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How “smart cities” will change supply chain management

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Structured abstract

- **Purpose**: The purpose of this study is to analyze the impact of smart city initiatives and big data on supply chain management (SCM). More specifically, we investigate the connections between smart cities, big data, and supply network characteristics (supply network structure and governance mechanisms).
- **Design/methodology/approach**: An integrative framework is proposed, grounded on a literature review on smart cities, big data and supply networks. Then, the relationships between these constructs are analyzed, using the proposed integrative framework.
- **Findings:** Smart cities have different implications to network structure (complexity, density and centralization) and governance mechanisms (formal vs. informal). Moreover, this work highlights and discusses the future research directions relating smart cities and SCM.
- **Research limitations/implications**: The relationships between smart cities, big data and supply networks cannot be described simply by using a linear, cause-and-effect framework. Accordingly, we have proposed an integrative framework that can be used in future empirical studies to analyze smart cities and big data implications on SCM.
- **Practical implications:** Smart cities and big data alone have limited capacity of improving SCM processes, but combined they can support improvement initiatives. Nevertheless, smart cities and big data can also suppose some novel obstacles to effective SCM.

- **Originality/value:** Several studies have analyzed IT innovation adoption in supply chains, but to the best of our knowledge, there has been no study focused on smart cities.

Keywords: Sustainable supply chains, Logistics, Sustainability

Article classification: Research paper

1. INTRODUCTION

The growth of urbanization has been dramatic in the last decade. Indeed, according to Lierow (2014), it is expected that 70 percent of the world's population will live in cities by 2050. This rate has increased the pressure for adjusting the actual infrastructures, and investing in new ones, in order to support the flow of goods and people, as well as to minimize the associated impact related to the environmental degradation, quality of life, etc (Caragliu et al, 2009). To manage this issue, an increasing number of cities around the world are adopting the concept of "smart cities" (Allwinkle and Cruickshank, 2011). A smart city is "a city seeking to address public issues via information and communication technology-based solutions on the basis of a multi-stakeholder, municipally based partnership" (Manville et al, 2014, p.24). It encompasses an extremely diversified set of public initiatives: from building better transportation systems to supporting creative innovation, or designing energy-saving policies. Overall, the aim of such initiatives is to provide a higher quality of life, making a city more attractive to a knowledge-based population (Dirks et al, 2010).

The main motivation for this exploratory study is to analyze the impact of smart city initiatives on supply chain management (SCM). In particular, the adoption of smart city concepts poses both opportunities and constraints to supply chain management. For example, "congestion pricing" is a practice where the usage of electronic toll system regulates potential excess of the traffic. Through different ranges of charges this practice tends to balance the flow, reducing partly the level of congestion and travel time. Although practical smart cities advancements are already being implemented in several sectors, there is a lack of academic research that investigates this issue from a theoretical perspective. Although there have been some attempts to review the literature on smart cities (e.g. Allwinkle and Cruickshank, 2011; Caragliu et al, 2009), they were focused on urban studies and did not consider a supply chain perspective. In this study, we aim at filling this gap by analyzing the connections between smart cities and SCM, using a supply network perspective. In order to do so, we propose an integrative framework based on a two-way link between smart cities-big data and supply networks.

Following Scott and Davis' (2006) argumentations that supply chains are "open systems" mutually dependent on the surrounding environment and constantly adapting to it, we posit the existence of different synergies between smart cities-big data and supply chains. These effects occur in both sides, i.e. from smart cities-big data to supply chain and from supply chain to smart cities-big data. Moreover, the structuration theory argues that agent and structure co-evolve and interact mutually in complex social interactions (Giddens, 1984). Considering that smart cities are based on the collaboration between firms, end-users and local stakeholders (Manville et al, 2014), we add to the present knowledge by recognizing a co-evolution approach, in which the social interactions are also considered.

This paper is structured as follows: First, we provide a brief literature review on smart cities, big data and supply networks. Then, we propose an integrative framework that is used to analyze how smart cities and big data relate to supply networks. Lastly, we discuss implications of the study and potential lines of research related to this issue.

