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Emmanouil Tranos
John Steenbruggen
*Peter Nijkamp**

Faculty of Economics and Business Administration, VU University Amsterdam.

** Tinbergen Institute, The Netherlands.*

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Emmanouil Tranos, John Steenbruggen and Peter Nijkamp*, Dept. of Spatial Economics, VU University Amsterdam

** Tinbergen Institute, The Netherlands.*

1. Introduction

This contribution discusses the value that data from mobile phone providers can bring into urban analysis. The novel argument used in this chapter is that the pervasiveness of mobile phone telephony has transformed mobile phones from a communications device to a tool for socio-spatial research. Put simply, mobile phone providers can potentially gather relevant data on a very refined spatio-temporal scale for every 85 out of 100 inhabitants in the world (International Telecommunication Union 2012). Such data can include basic information about personal communication patterns, interactions and mobility which can enable researchers to better understand spatial human behavior, the predictability of which is well documented (Song et al. 2010). These advances that have mostly taken place in the complexity science domain, which largely focuses on individual behavioural patterns, can also result in applications in the spatial analysis domain.

The present chapter has, therefore, two aims. Firstly, we critically discuss the existing state of the art of urban analysis based on big data from mobile phone operators. Based on this review, the chapter takes a methodological turn to present some preliminary urban analysis results using data from a mobile phone operator in Amsterdam, The Netherlands. The structure of the chapter is as follows. Section 2 provides a brief review on how data from mobile phone providers has been utilized up to now in the urban analysis literature, while in Section 3 a more critical perspective on how such research is related to urban theory and planning is presented. Some empirical results, which are based on panel data regressions on Amsterdam, are presented in Section 4. The chapter ends with some concluding remarks and ideas for future research.

2. Urban dynamics[1]

The widespread deployment of mobile communications, supported by personal handheld electronics, is having a significant impact on urban life. People are changing their social and working habits because of this new technology (Rheingold 2002). Activities that once required a fixed location and connection can now be achieved with higher flexibility, resulting in the users' ability to act and move more freely. As a consequence, human mobility becomes more complex and volatile. Understanding the dynamics of citizens' daily mobility patterns is essential for the planning and management of urban facilities and

[1] Section 2 and 3 draw from Steenbruggen et al. (forthcoming)

services. Given the long research history in the fields of urban geography and urban modelling, new sources of spatial data such as data from mobile phone operators offer the potential to significantly and structurally improve the analysis and modeling of urban dynamics (Batty 1989; Knox 1994). The combination of new data sources and methods opens new possibilities in modeling urban dynamics. Over the past few years a number of innovative approaches have emerged to satisfy a growing demand for precise, timely and accurate spatio-temporal information, especially on urban dynamics and spatial mechanisms (see Becker et al. 2011). Dynamic spatial urban models enable also the assessment of future growth and planning scenarios (Kaiser et al. 1995; Klostermann 1999). The increased interest in such urban models is driven among other factors, by the availability of new datasets of high spatio-temporal resolution and new geographic information systems for their processing (Clarke et al. 2002).

Innovative ways for assessing urban dynamics in real time with the use of digital data sources have recently been explored. For instance, the concept of pervasive computing depicts the capability to obtain information from the embedded environment to build dynamic and large computational models (Lyytinen and Yoo 2002). Individual based urban dynamics can be monitored and assessed by a variety of geospatial technologies such as Global Positioning System GPS receivers, remote sensing technology (Herold et al. 2003; Blaschke et al. 2011), in-situ sensor networks (Hart and Martinez 2006), social media data (Girardin et al. 2008a, 2008b; Frias-Martinez et al. 2012) and data derived from mobile telephone networks. Since 2005, case studies of several cities have been found to be important means of gaining insight into complex and rapidly changing spatial urban phenomena.

One of the first implementations to monitor urban mobility in order to study locations and intensities of urban activities based on the use of location and traffic data derived from telecom base stations was done by the MIT SENSEable City Lab[2]. The main incentive was the realization that, despite the booming of mobile communications, data from cell phones had scarcely been used and could become a powerful tool for urban analysis (Ratti et al. 2006).

