = b_1 hab\_pc\_ln_i + b_2 rail_i + b_3 motorway_i + b_4 retail_i + b_5 industrial_i + b_6 business_i + b_7 citycenter_i + b_8 outercitycenter_i + b_9 area\_ln_i + a_0 + \varepsilon_\iota \qquad (3)$$

[2] The initial data was provided at a 6-digit post code level (CBS 2012) and then aggregated to the GSM areas.

Table 2 presents the results of model (3). We observe that high-high LISA clusters are concentrated in GSM zones with high resident population on working days, while the opposite effect is observed on non-working days. The impact of commuting is reflected in the high coefficient for railways, as it is positive and significant on working days, but non-significant on non-working ones. In addition, clustered aggregated human activity does not take place on areas with high share of motorways on non-working days, while the same coefficient is non-significant on working days. On the contrary, the coefficient of retail becomes positive and significant during non-working days when people have more free time. The impact of industrial usage on the concentration of LISA high-high clusters is also the expected one as is positive during working days and negative during non-working reflecting the working cycle of that type of activities. GSM cells with high share of business related activities attract clusters of aggregated human activity both during working and non-working days, but, in quantitative terms, the effect of the former is almost double the effect of the latter. Finally, the effect of city and outer city central locations attract clusters of aggregated human activity as reflected in mobile phone usage. The coefficient for city centre location during non-working days is more than double the same coefficient for working days, while it is also significantly increased for outer city centre locations. Moreover, local centres do not attract LISA high-high clusters. Just like the results of model (1) presented in Table 1, the effect of outer city centre locations is higher that the effect of the city centre locations highlighting the importance of such locations in the function of Amsterdam. Finally, the negative sign of the area coefficients depicts the structure of the GSM zones, the size of which is smaller towards the city centre and larger outside Amsterdam in order to accommodate the increased mobile phone usage within the city.

Table 2: Summation of LISA high-high clusters and land use types

Dep. Var.:	**(1)** ***lisa_sum$_i$*** **for working days**	**(2)** ***lisa_sum$_i$*** **for non-working days**
hab_pc_ln	0.0384***	-0.0176***
	(0.00535)	(0.00675)
rail	3.458***	0.955
	(0.467)	(0.589)
motorway	-0.259	-2.789***
	(0.307)	(0.387)
retail	0.307	1.008***
	(0.210)	(0.264)
industrial	0.779***	-1.359***
	(0.146)	(0.184)
business	1.355***	0.708**
	(0.254)	(0.321)
citycenter	1.556***	3.588***

	(0.150)	(0.189)
outercitycenter	4.838***	6.717***
	(0.126)	(0.159)
localcenter	-1.034***	-0.847***
	(0.215)	(0.271)
area_ln	-0.0278	-0.0360
	(0.0222)	(0.0279)
Constant	0.536*	1.162***
	(0.311)	(0.392)
Observations	19,560	19,560
R-squared	0.139	0.162

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

4. Mobile phone usage and land-use types

Building upon the results of the previous model, this section aims to advance this analysis and explore how mobile phone usage extends in time and space. In order to do so, we estimate the empirical model presented below.

$$erl_{it} = B_1 hab\_pc\_ln_i wd_t H_t + B_2 rail_i wd_t H_t + B_3 motorway_i wd_t H_t + B_4 retail_i wd_t H_t + B_5 industrial_i wd_t H_t + B_6 business_i wd_t H_t + B_7 citycenter_i wd_t H_t + B_8 outercitycenter_i wd_t H_t + B_9 WEATHER_t + B_{10} MONTH_t + a_0 + \varepsilon_{it} \quad (4)$$

The left-hand side variable represents the total mobile phone activity in terms of Erlangs in a GSM zone *i* during time *t*. Instead of using the whole dataset with the 815 GSM cells, model (2) is estimated for those 258 GSM which are placed within the A10 ring motorway around Amsterdam. This choice enables us to focus on a more homogeneous core urban area. Regarding the temporal dimension, just like above, our data refer to hourly intervals for the year 2010. Mobile phone activity is regressed against the different land-use types for the city of Amsterdam which were presented in the previous section. The only difference is that the variable $localcitylenter_i$ is excluded as there are none local centres within A10.

Instead of testing the impact of these land-use variables on mobile phone usage in a static way, we are interested here in exploring the temporal variability of such relationships. In order to do so, the variables representing the different land-use types are interacted with two other variables. Variable *H* is an array of dummy variables representing the different hours of the day. These interaction terms will enable to study how different land-use types are related with mobile phone usage during the different times of the day. In addition, in order to distinguish the effect of working and non-working days, a third interaction is introduced. Variable *wd* is a dummy variable which takes the value 1 for working days and 0 for non-working days. The latter category includes weekends and official holidays. In total, each land use type variable interacts with 24 hourly dummies and 1 dummy indicating working days.

On top of the land-use variables, more control variables are included in the model in order to better capture the spatio-temporal relation between mobile phone and usage and land-use types within the city of Amsterdam. Firstly, we introduce weather-related variables. The underlying assumption is that better weather conditions will increase people's mobility and the time they spend outside buildings. The array *WEATHER* includes the relevant variables. A set of dummy variables with the prefix *t* indicates different temperature classes: t_sub0 indicates sub-zero temperatures; *t_0_5* indicates temperatures between zero and 5 degree Celsius; respectively, *t_5_10* indicates temperatures between five and 10; *t_15_20* between fifteen and twenty; and *t_above20* temperatures above twenty degree Celsius. In addition, *r* is a dummy variable which takes the value 1 when rain occurred during the observation period, while *s* indicates snow. The temporal resolution of these variables matches the mobile phone one as the data was collected on an hourly basis (KNMI 2012). However, because of the high spatial resolution of the analysis, these variables appeared to be space-invariant, as temperature, precipitation and snow data for Amsterdam are only collected from one weather station which covers all the study areas and is located in Schiphol airport.

Secondly, *MONTH* is an array representing dummy variables for the different months. This captures the seasonality of our mobile phone communications. For instance, during summer months more mobility is expected and therefore, mobile phone usage is likely to be higher during these months. Finally, the variable *area_ln* controls for the area of the GSM zone and is expressed as a natural logarithm (m^2).

Because of the triple interaction terms, in total this model includes 402 variables: 8 land-use variables * 2 (working and non-working days) * 24 (hours of the day) + 7 weather variables + 10 dummy variables for the months[3] + 1 variable reflecting the natural logarithm of the GSM cell area. For presentation reasons, the overall regression table is placed in the Annex, while the significant coefficients of the interaction terms are presented in Figure 8.

In total, Figure 8 decomposes the heartbeat of Amsterdam. Starting with Figure 8a, we see the temporal variation of mobile phone usage within residential areas. The variable *hab_pc_ln* represents the official residential population in each GSM cell. Mobile phone usage is higher during working days early in the morning (6am-9am) reflecting the morning rush of working days. After 9am and until 8pm, the mobile phone usage is higher on non-working days for residential areas. This is not surprising, as it reflects the more relaxed daily pattern of non-working days.

[3] The data only includes mobile phone usage for eleven months for 2010 and one month is excluded due to co-linearity.

However, in total the elasticity of residential areas is rather low as it varies between -0.002 and 0.112 and, in any case, is the lowest among the different land-use type variables included in this model.

Not surprisingly, the highest sensitivities are observed for the transport related variables. Figure 8b and 8c indicate how mobile phone usage varies at an hourly basis on working and non-working areas in rail and motorway land-use types. The pattern is similar for both land-use types, both in qualitative and quantitative terms. Between 6am-10am for rail networks and 6am-8am for motorways mobile phone usage increases dramatically and reaches the first peak of the day. Then, mobile phone usage reaches a ceiling and increases again to reach the highest peak of the working days between 4-5pm. Then, mobile phone usage drops continuously until night with a small plateau between 8-9pm. Mobile phone usage is only higher on non-working days after midnight and until 5am. In quantitative terms, motorway land-use types are related to higher mobile phone usage than railways at peak times (5.718 and 4.486 respectively). On the other hand, lower (negative) coefficients are related to motorways during night time than with railways. The latter might also be related to railway stations (such as Amsterdam Central Station) which always attract population. Regarding non-working days, mobile phone traffic follows a similar pattern with working days, but with substantially lower coefficients which depict considerably lower phone activity.