2. LITERATURE REVIEW

2.1. Smart cities

The concept of “smart city” has its roots on the notion of “intelligent cities”. Intelligent cities are physical environments in which information and communication technology (ICT), and sensor systems become embedded into physical objects and urban settings (Wright and Steventon, 2006). For example, traffic management can elaborate in real-time dynamic maps to monitor some critical environmental parameters such as CO2 levels (Sanchez et al, 2011). In this approach, ICT substitutes many of the coordination and control roles of hierarchy, motivating new organization forms that focus on process instead of function (Setia and Patel, 2013). The “intelligent city” has led to the emergence of a broader concept known as “smart cities” (Caragliu et al, 2009; Hollands, 2008). In particular, “a smart city uses ICT to optimize the efficiency and effectiveness of useful and necessary city processes, activities and services typically by joining up diverse elements and actors into a more or less seamlessly interactive intelligent system” (Manville et al, 2014, p. 17). The main difference with respect to intelligent cities is that, besides ICT features, smart cities also encompass environmental issues, human and social capital (Allwinkle and Cruickshank, 2011; Caragliu et al, 2009). According to Giffinger et al (2007), a smart city incorporates at least one of the following dimensions: smart economy (e.g. innovation, entrepreneurship, productivity), smart mobility (e.g. accessibility, sustainable transport systems), smart environment (e.g. pollution, sustainable resource management), smart people (e.g. level of qualification, creativity, flexibility), smart living (e.g. quality of life) and smart governance (e.g. public and social services, transparent governance).

Smart cities generate several opportunities to SCM. For example, they can provide open data systems based on diversified sources (e.g. public data, citizen-produced content or urban sensors). This can be particularly critical in the mobility aspects of the supply chain. For example, the New York City traffic management system detects "congestion choke points" in real time and adjust traffic signals accordingly to the data that 100 microwave sensors, 32 traffic video cameras and E-ZPass readers at 23 intersections sent to a control center. More importantly, the traffic information will also be available to drivers through cell phones (Schwartz, 2011). Furthermore, smart traffic systems can provide short-term predictions of the rates of traffic flow and travel speed across a defined area, improving vehicle routing and transportation planning (Manville et al, 2014).

Another possibility is the usage of automated transportation systems like the automation of long-haul trucking (e.g. Mercedes Future Truck 2025) and urban self-driving vehicles (e.g. Google) (Rudin, 2014). These systems will allow to save fuel, improve safety, and increase driver’s productivity. In addition, vehicle-to-vehicle (V2V) and vehicle-to-road (V2I) communication capabilities will improve significantly transportation activities (Rudin, 2014). These systems will allow exchange of information about the traffic and weather conditions and the exact location and speed of vehicles, improving the transportation process without heavy investments in physical infrastructure. Moreover, according to Schiller (2014), innovations like Uber and self-driving cars will "re-invent how our roads, transit systems, and freight and logistics networks function" (Schiller, 2014, p.1).

Nevertheless, smart cities also generate novel obstacles that should also be taken into account. A basic idea of smart cities is a “smarter” use or resources, but this may have some limits with the increasing urbanization. Traffic jams, for example, are inevitable with the current transportation systems, no matter how sophisticated are the technologies employed. At most, damages can be reduced, but not eliminated significantly. Indeed, practices such as congestion charges, low emissions zone (i.e. vehicles shall comply with low emissions requirements or pay a fee), or car-free policies may affect urban logistics (Browne and Gomez, 2011). For example, Singapore is applying strict policies against personal vehicle use, like an electronic road pricing scheme and very high permit and sales tax rates for new vehicles (Cohen, 2014). How this will affect urban logistics is still an unsolved issue.

Another important issue is related to the risks of incomplete automation, i.e. getting trapped in the transition of a new technology and never obtaining its full benefits (Schiller, 2014). For example, with respect to Mercedes self-driving trucks mentioned beforehand, potential risks include how to assure that data from the vehicles is secure, how liability will work in the case of a crash, and regulations about truck drivers rest (Davies, 2014). Moreover, there is the risk of a heterogeneous combination of regular and autonomous vehicles that don’t work together adequately, i.e. the safety benefits of self-driving cars are obtained, but not the traffic-reducing ones (Rudin, 2014).