Various different case studies have subsequently been derived based on this work. Urban research using mobile phone data has, for example, taken place in Graz and Milan (Ratti et al. 2007). This novel approach to urban studies was an effort to understand the increasing complexity of human settlements by investigating the human dynamics in these cities and not focusing on their physical shapes. The above study aimed to investigate human dynamics by revealing the locations and intensities of urban activities and to analyze spatial mobility patterns. They used Erlang[3] data with one-hour time intervals to create thermography maps, highlighting the intensity of urban-social activities and their evolution in space and time. This provided a spatio-temperal signature showing the intensity of telecom traffic at a specific position in time and space in the city.

Different statistical methods can be found in research focused on Rome. Spatial signatures based on a K-means clustering technique were applied to conceptualize the city's complex human dynamics as a real-

[2] MIT SENSEable City Lab.: http://senseable.mit.edu

[3] A measure of network bandwidth usage. For more details see Section 4 in this chapter.

time system (Calabrese and Ratti 2006; Reades et al. 2007, 2009; Calabrese et al. 2011). Other authors take similar approaches such as the calculation of digital footprints (Girardin et al. 2008a), digital signatures (Calabrese et al. 2010) and spatio-temporal signature (Girardin et al. 2008b). These signatures can be a basic approach for anomaly detection. This is strongly related to concepts such as 'chronotype' (Bertolini and Dijst 2003) and 'space-time typologies' (Zandvliet and Dijst 2006) as a way to understand how place works in Castells' *network society* (Castells 1996).

Furthermore, Jiang et al. (2012) used data from a mobile phone operator to discover the spatial and temporal dimension of human activity patterns in Chicago. Similarly, Toole et al. (2012) used such data to discover urban land uses, while Kang et al. (2012) explored the correlation between mobile phone activity and resident population. A critical view on these concepts can be found in Resch et al. (2012).

It seems plausible that cities in the future will exhibit a complex dichotomy between their material-physical appearance and their digital, cyber-based functioning. The mobile phone is just an early predecessor to a much more comprehensive and spatially interwoven constellation of visual and virtual dimensions of the urban space. This megatrend will most likely exert far reaching impacts on the evolution and governance of cities.

3. From analytics to urban theory and planning

There is great discussion in the literature regarding the impact of Information and Communications Technologies (ICTs) on cities. From the seminal work of Graham and Marvin (1996, 2001) on 'Splintering Urbanism' to Batty's (1997) ideas on 'Virtual Geography' and Castells' (1996) 'Space of Flows,' there is a consensus on one thing: 'the city itself is turning into a constellation of computers' (Batty 1995, p. 155). One of the outcomes of this transformation is that individual interaction can be monitored in (almost) real time in a detailed spatial resolution, providing data that would have been unheard of a decade ago.

Nonetheless, the importance of urban analytics based on 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 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 lifestyle. The latter refers to a *real-time city* which acts and is monitored instantaneously (Townsend 2000). This new characteristic of increased action in time and space from the urban user stand-point, and reaction in terms of monitoring, creates a new exiting opportunity for urban planners and urban governing. Graham (1997, p. 117) highlights this new real-time dimension:

> "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, atomized and strongly competitive . . . 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)".

Critical approaches can be employed to further highlight the value of real-time urban analytics, such as those based on mobile phone data, in urban theory. The basis of such an approach is the widely accepted 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). 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, p. 71) criticizes this strand of research by highlighting that space and time are conceptualized in classical physics as independent objects: 'Space is a passive arena, the setting for objects and their interaction.' Nonetheless, post-modern urban theory argues that there is little gain by separating space and time, as there is only the joint effect of *space-time* (Thrift 1996). Thus, similarly to the non-linearity and multiplicity of time, places are non-contiguous, dissimilar, overlapping and dynamic entities (Graham and Healey 1997).