The next variables studied here are industrial and business land-use activity types in Figure 8d and 8e. Both of these land-use types reflect similar patterns regarding mobile phone usage. On working days positive coefficients, which are related with positive impact on mobile phone activity, which occur between 6am-10pm (7am for business areas). Then mobile phone activity peaks between 9am-3pm for industrial and 9am-5pm for business areas. Although the latter has a wider window of peak traffic, the former has a slightly higher peak. Before 6am (industrial) and 7am (business), the coefficients are negative indicating very limited mobile phone activity in these areas. However, it is only at night time when working days' coefficients are lower than non-working ones. During day times, non-working day patterns are similar to those on working ones, but in quantitative terms mobile phone activity is much lower. At peak time (10am), one per cent increase in business related land-use cover in a GSM cell, will result in 280 per cent increase in mobile phone activity measured in Erlangs. However, the increase will only reach 84.8 per cent for a non-working day.

The next three land-use variables appear to have a similar impact on mobile phone usage, as can be seen from Figures 6f, 6g and 6h. These are locations related to retail activities, city and outer city center functions. Main characteristic of these three variables is the rather small difference between working and non-working day coefficients, with the former being higher than the latter after 5am or 6am. Regarding peak times, retail and local centers have their peak between 4pm-

5pm, at the end of the working day. However, although mobile phone activity drops after 5pm for retail areas, it remains rather high for local centres even until 8pm, indicating post-work activity at a neighbourhood level. On the other hand, city centre locations have a stable peak between 10am-5pm, which gradually decreases after that time. Finally, another important element of retail and city centre locations is that coefficients remain positive and relatively high (at least for non-working days) between midnight and 3am, reflecting night life leisure activities.

Regarding the other control variables of the model (see Appendix for the coefficients), temperature has a rather linear effect on aggregated human activity as depicted by mobile phone usage. Dummies indicating temperatures below 10 degrees Celsius have a negative impact on the use of mobile phone usage, while for dummies depicting temperatures above 15 degrees the impact is positive. In quantitative terms, temperature has the highest effect for the sub-zero temperature dummy (-0.321) followed by the effect of temperatures above 20 degrees (0.186). The effect of temperature is not surprising, as hot weather can be related with higher personal mobility (e.g. leisure trips) and therefore higher mobile phone usage (Fridstrøm 1999; Koetse and Rietveld 2009). After controlling for temperature, the effect of the different month dummies indicates the impact of temporal factors not related to weather conditions. Such factors might be related with school cycles and summer holidays as illustrated by the fact that the lowest impact is observed for months July and August (-0.267 and -0.277).

In total, the above analysis provides a statistical representation of the heart-beat of Amsterdam. Mobile phone usage varies across space and time. While residential areas represent the lowest end of the spectrum, transport related land-use types are related with the highest mobile phone usage. The former could be related with the increased use of land line telephony and other communications means such as Voice over IP in residential areas instead of mobile phones. The latter highlights the impact of mobile phone telephony in urban places, as this trend has converted transport hubs and corridors from anchor points of the daily commuting patterns to telecommunication portals. Regarding the other land-use types included in the model, the gap between working and non-working days becomes evident in industrial and business locations, while retail and central areas have similar patterns. Finally, the difference between central and outer-city central locations is interesting, with the latter lagging behind the former by a coefficient difference of 0.5 during working days.

5. Conclusions

This study has demonstrated the unprecedented research potential of mobile phone data in mapping out the space-time dynamics of daily activities in cities. In particular, the popularity and near-to-100 percent penetration of mobile phones has generated a wealth of bottom-up, digitally collected data of high spatio-temporal resolution that lend themselves for advanced applications in urban mobility and land-use management. This paper has provided statistical empirical evidence on how urban mobile phone usage varies across space and time. In addition, it has raised questions on the definition of central locations and how they are related to mobile usage, assuming that mobile phone usage represents human presence.

The approach presented in this study has highlighted the importance of space-time models in post-modern urban studies. The high spatio-temporal resolution of the mobile phone data provides an in depth understanding of how land-use types are related with urban dynamics. This understanding moves beyond the Cartesian perception of urban spaces and instead provides insightful narratives of urban places. From a spatial perspective, transport related land-use types were always associated with commuting and mobility patterns. However, the high granularity of the mobile phone data reveals the different human perceptions of such places, according to which transport related land-use types promote the use of mobile phone telephone: from a phone call to indicate the end of the working day to other type of social or even professional calls.

The analysis reveals the usability of mobile phone data to quantify fast urban dynamics. This knowledge can feed urban authorities and planning agencies with precious knowledge about population concentration and its dynamics. Such knowledge can be directly utilised in a planning framework as a supporting framework for urban policies related with issues such as public transportation and land use design. Moreover, such analysis can provide planning authorities with valuable input regarding fast urban dynamics. For instance, the popularity of urban areas might change much faster than census circles and therefore such changes cannot be depicted by official statistics. The use of data from mobile phone operators as well as other types of big data in urban modelling can provide urban authorities with the necessary signals in order to address such rapid changes.

In regards to future research, the high spatial and temporal resolution of these data call for a more in depth modelling of the dynamics of central locations within cities. As this paper highlighted, a static approach of the core areas of human activity prevents us from fully understanding urban structure and cities because of their – hidden – dynamic nature. We are now able to adopt a dynamic perspective in urban analysis, because of the abundance of relevant data and also because of methodological advances, in order to understand cities and urban systems in a way that we were not able before.

References

ADUML (1991) Plan de Developpement Urbain de la Communication. Agence de Developpement d'Urbanisme de la Metropole Lilloise, 2 place du Concert, F 59043, Lille, France

Ahas R, Mark Ü (2005) Location based services—new challenges for planning and public administration? Futures 37(6):547-561

Anselin L (1995) Local indicators of spatial association – LISA. Geographical Analysis 27(2):93-115

Arribas-Bel D (2014) Accidental, open and everywhere: Emerging data sources for the understanding of cities. Applied Geography 49:45-53

Batty M (1997a) The computable city. International Planning Studies 2(2):155-173

Batty M (1997b) Virtual Geography. Futures 29(4/5):337-352

Batty M (2010) The pulse of the city. Environment and Planning B: Planning and Design 37(4):575-577

Becker RA, Caceres R, Hanson K, Loh JM, Urbanek S, Varshavsky A, Volinsky C (2011) A Tale of One City: Using Cellular Network Data for Urban Planning. Pervasive Computing 4:18-26

Bisker S, Gross M, Carter D, Paulos E, Kuznetsov S Personal, public: Using DIY to explore citizen-led efforts in urban computing. In: CHI 2010 Proceedings, Atlanta, Georgia, April 10–15 2010.