Even though these practices can partially affect the mobility of the supply chain, there can be some cases where the policy articulation of these restrictions forces firms to design new distribution strategies to urban centers, such as urban freight consolidation centers (van Rooijen and Quak, 2010) and/or to seek for alternative transportation modes such as electric scooters and compact bike-lane vehicles (MIT, 2014a).

Smart cities initiatives are largely dependent on collecting and managing the right kinds of data, analyzing patterns and optimizing systems functioning (Dirks et al, 2010). Here, the additional two key elements are the data per se (i.e. big data) and the process of examining this data (big data analytics). The concept of "big data" can be defined as large pools of unstructured data that can be captured, stored, managed and analyzed (Manyka et al, 2011). Big data per se cannot be useful if it is not complemented by process of examination and assessment. In this study, we posit the existence of synergies between smart cities and big data. Indeed, smart cities will provide firms with necessary infra-structure to leverage big data, governance mechanisms to support multi-stakeholder collaboration, IT infrastructure to disseminate it (e.g. wireless urban sensors, public wi-fi) and the potential workers with the necessary skills. In the next section, we present the concept of big data and discuss some SCM implications.

2.2. Big Data

Big data analytics is the process of examining large amounts of unstructured data to uncover hidden patterns, unknown correlations and other useful information (Rouse, 2012). According to Rouse (2012), eighty percent of the world’s data is unstructured (e.g. video or audio files) or semi-structured (e.g. word documents, social media comments). In particular, the big data that interests firms is what is called “found data”, i.e. the digital exhaust of web searches, credit card payments and cell phones (Harford, 2014). Besides social media content, clickstream tracking and firms’ transactions, another source of big data is the millions of networked sensors that are being embedded in devices such as smart energy meters, containers, transportation vehicles, industrial machines and mobile phones, which provide trillions of bytes of information about manufacturers, suppliers and customers (Manyka et al, 2011). Indeed, around 12 million of Radio-Frequency Identification (RFID) tags have been sold in 2011, and the estimations by 2021 raise this number to 209 billion as the internet of Things takes off (Marr, 2014).

Finally, other data inputs include video data from surveillance devices; social media from Twitter and other platforms; the results of citizen collaboration coming from apps such as SeeClickFix[1] and Open311[2]; information produced by machine-to-machine (M2M) infrastructure; and administrative data collected directly from citizens (IBM, 2013). However, in most of the cases, this enormous amount of data is underutilized (Martinez and Rodriguez, 2012). The reason is that only few of the new sources of information (e.g. social media content, video, etc) is formatted in the traditional rows and columns of relational databases (Davenport et al, 2012). This implies that there are significant opportunities that are getting lost. Indeed, according to McKinsey, retailers could increase their profit margins by more than 60% through the full exploitation of big data analytics (Manyka et al, 2011).

Smart cities provide an ideal background for exploitation of big data, and the interactions in the value chain can generate "exhaust data" (Manville et al, 2014). Indeed, many big data applications are implemented far from the purposes for which the data was collected (Mayer-Schonenberger, 2013). For example, location information that cell phone companies gather (so that they can efficiently route calls) can be used to make predictions such as consumer displacements and micro-consumption patterns (Hayashi, 2014). Therefore, there is a vast potential to tap in with respect to this. For example, Helsinki has more than 1,200 open data sets and around 100 applications have been created to properly use these open data bases (Cohen, 2014). By relying on fine-grained information from these data sets, firms can improve

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[1] www.seeclickfix.com

[2] www.open311.org

strategic (e.g. distribution network design), tactic (e.g. production planning) or operational (e.g. vehicle routing) SCM decisions, as we explain in the following paragraph.

The SCM applications of big data can be utilized in all the key processes of SCM. For example, big data is useful to define distribution strategies based on actual consumer patterns (e.g. location-based data generated by mobile phones) rather than surveys and samples (Martinez and Rodriguez, 2012). Additionally, retailers can use big data algorithms (instead of small data samples and spreadsheets) to fine-tune inventory planning, based on real-time in-store and online sales (Manyka et al, 2011). The use of clickstream tracking in forecasting for inventory management in non-transactional websites can reduce the inventory holding and backordering by 3% to 5% of costs (Huang and Van Mieghem, 2014). Moreover, sensors embedded in products can also be useful for SCM. The emergence of real-time location data has allowed new location-based services. For example, firms know where and how consumers drive their cars and can define distribution and inventory location, based on that information (Manyka et al, 2011). Finally, Shu and Barton (2012) suggest how firms can use individualized trace data (ITD), i.e. real-time data. They argue that this generates both opportunities (e.g. to give early warnings of supply chain problems that may emerge later) and challenges (e.g. managers may overreact to normal variation present in real-world systems). This latter implication raises additional SCM risks, such as worsening the “bullwhip effect” or increasing inventory costs.