Urban analysis based on mobile phone data could be an answer to the above criticism against positivistic approaches to urban theory. The use of mobile phone-based urban analytics enables the research community to analyze and model the *pulse of the city* (Batty 2010). Such measures do not focus on the physical form, but rather on human activity per se and its projection on cities. 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 lifestyles. Space is not separated by time as the domain of such urban analytics is space-time from an (almost) real-time perspective.

Despite the importance of such exercises, mobile phone-based urban analytics are not an end on their own. The applicability of such analytics in supporting urban planning could provide new opportunities for urban management and development. Ahas and Mark (2005) predict that geolocated data from mobile phone operators will be utilized in three areas of 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; and (3) to model, plan and design transportation and transport infrastructure. Moreover, they also suggest the use of such data and analytics in marketing (2005). Despite the relatively recent character of mobile phone-based urban analytics, the previous section presented examples of studies, the results of which can benefit urban planning with direct knowledge feedback.

In addition, more examples of the applicability of mobile phone-based urban analytics in urban planning can be found in the recent literature. The notion of 'swarm' is among them. The latter has its roots in the military field and refers to the spreading of commands among autonomous units, allowing an enemy attack from different directions (Arquilla and Ronfeldt 2000). Drawing upon this, it can be argued that the effectiveness of a study of how people and groups interact in space is based on the understanding of swarming behaviors (Evans-Cowley 2010). Swarm behavior can be studied at an aggregated – urban – level with the use of mobile phone data. This can result in a new understanding of cities as systems of interacting individuals contrary to the traditional unitary approach according to which cities are approached as compact individual units (Evans-Cowley 2010; Townsend 2000; Kostakos et al. 2008).

The above discussion is limited to top–down approaches. Nonetheless, due to the pervasiveness of mobile phones, 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 use of mobile phone data, volunteer participation and existing technology. A well-discussed 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 properties before they were demolished, a task which could not have been undertaken by the overwhelmed city authorities (Gadbois 2008). 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). In total such data can lead to the coordination of transportation in real time (Townsend 2000).

After presenting the state of the art of urban analysis with the use of high resolution, spatio-temporal data from mobile operators and placing such analysis in a wider urban planning framework, the next section presents some empirical results in this domain.

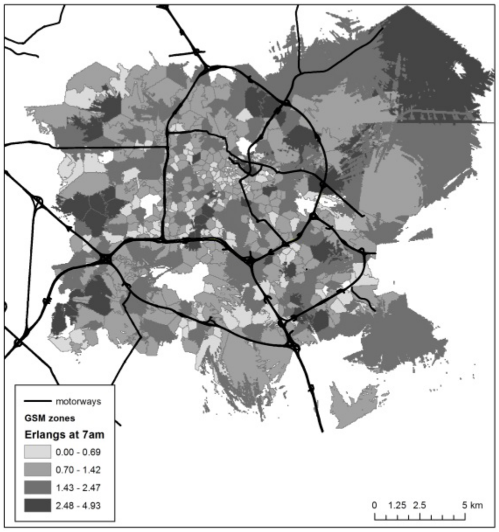
4. Empirical application

In this section, the main modeling exercise takes place. The aim is to identify how mobile phone usage varies across space and time. In order to do so, the high spatio-temporal resolution of the mobile phone data is utilized in a regression analysis framework, which will enable us to extract conclusions on a very fine-grained scale.