Caceres N, Wideberg J, Benitez F (2008) Review of traffic data estimations extracted from cellular networks. IET Intelligent Transport Systems 2(3):179-192

Calabrese F, Di Lorenzo G, Ratti C Human mobility prediction based on individual and collective geographical preferences. In: Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on, 2010. IEEE, pp 312-317

Calabrese F, Diao M, Di Lorenzo G, Ferreira Jr J, Ratti C (2013) Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. Transportation research part C: emerging technologies 26:301-313

Calabrese F, Ferrari L, Blondel VD (2014) Urban Sensing Using Mobile Phone Network Data: A Survey of Research. ACM Computing Surveys (CSUR) 47(2):25

Calabrese F, Smoreda Z, Blondel VD, Ratti C (2011) Interplay between telecommunications and face-to-face interactions: A study using mobile phone data. PloS ONE 6(7):e20814

Candia J, Gonzalez MC, Wang P, Schoenharl T, Madey G, Barabási A-L (2008) Uncovering individual and collective human dynamics from mobile phone records. Journal of Physics A: Mathematical and Theoretical 41(22):224015

Castells M (1996) The Rise of the Network Society. Blackwell, Oxford

CBS (2012) Land Use dataset. Centraal Bureau voor de Statistiek (Statistics Netherlands), Den Haag

Evans-Cowley J (2010) Planning in the Real-Time City: The Future of Mobile Technology. Journal of Planning Literature 25(2):136-149

Fridstrøm L (1999) Econometric models of road use, accidents, and road investment decisions. vol Volume II. Institute of Transport Economics, Oslo

Graham S (1997) Cities in the real-time age: the paradigm challenge of telecommunications to the conception and planning of urban space. Environment & Planning A 29(1):105-127

Graham S, Healey P (1997) Relational Concepts of Space and Place: Issues for Planning Theory and Practice. European Planning Studies 7(5):623-646

Graham S, Marvin S (1996) Telecommunications and the city. Routledge, London and New York

Graham S, Marvin S (2001) Splintering urbanism. Routledge, London, New York

Jacobs-Crisioni C, Rietveld P, Koomen E, Tranos E (2014) Evaluating the impact of land-use density and mix on spatiotemporal urban activity patterns: an exploratory study using mobile phone data. Environment and Planning A 46(11):2769-2785

KNMI (2012) Daily weather data of the Netherlands. Royal Netherlands Meteorological Institute, De Bilt

Koetse MJ, Rietveld P (2009) The impact of climate change and weather on transport: An overview of empirical findings. Transportation Research Part D: Transport and Environment 14(3):205–221

Lambiotte R, Blondel VD, Kerchove Cd, Huens E, Prieur C, Smoreda Z, Dooren PV (2008) Geographical dispersal of mobile communication networks. Physica A 387: 5317–5532

Licoppe C, Diminescu D, Smoreda Z, Ziemlicki C (2008) Using mobile phone geolocalisation for 'socio-geographical' analysis of co-ordination, urban mobilities, and social integration patterns. Tijdschrift voor Economische en Sociale Geografie 99(5):584-601

Louail T et al. (2014) From mobile phone data to the spatial structure of cities. arXiv preprint arXiv:14014540

Massey D (1992) Politics and space/time. New Left Review 196:65-84

Miller HJ (2010) The data avalanche is here. Shouldn't we be digging? Journal of Regional Science 50(1):181-201

NDW (2012) National Data Warehouse for Traffic Estimation. http://www.ndw.nu/pagina/en/78/database/79/real-time_traffic_data/. Accessed 28 December 2014

Pei T, Sobolevsky S, Ratti C, Shaw S-L, Li T, Zhou C (2014) A new insight into land use classification based on aggregated mobile phone data. International Journal of Geographical Information Science(ahead-of-print):1-20

Ratti C, Pulselli RM, Williams S, Frenchman D (2006) Mobile Landscapes: using location data from cell phones for urban analysis. Environment & Planning B 33(5):727-748

Reades J, Calabrese F, Ratti C (2009) Eigenplaces: Analyzing cities using the space-time structure of the mobile phone network. Environment and Planning B 36(5):824-836

Sassen S (1991) The global city. New York, London, Tokyo. Princeton University Press, Princeton, New Jersey

Sevtsuk A, Ratti C (2010) Does Urban Mobility Have a Daily Routine? Learning from the Aggregate Data of Mobile Networks. Journal of Urban Technology 17(1):41-60

Soja E (1989) Postmodern Geographies. Verso, London

Song C, Koren T, Wang P, Barabási A-L (2010a) Modelling the scaling properties of human mobility. Nature Physics 6:818-823

Song C, Qu Z, Blumm N, Barabási A-L (2010b) Limits of Predictability in Human Mobility. SCIENCE 327:1018-1021

Steenbruggen J, Tranos E, Nijkamp P (2014) Data from mobile phone operators: a tool for smarter cities? Telecommunications Policy in press

Thrift N (1996) Inhuman geographies: landscapes of speed, light and power. In: Thrift N (ed) Spatial Formation. Sage, London, pp 256-311

Toole JL, Ulm M, Gonzalez MC, Bauer D Inferring land use from mobile phone activity. In: UrbComp '12, Beijing, China, 2012. pp 1-8

Townsend AM (2000) Life in the Real-Time City: Mobile Telephones and Urban Metabolism. Journal of Urban Technology 7(2):85-104

Tranos E (2013) The Geography of the Internet: Cities, Regions and the Internet Infrastructure in Europe. New Horizons in Regional Science. Edward Elgar, Cheltenham, UK

Tranos E, Nijkamp P (2014) Urban and regional analysis and the digital revolution: challenges and opportunities. In: Derruder B, Conventz S, Thierstein A, Witlox F (eds) Hub cities in the knowledge economy. Ashgate, Surrey, pp 145-162

Table 1: Central locations and mobile phone activity

	(1)	(2)	(3)	(4)
	working days		non-working days	
citycenter	0.672***	0.599*	1.161***	1.181***
	(0.0738)	(0.323)	(0.0640)	(0.265)
outercitycenter	1.497***	2.144***	1.715***	2.099***
	(0.0549)	(0.173)	(0.0525)	(0.173)
localcenter	- 2.432***	-3.564	- 2.775***	-3.570
	(0.496)	(3.032)	(0.514)	(3.018)
hourly interactions	NO	YES	NO	YES
constant	- 1.990***	- 1.958***	- 1.969***	- 1.950***
	(0.0254)	(0.0257)	(0.0246)	(0.0249)
Observations	19,560	18,611	19,560	18,582
Pseudo R-squared	0.117	0.166	0.151	0.181

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

Table 2: Summation of LISA high-high clusters and land use types

	(1)	(2)
Dep. Var.:	lisa_sum for working days	lisa_sum for non-working days
hab_pc_ln	0.0384***	-0.0176***
	(0.00535)	(0.00675)
rail	3.458***	0.955
	(0.467)	(0.589)
motorway	-0.259	-2.789***
	(0.307)	(0.387)
retail	0.307	1.008***
	(0.210)	(0.264)
industrial	0.779***	-1.359***
	(0.146)	(0.184)
business	1.355***	0.708**
	(0.254)	(0.321)
citycenter	1.556***	3.588***
	(0.150)	(0.189)
outercitycenter	4.838***	6.717***
	(0.126)	(0.159)
localcenter	-1.034***	-0.847***
	(0.215)	(0.271)
area_ln	-0.0278	-0.0360
	(0.0222)	(0.0279)
Constant	0.536*	1.162***
	(0.311)	(0.392)
Observations	19,560	19,560
R-squared	0.139	0.162

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

Figure 1: GSM cells rank plot based on average Erlangs for Amsterdam

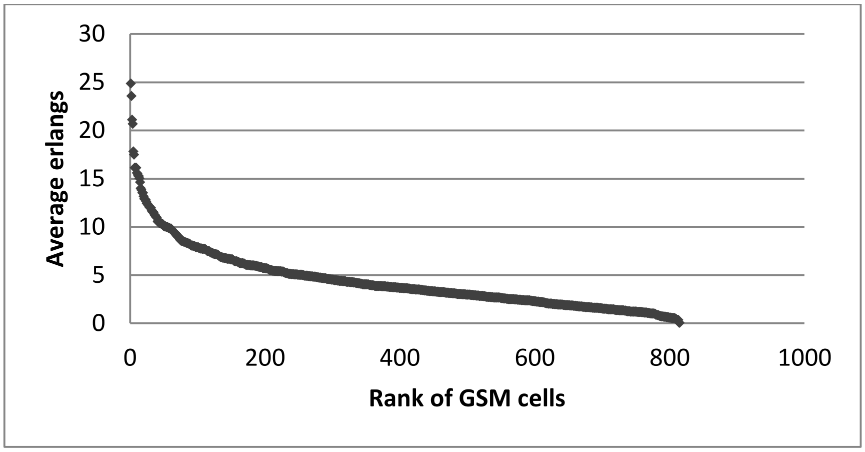


Figure 2: The heartbeat of Amsterdam: the temporal variability of average Erlangs on an hourly basis