Moreover, big data has some important drawbacks. Assuming that possessing more data provides necessarily “better” models of reality may be an over-simplistic assumption. For example, although big data is very effective when detecting correlations, it may fail when pinpointing which correlations are meaningful. Also, there is the risk of detecting too many irrelevant correlations with no causal relationship, even though results appear statistically significant. Big data is more effective for analyzing things that are extremely common, not for trying to detect unusual phenomena (Marcus and Davies, 2014). For example, it may fail to detect a small, less frequent pattern. In addition, the reality is much more complicated than a preliminary analysis could suggest. Data is often “dirty”, because of inaccurate information inputs, and it needs frequent cleaning. Moreover, found data sets are rarely exchangeable. Companies that have access to huge sources of big data (e.g. Amazon, Google, Facebook, Twitter, Tesco) are not willing to share their data with anyone else. Furthermore, although computers can analyze millions of documents and provide reports, they can’t interpret the findings (Kopytoff, 2014). The reason is that they are designed to focus more on correlation than causality. Thus, big data do not solve the biggest issue: discovering how to locate the key problem and how to improve a system effectively (Harford, 2014).

Finally, as big data evolves, the architecture will develop into a network of firms, customers and government continuously sharing information and optimizing decisions (Davenport et al, 2012). In order to fully assess the derived effects, it is necessary to use a network perspective.

2.3. Supply networks

According to Borgatti and Li (2009), the network perspective is becoming a *lingua franca* among many sciences e.g. anthropology, physics, etc. They argue that network theory allows researchers to move from a transaction to a relational perspective that takes into consideration the environment around firms. Additionally, there has been a great interest in applying the concept of networks to analyze complex interactions within supply chains (Alvarez et al, 2010; Pilbeam et al, 2012). Thus, when analyzing the interplay between smart cities and SCM, we believe it is crucial to embrace a network perspective.

Choi et al (2001) define a supply network as “a network of firms that exist upstream to any one firm in the whole value system” (p.352). The concept of supply networks has been investigated under different perspectives. Supply networks have been largely studied in SCM (Choi and Hong, 2002, Choi et al, 2001, Kim et al, 2011; Harland et al, 2001), in organizational literature (Alter and Hage, 1993; Gulati et al, 2000) and industrial marketing (Hakansson and Snehota, 1995). Whereas the literature on strategic networks claims that a lead firm actively controls the chain (Jarillo, 1988; Gulati et al, 2000), other studies advocate that networks emerge spontaneously (Choi et al, 2001, Kim et al, 2011). According to the network emergence argument, once the formation of a network is initiated by the lead firm, its structure takes on a shape by itself (Choi and Hong, 2002). Within the supply network characteristics, we focus on the structure of the supply network and the governance mechanisms. These two categories synthesize the network characteristics and provide a useful framework to analyze how a network will react to a particular element.

In the next section we describe the integrative framework that will be used to analyze the connections between smart cities-big data and supply networks.

3. ANALYSIS

3.1. Integrative framework

In this section, we propose an integrative framework that encompasses two aspects of supply networks: network structural characteristics and governance mechanisms, as well as smart cities-big data context. The proposed framework fits the main objective of this study, which is to analyze the interplay between smart cities-big data and supply networks. The integrative framework is depicted in Figure 1.

INSERT FIGURE 1 AROUND HERE

Now, we comment briefly each part of the proposed framework. First, the supply network characteristics. Kim et al (2011) propose three variables to characterize the structure of supply networks: density (i.e. the number of ties occupied by a network with respect to the total number of ties), centralization (i.e. the extent to which decisions are concentrated in a network member) and complexity (i.e. coordination load on the network). With respect to governance mechanisms, two types are considered: formal and informal. Another key idea behind this framework is the link between smart cities and big data concept. In this study, we argue that, in order to seize the smart cities opportunities, firms should explore the synergies with the big data concept.