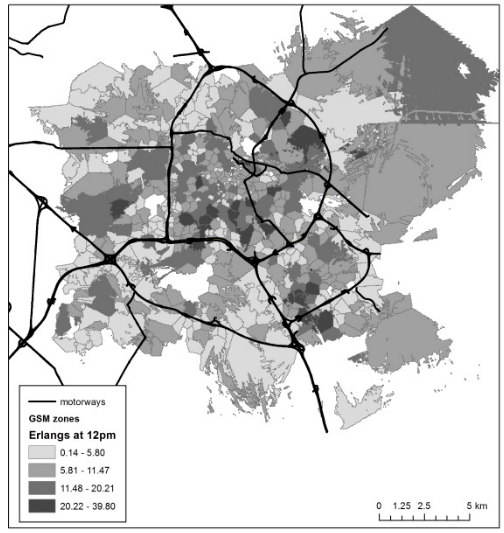
Before presenting our analysis, a short description of the mobile phone dataset is presented. The main dataset used for this chapter has been derived by KPN, one of the main mobile phone operators in The Netherlands. The dataset includes aggregated telecommunication counts at the level of the GSM (Global System for Mobile Communications) cell on an hourly basis. Figure 1 presents the study area, which is the city of Amsterdam, and the different GSM zones. In total 520 such zones are included in the analysis. Various telecommunications counts are 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) sent from a specific zone, the average call length and so forth. In the analysis presented in this section, two variables are utilized: the Erlang, which is an aggregation of all telecommunication activity[4], and the number of new calls initiated in a GSM zone during a one-hour period. The data concerns all the phone activity in the study area during the month of April, 2010. Figure 1 also presents the average number of

[4] Two phone calls of five minute duration each result in the same amount of Erlang as one phone call of a ten minute duration.

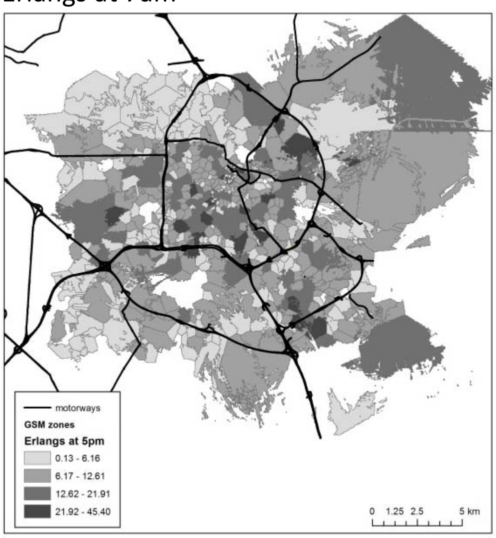
Erlangs for each zone for the study period during different times of the day as an average of the study period.



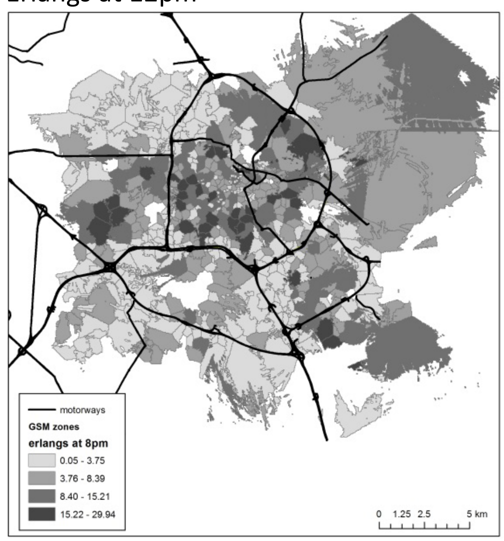
Erlangs at 7am



Erlangs at 12pm



Erlangs at 5pm



Erlangs at 8pm

Figure 1: Amsterdam area, GSM zones and average Erlangs during different times of the day (April 2010)

The key focus in this analysis is the relation between mobile phone usage and urban space given the temporal variability, which is illustrated in Figure 1. Urban space is represented here by the different land use types and the spatial unit of our analysis is the GSM cell areas. The temporal dimension varies from day-to-day to hourly resolution. A few introductory words need to be said regarding the land use classification. The initial land use data comes from the Central Bureau for Statics in The Netherlands (CBS 2008) and consists of various very detailed land use types. Because the main focus of the analysis is not to produce an exhaustive land use model, but instead to understand how mobile phone usage varies across urban space, an aggregation of the initial land use types takes place.