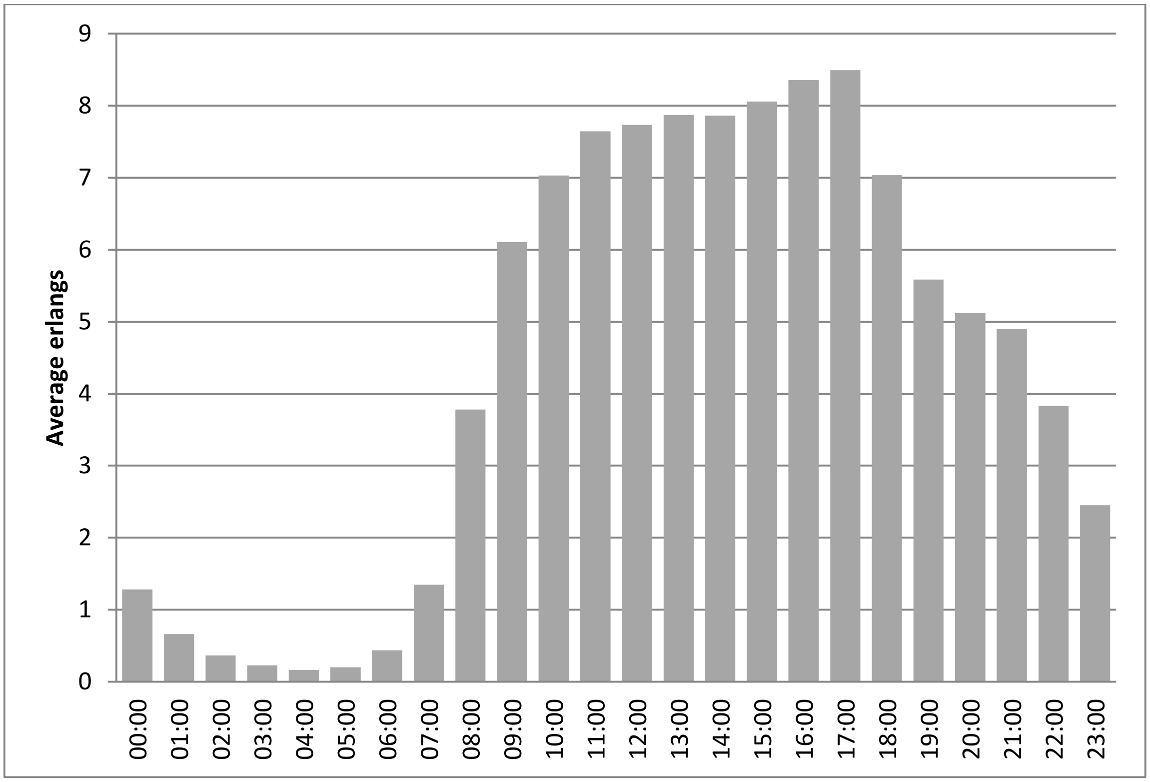
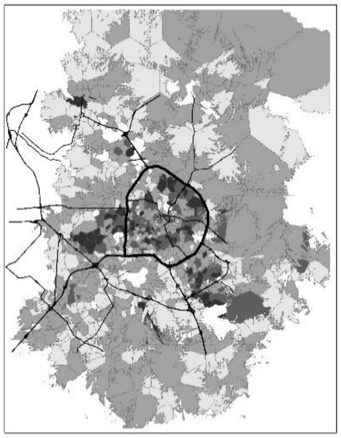
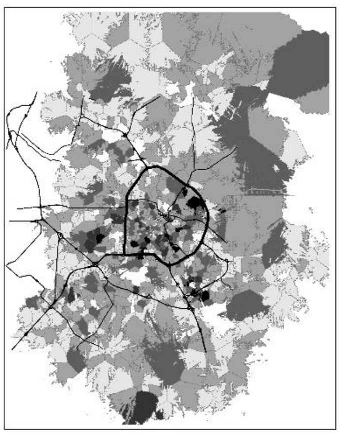
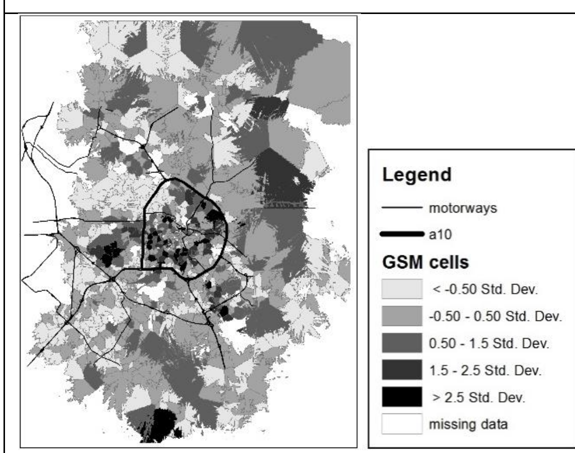
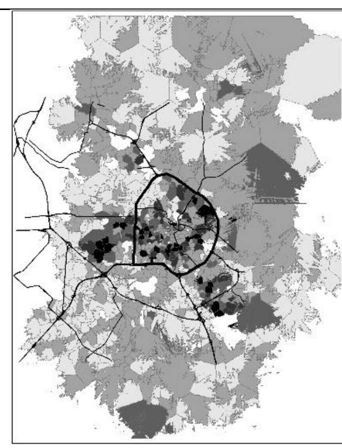
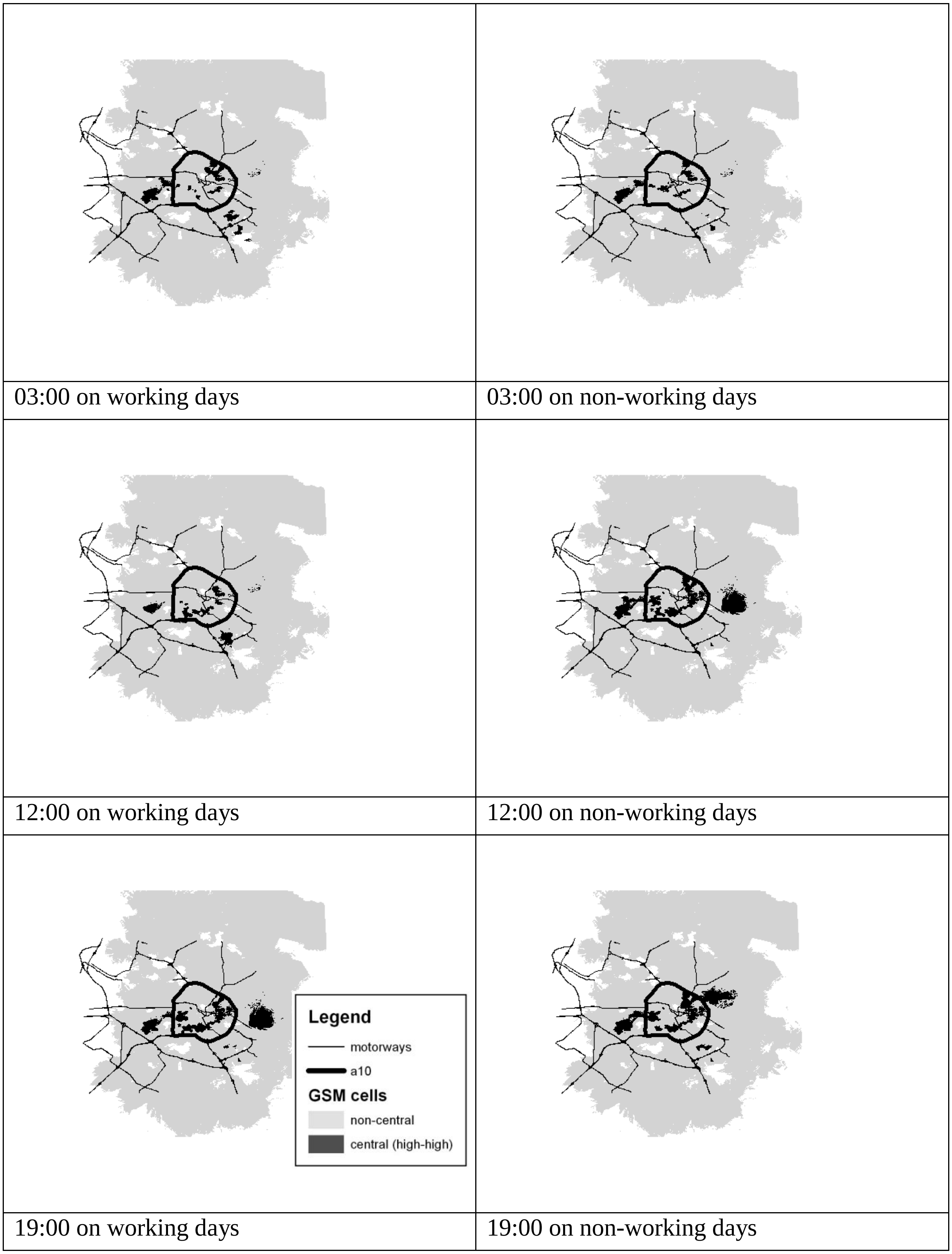