3.2. How smart cities and big data interact with network density

Kim et al (2011) defined network density as “the number of total ties in a network relative to the number of potential ties” (p.196). More specifically, network density refers to the pattern of relationships within the network, not the geographical distances between supply chain partners. Thus, in a totally dense network, all nodes would connect to each other.

Smart cities, big data and network density appears to have a mutually reinforcing relationship. On one side, smart city and big data initiatives positively affect the establishment of ties in the network. For example, logistics providers can use big data to compensate for the lost links due to retailers’ evolution to direct-to-consumer service (Burnson, 2013). The reverse also applies. High network density can positively affect smart city and big data initiatives and having more ties increases access to information (Borgatti and Li, 2009). For example, open data initiatives are enabled by a high-density network (Manville et al, 2014). This relationship can also be analyzed under the theoretical lens of social embeddedness (Granovetter, 1985). A highly embedded supply chain increases network cooperation (Sarkis et al, 2011). Furthermore, network effects (i.e. the value of the network increases when the number of participants increases) could also explain firm adhesion to smart city initiatives. In particular, embeddedness is a result of repeated interactions between parties (Granovetter, 1985), thus more network density will imply more interactions and reinforce network effects, motivating firms to adhere to smart cities initiatives. For example, Cooperative Intelligent Transport Systems and Services (C-ITS) are based on the principle that all cooperative parties locally exchange information between each other. From a technological perspective, this means to upgrade the electronic dimension of vehicles and the interaction of drivers, passengers and pedestrians with urban infrastructures beyond the road transport system. This technology will enable foresighted driving and self-organization at local level, i.e. up-to-date traffic information, improved road safety, and traffic fluidity by traffic homogenization (European Commission, 2013a).

Actually, in the mid-range future of 15-20 years, the transportation scenario will become significantly more heterogeneous. In this scenario, there will be multiple redundant transportation networks rather than a single, most efficient one (Rudin,2014). This may require some changes with respect to network centralization, as explained in the next section.

3.3. How smart cities and big data interact with network centralization

Centralization is the degree to which the power of decision making is concentrated across the network (Choi and Hong, 2002). When centralization is high, network efficiency is improved, but flexibility is negatively affected (Kim et al, 2011). Traditionally, supply chains have been centralized around lead firms with more power and resources (Gulati et al, 2000).

We can distinguish between two main types of SCM flow: material or information. Smart cities will impact differently on each type of flow. With respect to material flows, researchers claim that cities are evolving into decentralized architectures, organized as “compact urban cells” (MIT, 2014b). Similarly, Rudin (2014) foresees a density increase at regional shopping and entertainment centers, also called “edge cities”. This will have significant impact on urban logistics. For example, there will be less consumer displacements, more time spent in semi-autonomous neighborhoods and more local supply chains (Lierow, 2014).Drawing from the notion of social embeddedness (Granovetter, 1985), this phenomenon may forge new dynamic networks of social relationships, that will influence new processes. Accordingly, a recent European Commission study on local supply chains concluded that they have less vertical complexity (i.e. less intermediaries) and are composed mainly of small and medium enterprises (SME) often committed to sustainable practices (European Commission, 2013b).

Smart cities and big data can support these trends. For example, the usage of mobile phones geographical information can allow firms to identify consumption patterns, and design distribution strategies accordingly (Martinez and Rodriguez, 2012). More specifically, a continuous distribution strategy of supplying stores several times a day e.g. 7-Eleven Japan (Chopra and Meindl, 2013) can be leveraged, by providing access to patterns of geographical distribution of consumption throughout the day. Another phenomenon related to supply networks decentralization is the emergence of micro-retailing i.e. “nanostores” (Blanco and Fransoo, 2003). Such stores will benefit considerably from the higher coordination and information flows across the network that are generated by smart cities and big data. For example, the combined use of open data bases with real-time information (e.g. weather patterns, traffic) and smart mobility initiatives (e.g. electric scooters, compact bike-lane vehicles) will allow more efficiency in urban logistics. In particular, it will improve efficiency in the “last mile” delivery in micro-retailing settings (MIT, 2014a), which is a part of the logistics process traditionally characterized by high unit costs.