Equation (1) presents the first model we estimate. According to this general model, mobile phone activity (mob_{it}) in area *i* and time *t* is affected by a vector X_i of land use types, a vector T_t of time variant variables and a vector of control variables $control_i$. Such a model exploits the panel data nature of the mobile phone data. In other words, we consider the dual dimension of our dataset: space and time.

$$mob_{it} = B_1 X_i + B_2 T_t + a_1 control_i + a_0 + \varepsilon_{it} \tag{1}$$

Table 1 presents the estimation of this model. Two different mobile phone variables are used here as dependent variables: the natural logarithm of *erlang* (column 1) and the natural logarithm of *new calls* (column 2). Seven different land use type variables are utilized here: business areas, residential, traffic, recreation, inland water, nature, and other. The above land use types are inserted in the models as the percentage of the land use type in the cell's overall area. Moreover, four time-variant variables are also used here as dummy variables: working hours (*working*), rush hours (*rush*), weekends (*weekend*) and holidays (*holiday*). Finally, two control variables are used in order to address the size of the different cells: *area* represents the natural logarithm of the area of each cell in hectares and *volume* represents the natural logarithm of the built volume of each cell (i.e. height × area) following the work of Koomen et al. (2009). The role of both of these control variables is to address potential size effects of the GSM zones.

With regard to the model estimation, panel data regressions have been utilized. In more detail, a generalized least squares (GLS) estimator is used to estimate (1) as a random effect panel model. Most importantly, because first order serial autocorrelation can be a source of bias in our data, the xtregar module of Stata software is used here to address this issue. Serial autocorrelation in our case reflects the dependence of the mobile phone intensity in cell *i* in time *t* on time *t-1*.

The main observation is the lack of significant impact of most of the land use variables on mobile phone intensity. The only exception is residential land use types, which has a significant positive impact on mobile phone intensity. This is surprising as these first results indicate no spatial variation of mobile phone usage. On the other hand, time variant variables are highly significant. Their impact is always positive across the different specifications. This does not apply to the weekend variable, which has a positive impact on the number of new calls (natural logarithm) but a negative one on the total traffic activity (erlang). The intuition of the above could be that people tend to make more but shorter calls during the weekends.

In order to further analyze the temporal relation between mobile phone intensity and land use types, the initial mode (1) is enriched with interaction terms:

$$mob_{it} = B_1 X_i * T'_t + a_1 control_i + a_0 + \varepsilon_{it} \tag{2}$$

In this case, the dummy variable T'_t distinguishes between working and non-working days. Model (2) is estimated as model (1), using both the natural logarithm of Erlang and new calls as the dependent variable. The results are presented in Table 2. It seems that even the interaction effects of working and non-working days with the different land use types are not able to depict the spatio-temporal variation of mobile phone intensity in the city of Amsterdam. Indeed, the only significant variables are the interactions between working and non-working days with residential land use types. A positive effect of the same magnitude is observed for both of them. The results are only slightly different when the number of new calls is used as the dependent variable. In this case the positive effect of business and traffic land use types during the working days is also illustrated by the regression.

Table 1: Estimation of model (1)

	erlang (ln)	**new calls (ln)**
Traffic	0.004	0.008
	(0.004)	(0.006)
Residential	0.022	0.029
	(0.003)**	(0.005)**
Business	0.001	0.006
	(0.003)	(0.005)
Recreation	0.001	-0.001
	(0.003)	(0.005)
Nature	0.006	0.008
	(0.014)	(0.023)
Inland	0.002	-0.002
	(0.003)	(0.005)
Other	0.008	0.005
	(0.005)	(0.008)
Working	1.29	1.777
	(0.008)**	(0.013)**
Rush	0.986	1.3
	(0.006)**	(0.010)**
Weekend	-0.038	0.303
	(0.017)***	(0.018)**
Holiday	0.137	0.507
	(0.025)**	(0.025)**
Area	0.333	0.479
	(0.038)**	(0.060)**
Volume	-0.005	-0.031
	(0.015)	(0.023)
Constant	-4.891	-3.9
	(0.512)**	(0.812)**
N	371,981	371,981