Figure 3: Mobile phone usage during the day in Amsterdam

	
03:00 (Gini: 0.577)	09:00 (Gini: 0.350)
	
12:00 (Gini: 0.370)	17:00 (Gini: 0.368)
	
19:00 (Gini: 0.431)	23:00 (Gini: 0.534)

Note: Mobile phone usage measured as Erlangs per hour at the level of the cell

Figure 4: Central GSM zones – LISA high-high clusters



Note: Mobile phone usage measured as Erlangs per hour at the level of the cell; LISA p<0.01

Figure 5: Spatial median of LISA high-high clusters at an hourly level

Figure 5a: working days	Figure 5b: non-working days

Note: Bold line represent the A10 motorway and the numbers the different times of the spatial medians of the LISA high-high clusters

Figure 6: Mean distances in meters of the LISA high-high clusters from the Amsterdam Central Station at an hourly basis

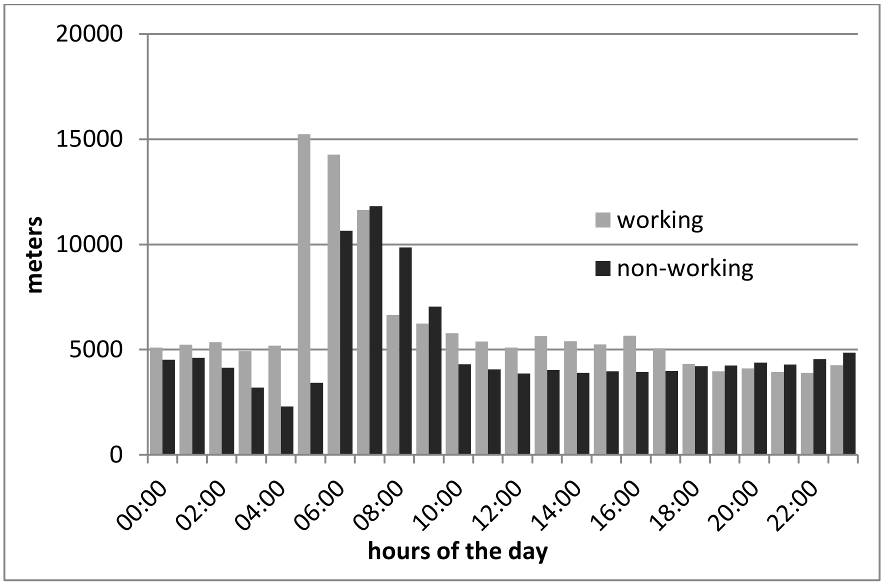


Figure 7: Amsterdam's central locations according to the official land use delimitation

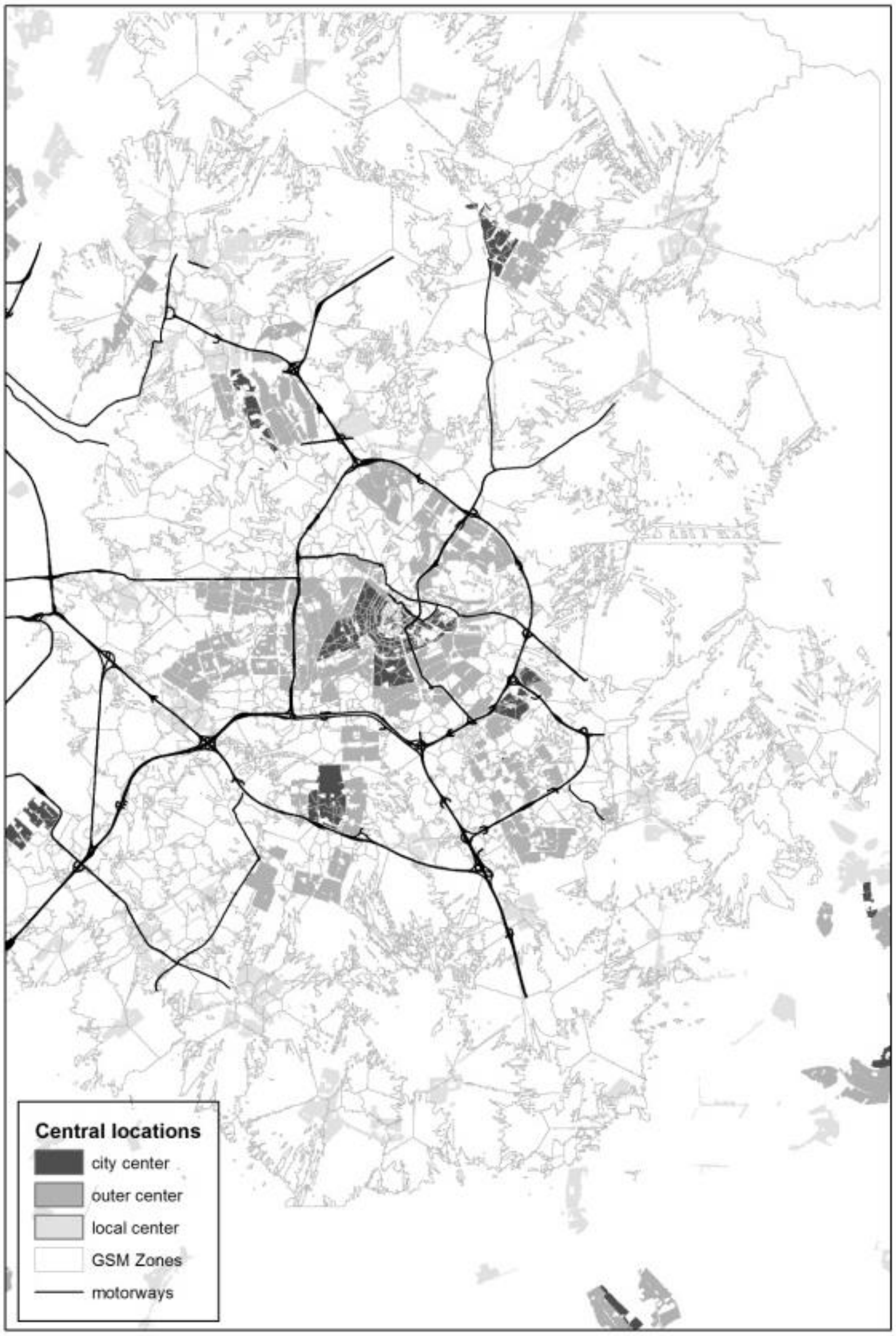
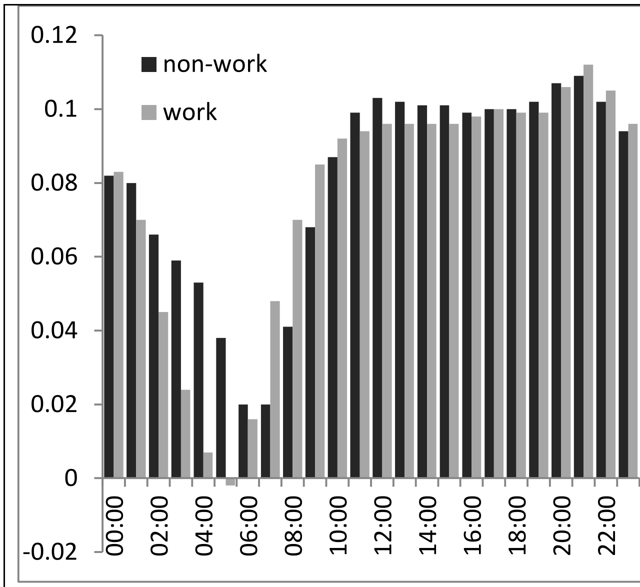
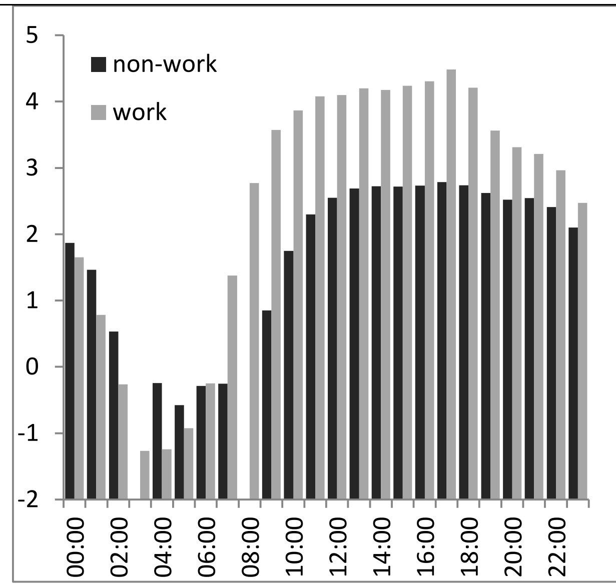