*** $p < 0.05$; ** $p < 0.01$

Land use types: (%) of the GSM zone

Table 2: Estimation of model (2)

	erlang (ln)	**new calls (ln)**
Traffic × work	0.005	0.012
	(0.003)	(0.005)***
Residential × work	0.02	0.029
	(0.002)**	(0.004)**
Business × work	0.001	0.009
	(0.003)	(0.004)***
Recreation × work	0	0
	(0.002)	(0.004)
Nature × work	0.01	0.015
	(0.015)	(0.023)
Traffic × non-work	−0.004	0.003
	(0.003)	(0.005)
Residential × non-work	0.019	0.03
	(0.002)**	(0.004)**
Business × non-work	−0.005	0
	(0.003)	(0.004)
Recreation × non-work	−0.004	−0.001
	(0.003)	(0.004)
Nature × non-work	−0.008	0
	(0.015)	(0.023)
Area	0.331	0.48
	(0.039)**	(0.061)**
Volume	0	−0.031
	(0.014)	(0.023)
Constant	−4.468	−3.411
	(0.495)**	(0.782)**
N	371,981	371,981

*** $p < 0.05$; ** $p < 0.01$

Land use types: (%) of the GSM zone

work and non-work: working and non-working days

While the above models attempted to address the day-to-day variability across the different land use types, we still need to exploit the very detailed temporal resolution of the mobile phone data in order to better understand how mobile phone usage changes over time and space. In order to do so, three-way interaction terms are introduced in model (3):

$$mob_{it} = B_1 X_i * T'_t * H_t + a_1 control_i + a_0 + \varepsilon_{it} \quad (3)$$

While *T'* distinguishes between working and non-working days, *H* introduces hour-to-hour variability. The estimation of this model is presented in Table 3 (see Annex). Across the top are the different land use types on working and non-working days and in the first column the different times of the day are presented. In order to make the table more readable, green reflects positive and significant impact while red reflects negative and significant impact. Overall, this regression represents the *heartbeat* of Amsterdam. For instance, we can see that the impact of traffic land use type becomes positive earlier on working days than on non-working days. Similarly, there is a 2–3 hour difference before the impact of residential, business, recreation and nature land use types becomes positive. In addition, we can see that the magnitude of the impact is higher on working days for traffic land use and its variation during these days is also higher. The difference between working and non-working days is marginal for residential areas, but this is not the case for business areas, where the impact is more than double that of working days. Finally, more analysis needs to be done for the recreation and nature land use types, as the magnitude of impact is higher than the expected one. Nonetheless, the estimated signs of the relations come as no surprise as they reflect the heartbeat of Amsterdam. The exact same pattern could be observed if the natural logarithm of new calls was used as the dependent variable (the results can be provided upon request).

5. Concluding remarks

The digital world is no longer a dream, but a rapidly evolving reality. This chapter critically discussed some applications of new, digital, data derived by mobile operators in urban analysis. Despite the existence of some first implementations in the urban analysis field, there is still a great potential for new applications in this research domain, especially in understanding cities from a spatio-temporal perspective. Our empirical application, although still under development, is a step towards this direction.

In a nutshell, our results indicate that mobile phone data can be used to understand how urban space is used over time. Mobile phone usage represents, to a certain extent, population concentration. Thus our modeling results indicate how an urban population uses different places in the city of Amsterdam during the course of a day and across different days. The results presented here can provide the basis of a more concrete urban analysis where the spatio-temporal variation of mobile phone usage could be used as a proxy for population concretion and related economic and social activities.

To sum up, data from mobile phone providers can provide a new pool of knowledge for urban scientists. And this is where the caveat lies. Despite the breadth of information in these millions of lines of mobile phone data, we, as the scientific community, face the challenge of generating new knowledge for the way our cities function and evolve. After proving the value of such new data sources, it is the time to move on from the *analytics* domain and create new knowledge in the domain of urban geography and urban economics by utilizing this new data source, which in the end will provide valuable insights in to urban planning.