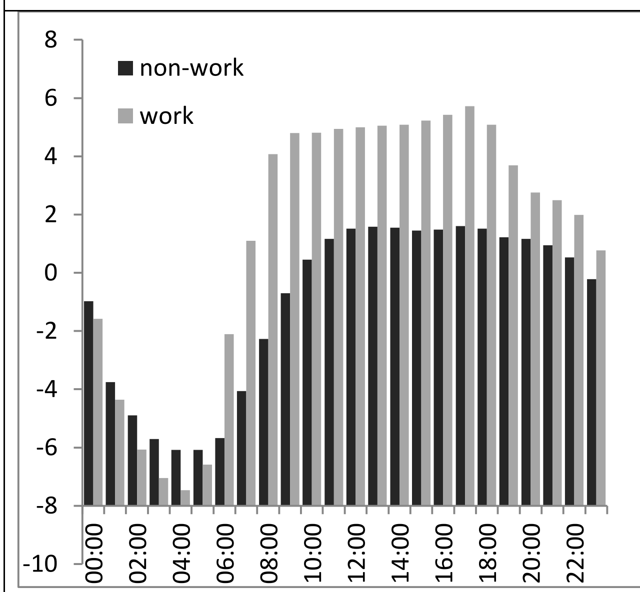
Figure 8: Model (4) coefficients for different land use types at an hourly basis (B_1-B_8)



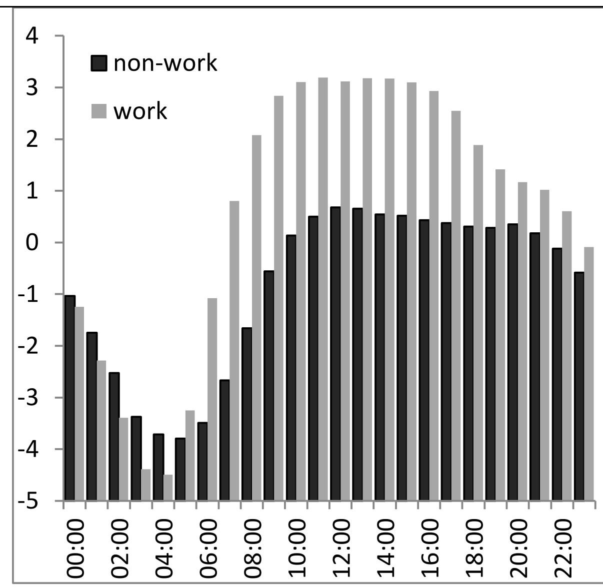
(a) Residential



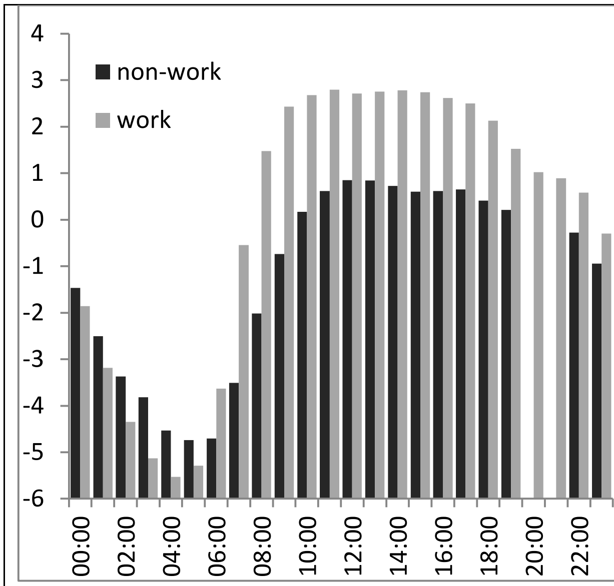
(b) Rail



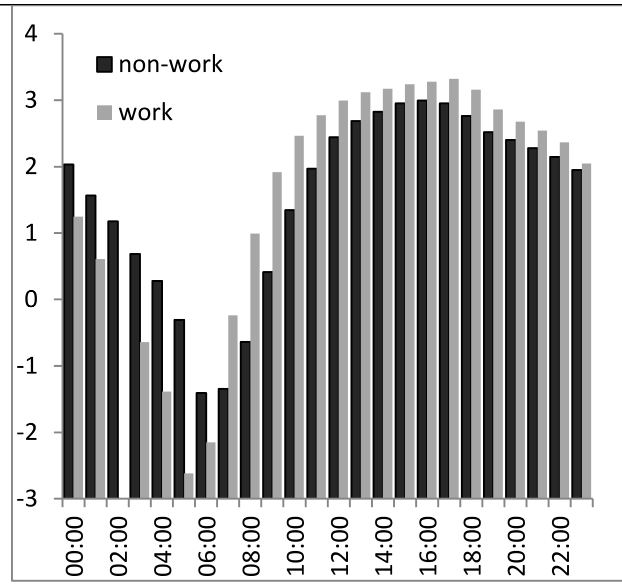
(c) Motorway



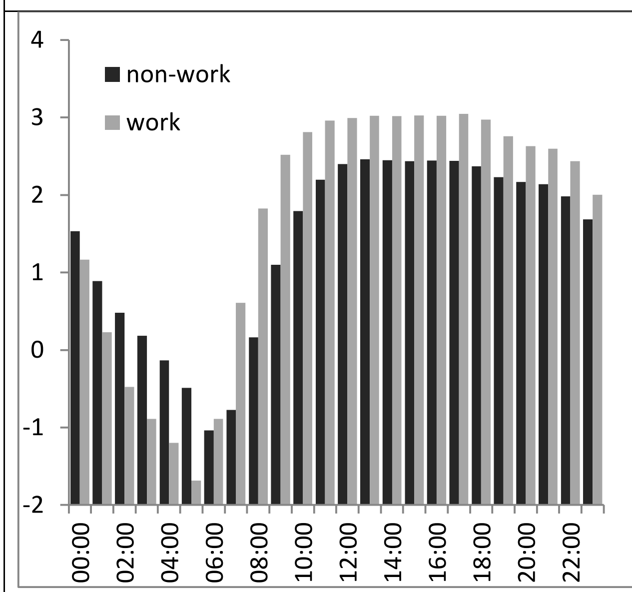
(d) Industrial



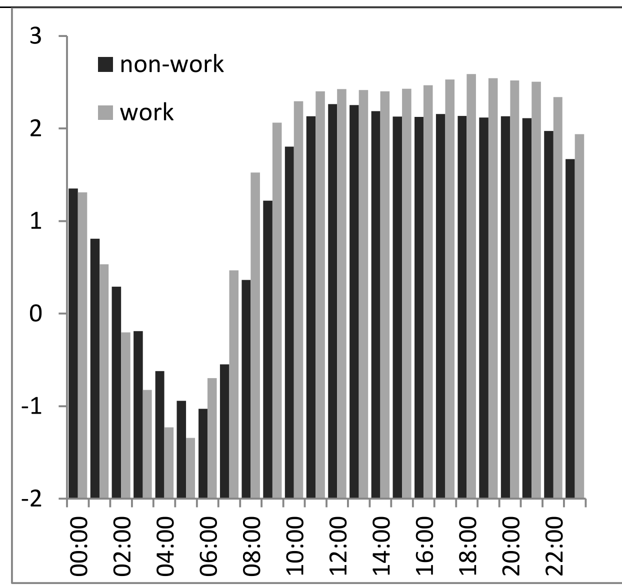
(e) Business



(f) Retail



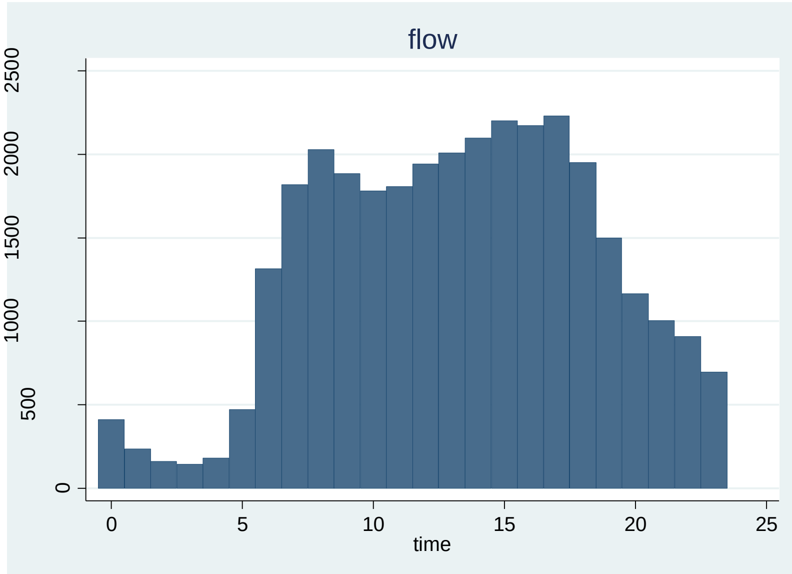
(g) City center



(h) Outer city center

Note: vertical axis represent b coefficients, horizontal the different times of the days; the gap in the lines replresent non-significant coefficients

Appendix 1: Average car flow in Amsterdam motorways per hour in 2010



Source: (NDW 2012)

Appendix 2: Estimation of (4) based on OLS

time	land use	non-working days	working days	land use	non-working days	working days
00		0.082***	0.083***		-1.037***	-1.246***
		(40.24)	(60.56)		(-20.39)	(36.44)
01		0.080***	0.070***		-1.746***	-2.282***
		(39.35)	(50.78)		(-34.32)	(66.35)
02		0.066***	0.045***		-2.523***	-3.394***
		(32.42)	(32.87)		(-49.33)	(99.17)
03		0.059***	0.024***		-3.376***	-4.388***
		(28.75)	(17.81)		(-66.37)	(128.27)
04		0.053***	0.007***		-3.716***	-4.491***
		(25.99)	(4.78)		(-73.06)	(131.32)
05		0.038***	-0.002*		-3.794***	-3.248***
		(18.58)	(-1.75)		(-74.6)	(95)
06		0.020***	0.016***		-3.490***	-1.079***
		(9.97)	(11.52)		(-68.62)	(31.56)
07		0.020***	0.048***		-2.671***	0.803***
		(9.88)	(35.15)		(-52.52)	(23.48)
08		0.041***	0.070***		-1.662***	2.078***
		(19.89)	(51.05)		(-32.48)	(60.68)
09		0.068***	0.085***		-0.558***	2.841***
		(33.1)	(61.99)		(-10.91)	(83.1)
10	**habitants (ln)**	0.087***	0.092***	**industrial (share)**	0.134***	3.103***
		(42.69)	(67.14)		(2.63)	(90.74)
11		0.099***	0.094***		0.501***	3.191***
		(48.14)	(69.03)		(9.8)	(93.3)
12		0.103***	0.096***		0.677***	3.120***
		(50.25)	(70.17)		(13.25)	(91.23)
13		0.102***	0.096***		0.652***	3.181***
		(50.06)	(70.25)		(12.75)	(93.03)
14		0.101***	0.096***		0.541***	3.173***
		(49.28)	(70.45)		(10.58)	(92.98)
15		0.101***	0.096***		0.518***	3.096***
		(49.18)	(70.26)		(10.13)	(90.57)
16		0.099***	0.098***		0.432***	2.929***
		(48.57)	(72.09)		(8.44)	(86.26)
17		0.100***	0.100***		0.379***	2.549***
		(48.93)	(73.48)		(7.42)	(75.07)
18		0.100***	0.099***		0.307***	1.887***
		(49)	(73.07)		(6.01)	(55.59)
19		0.102***	0.099***		0.282***	1.415***
		(49.86)	(73.02)		(5.51)	(41.59)
20		0.107***	0.106***		0.354***	1.167***

		(52.15)	(78.18)		(6.88)	(34.3)
21		0.109***	0.112***		0.178***	1.021***
		(53.46)	(81.85)		(3.49)	(29.93)
22		0.102***	0.105***		-0.121**	0.608***
		(49.89)	(77.18)		(-2.37)	(17.79)
23		0.094***	0.096***		-0.583***	-0.088**
		(45.7)	(70.41)		(-11.4)	(2.57)
00		1.869***	1.653***		-1.465***	-1.860***
		(14.04)	(18.54)		(-26.08)	(49.33)
01		1.465***	0.785***		-2.502***	-3.183***
		(11.01)	(8.77)		(-44.41)	(83.86)
02		0.534***	-0.261***		-3.372***	-4.349***
		(3.99)	(-2.93)		(-59.71)	(115.12)
03		-0.073	-1.269***		-3.815***	-5.132***
		(-0.55)	(-14.24)		(-67.91)	(135.84)
04		-0.242*	-1.242***		-4.529***	-5.526***
		(-1.82)	(-13.94)		(-80.61)	(146.2)
05		-0.576***	-0.922***		-4.737***	-5.289***
		(-4.33)	(-10.35)		(-84.33)	(139.53)
06		-0.287**	-0.249***		-4.706***	-3.633***
		(-2.15)	(-2.79)		(-83.59)	(96.34)
07		-0.253*	1.378***		-3.508***	-0.546***
		(-1.9)	(15.44)		(-62.45)	(14.47)
08		0.092	2.773***		-2.015***	1.480***
		(0.68)	(31.09)		(-35.56)	(39.17)
09	**railways (share)**	0.850***	3.574***	**business (share)**	-0.739***	2.431***
		(6.35)	(40.11)		(-13.09)	(64.46)
10		1.747***	3.866***		0.167***	2.681***
		(13.06)	(43.43)		(2.95)	(71.13)
11		2.297***	4.077***		0.620***	2.795***
		(17.16)	(45.76)		(10.97)	(74.11)
12		2.550***	4.097***		0.848***	2.712***
		(19.06)	(45.98)		(15.02)	(71.88)
13		2.689***	4.202***		0.847***	2.758***
		(20.1)	(47.19)		(15)	(73.18)
14		2.725***	4.178***		0.724***	2.785***
		(20.36)	(47.03)		(12.81)	(73.98)
15		2.719***	4.239***		0.606***	2.741***
		(20.32)	(47.61)		(10.74)	(72.75)
16		2.732***	4.307***		0.615***	2.616***
		(20.42)	(48.69)		(10.9)	(69.86)
17		2.786***	4.486***		0.655***	2.501***
		(20.82)	(50.71)		(11.59)	(66.77)
18		2.739***	4.211***		0.408***	2.128***