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Table 3: Estimation of model (3); dependent variable: erlang (ln)

	Traffic_work	Traffic_non-work	Residential_work	Residential_non-work	Business_work	Business_non-work	Recreation_work	Recreation_non-work	Nature_work	Nature_non-work
L.U. type	−0.014	−0.012	0.017	0.018	−0.012	−0.008	−0.011	−0.009	−0.027	−0.025
	(0.003)**	(0.003)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**	−0.014	−0.014
00	BASE	BASE	BASE	BASE	BASE	BASE	BASE	BASE	BASE	BASE
01	−0.012	−0.012	−0.01	−0.006	−0.008	−0.006	−0.011	−0.007	−0.035	−0.021
	(0.000)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.002)**	(0.003)**
02	−0.02	−0.022	−0.019	−0.012	−0.015	−0.011	−0.021	−0.015	−0.067	−0.04
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.003)**	(0.004)**
03	−0.023	−0.024	−0.026	−0.016	−0.019	−0.014	−0.028	−0.021	−0.084	−0.059
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.003)**	(0.005)**
04	−0.022	−0.021	−0.031	−0.02	−0.023	−0.017	−0.031	−0.027	−0.088	−0.07
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.004)**	(0.005)**
05	−0.003	−0.014	−0.034	−0.025	−0.022	−0.02	−0.025	−0.027	−0.063	−0.085
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.004)**	(0.005)**
06	0.016	−0.004	−0.026	−0.029	−0.009	−0.021	−0.009	−0.024	−0.007	−0.077
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.004)	(0.005)**
07	0.03	0.004	−0.01	−0.024	0.011	−0.017	0.008	−0.015	0.045	−0.038
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.004)**	(0.005)**
08	0.045	0.011	0.002	−0.013	0.025	−0.008	0.021	−0.004	0.077	−0.003
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.004)**	(0.005)
09	0.048	0.017	0.008	−0.002	0.032	0.001	0.026	0.006	0.086	0.025
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)	(0.001)**	(0.001)**	(0.004)**	(0.005)**
10	0.045	0.021	0.011	0.005	0.036	0.007	0.026	0.012	0.088	0.047
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
11	0.045	0.023	0.012	0.008	0.037	0.012	0.027	0.016	0.089	0.054
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
12	0.045	0.024	0.012	0.01	0.038	0.014	0.027	0.017	0.088	0.054
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
13	0.045	0.023	0.012	0.009	0.038	0.015	0.027	0.017	0.088	0.057
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
14	0.045	0.022	0.012	0.009	0.039	0.015	0.028	0.017	0.088	0.055
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
15	0.046	0.021	0.012	0.008	0.038	0.015	0.029	0.016	0.089	0.052
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
16	0.048	0.02	0.013	0.008	0.037	0.015	0.031	0.016	0.091	0.05
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
14	0.048	0.02	0.014	0.008	0.035	0.014	0.032	0.016	0.092	0.051
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
18	0.044	0.02	0.014	0.008	0.03	0.011	0.03	0.014	0.084	0.047
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**

19	0.036	0.02	0.013	0.008	0.024	0.01	0.024	0.012	0.071	0.045
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
20	0.03	0.02	0.014	0.009	0.021	0.009	0.022	0.013	0.07	0.051
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
21	0.026	0.016	0.015	0.009	0.019	0.009	0.021	0.013	0.068	0.049
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
22	0.02	0.012	0.013	0.007	0.015	0.006	0.018	0.01	0.056	0.038
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
23	0.012	0.005	0.008	0.003	0.01	0.003	0.011	0.006	0.035	0.02
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.004)**	(0.006)**
	area (ln)	0.34	sumvolume (ln)	−0.006	constant	−4.406	N	371,981		
		(0.036)**		(0.013)		(0.464)**				

*** $p < 0.05$; ** $p < 0.01$; L.U.: land use types expressed as (%) of the GSM zone; work and non-work: working and non-working days