	motorways (share)		city center (share)	
	(20.47)	(47.6)	(7.23)	(56.83)
19	2.623***	3.562***	0.210***	1.522***
	(19.6)	(40.17)	(3.72)	(40.53)
20	2.519***	3.314***	-0.004	1.026***
	(18.73)	(37.38)	(-0.06)	(27.33)
21	2.547***	3.213***	0.042	0.893***
	(19.04)	(36.13)	(0.74)	(23.7)
22	2.409***	2.966***	-0.276***	0.583***
	(18)	(33.35)	(-4.89)	(15.5)
23	2.103***	2.474***	-0.941***	-0.300***
	(15.72)	(27.78)	(-16.66)	(7.98)
00	-0.974***	-1.584***	1.533***	1.166***
	(-8.48)	(-20.59)	(52.2)	(58.84)
01	-3.754***	-4.354***	0.888***	0.231***
	(-32.68)	(-56.19)	(30.21)	(11.57)
02	-4.893***	-6.067***	0.479***	-0.477***
	(-42.37)	(-78.71)	(16.23)	(24.04)
03	-5.713***	-7.045***	0.184***	-0.890***
	(-49.73)	(-91.43)	(6.28)	(44.91)
04	-6.086***	-7.468***	-0.134***	-1.200***
	(-52.99)	(-96.96)	(4.55)	(60.51)
05	-6.078***	-6.590***	-0.490***	-1.683***
	(-52.91)	(-85.56)	(16.68)	(84.87)
06	-5.678***	-2.110***	-1.039***	-0.890***
	(-49.43)	(-27.4)	(35.39)	(44.92)
07	-4.058***	1.100***	-0.773***	0.607***
	(-35.33)	(14.27)	(26.33)	(30.58)
08	-2.276***	4.073***	0.163***	1.825***
	(-19.69)	(52.82)	(5.52)	(91.98)
09	-0.707***	4.796***	1.099***	2.518***
	(-6.12)	(62.28)	(37.22)	(127.03)
10	0.453***	4.814***	1.794***	2.810***
	(3.92)	(62.53)	(60.76)	(141.79)
11	1.162***	4.938***	2.196***	2.958***
	(10.06)	(64.11)	(74.34)	(149.16)
12	1.515***	4.991***	2.397***	2.992***
	(13.12)	(64.8)	(81.15)	(150.91)
13	1.580***	5.048***	2.459***	3.021***
	(13.68)	(65.56)	(83.27)	(152.5)
14	1.543***	5.086***	2.450***	3.019***
	(13.36)	(66.18)	(82.97)	(152.63)
15	1.450***	5.231***	2.437***	3.024***
	(12.56)	(67.93)	(82.53)	(152.65)

16		1.479***	5.420***		2.445***	3.022***
		(12.8)	(70.88)		(82.8)	(153.51)
17		1.607***	5.718***		2.440***	3.047***
		(13.92)	(74.77)		(82.62)	(154.76)
18		1.516***	5.084***		2.369***	2.974***
		(13.13)	(66.48)		(80.24)	(151.06)
19		1.221***	3.684***		2.229***	2.759***
		(10.58)	(48.07)		(75.48)	(139.83)
20		1.162***	2.754***		2.166***	2.632***
		(10.01)	(35.93)		(72.97)	(133.4)
21		0.941***	2.495***		2.138***	2.599***
		(8.15)	(32.48)		(72.41)	(131.32)
22		0.531***	1.986***		1.983***	2.436***
		(4.6)	(25.83)		(67.16)	(123.14)
23		-0.224*	0.765***		1.684***	2.004***
		(-1.94)	(9.94)		(57.02)	(101.21)
00		2.031***	1.249***		1.351***	1.310***
		(60.65)	(54.87)		(43.52)	(62.8)
01		1.566***	0.605***		0.809***	0.533***
		(46.76)	(26.47)		(26.05)	(25.39)
02		1.173***	-0.021		0.291***	-0.202***
		(34.85)	(-0.94)		(9.33)	(9.68)
03		0.686***	-0.642***		-0.188***	-0.823***
		(20.49)	(-28.27)		(6.05)	(39.44)
04		0.279***	-1.386***		-0.620***	-1.230***
		(8.32)	(-61.01)		(19.97)	(58.95)
05		-0.306***	-2.617***		-0.942***	-1.342***
		(-9.13)	(-115.19)		(30.34)	(64.33)
06	**retail (share)**	-1.408***	-2.153***	**outer city center (share)**	-1.029***	-0.696***
		(-42.03)	(-94.76)		(33.16)	(33.39)
07		-1.346***	-0.238***		-0.549***	0.467***
		(-40.21)	(-10.48)		(17.69)	(22.36)
08		-0.639***	0.990***		0.363***	1.524***
		(-18.91)	(43.49)		(11.63)	(72.94)
09		0.410***	1.918***		1.222***	2.064***
		(12.17)	(84.39)		(39.15)	(98.93)
10		1.341***	2.464***		1.805***	2.294***
		(39.82)	(108.45)		(57.87)	(109.99)
11		1.968***	2.773***		2.131***	2.403***
		(58.45)	(122.02)		(68.29)	(115.16)
12		2.441***	2.994***		2.263***	2.427***
		(72.51)	(131.68)		(72.52)	(116.29)
13		2.688***	3.120***		2.252***	2.415***

	(79.82)	(137.5)	(72.17)	(115.81)
14	2.826***	3.174***	2.188***	2.403***
	(83.94)	(139.94)	(70.14)	(115.42)
15	2.949***	3.238***	2.129***	2.428***
	(87.61)	(142.65)	(68.25)	(116.43)
16	2.994***	3.279***	2.127***	2.469***
	(88.93)	(145.27)	(68.17)	(119.19)
17	2.953***	3.320***	2.155***	2.531***
	(87.73)	(147.09)	(69.09)	(122.17)
18	2.762***	3.157***	2.135***	2.590***
	(82.04)	(139.87)	(68.45)	(125.05)
19	2.519***	2.857***	2.119***	2.543***
	(74.83)	(126.31)	(67.91)	(122.48)
20	2.401***	2.677***	2.133***	2.518***
	(70.93)	(118.32)	(68)	(121.28)
21	2.279***	2.540***	2.113***	2.506***
	(67.7)	(111.8)	(67.74)	(120.38)
22	2.148***	2.363***	1.974***	2.341***
	(63.81)	(104.19)	(63.26)	(112.42)
23	1.950***	2.046***	1.671***	1.938***
	(57.92)	(90.05)	(53.57)	(92.99)

t_sub0	-0.321***	March	0.158***
	(-58.7)		-36.14
t_0_5	-0.185***	April	0.151***
	(-47.91)		-34.23
t_5_10	-0.132***	May	0.081***
	(-49.63)		-18.43
t_15_20	0.079***	June	-0.019***
	(28.21)		-3.87
t_above20	0.186***	July	-0.267***
	(44.03)		-51.22
r	0	August	-0.277***
	(0.06)		-55.55
s	0.037***	September	-0.096***
	(5.48)		-20.84
area_ln	0.648***	October	-0.041***
	(573.58)		-9.4
January	0.284***	November	Omitted
	(45.35)	Constant	-8.586***
February	0.233***		-576.32
	(46.86)	R-squared	0.7
		N	1,874,207

Note: t test in parentheses, variables starting with *t* indicate temperature dummies, *r is* rain, *s* is snow and *area_ln* is the natural logarithm of the area of the GSM cell; months indicate dummies for the different months