With respect to information flows, we observe that the correct implementation of big data depends on an enormous storage capacity and processing power. Thus, it will create opportunities for companies that are located in the middle of large amounts of data flows (e.g. information about products, buyers, suppliers, consumers, etc) and are capable of aggregating and analyzing them (Manyika et al, 2011). For example, firms can use big data to centralize decisions more efficiently. Cai and Xu (2013), using “big data” mining techniques, evaluated the impact of adopting plug-in hybrid electric vehicles in the taxi fleet on life cycle greenhouse gas emissions, based on individual real-time vehicle trajectory data for more than 10,000 taxis in Beijing in one week. Additionally, firms that learn to exploit big data will use real time information from sensors, radio frequency identification and other identifying devices to understand their business environments at a more rough level (Davenport et al, 2012). Therefore, smart cities and big data may stimulate more centralization of information flows. This could generate additional problems related to an excessive centralization. For example, local optimization based on the perspective of a focal firm could lead to sub-optimal decisions for the entire chain. A retailing company, for example, could position its urban consolidation centers with the objective of minimizing “last mile” distribution costs, but in areas less favorable to its suppliers.

In addition, it may be argued that smart cities also affect SCM knowledge flows. Thus, they might change the power structure within supply chains, by providing low-cost, valuable knowledge to small firms in the supply chain through “crowdsourcing” (i.e. when businesses obtain knowledge from an online community). For example, they may provide a small supplier or logistics provider with accurate knowledge about land use, noise levels or dynamic phenomena like urban heat islands (The Copenhagen Wheel, 2014).

3.4. How smart cities and big data interact with network complexity

Complexity theory has attracted increasing interest in management research, as evidenced by the special *Management Science* issue on this subject (Amaral and Uzzi, 2007). Complexity has received several definitions in the management literature: the variety and uncertainty associated with a system (Frizelle, 1998); the number of elements and the degree to which those elements are differentiated (Choi and Krause, 2006); the amount of coordination load on the network (Choi and Hong, 2002). In this study, we distinguish between two approaches to complexity: a supply network perspective (Choi and Hong, 2002; Kim et al, 2011), and an information-theoretical perspective (Sivadasan et al, 2002, Frizelle, 1998).

From a *supply network perspective*, the interplay between smart cities and network complexity can be understood by analyzing the concept of complex adaptive supply networks (CASN). A CASN is a system of interconnected autonomous entities that is self-organized (Choi et al, 2001; Surana et al, 2005; Pathak et al, 2007). Similarly, smart cities can be viewed as networks of elements that interact dynamically as a complex, self-organizing system (Manville et al, 2014). In a system, when there is a large number of components and enough interactions among them, patterns tend to emerge, leading to self-reinforcing feedback cycles and predictable collective behavior (Anderson, 1999). However, systems in which all components are fully connected tend to be unstable (Simon, 1996). In this setting, a high number of interactions between stakeholders with conflicting objectives may complicate the decision-making processes, increasing the network complexity (Anand et al, 2012). Thus, the urban trend towards micro-retailing, with multi-tiered structures, multiple modes of transportation and a multitude of distribution points implies more structurally complex distribution networks (Blanco and Fransoo, 2013). This could require different organizational decisions at supply network level, for example vertical integration.

Conversely, supply network complexity may affect smart cities and big data. More specifically, it positively affects the ability to access and share information across the supply chain, because more actors are involved in exchanges within the network (Caridi et al, 2010). Thus, big data applications (e.g. open data) can benefit from the input generated by a higher diversity of actors in a structurally complex network. However, Skilton and Robinson (2009) argue that tight coupling among firms is more difficult to achieve in complex supply networks, so failures in information exchange may be a problem. Thus, the impact of supply network complexity on smart cities and big data will largely depend on the degree to which firms can achieve a satisfactory coupling by using the different types of governance mechanisms.

From an *information-theoretical perspective*, Sivadasan et al (2002) defined two types of complexity: structural complexity (i.e. the variety embedded in the system) and operational complexity (e.g. the uncertainty in the system). Structural complexity can be measured as the amount of information necessary to describe the state of a planned system, whereas operational complexity can be operationalized as the amount of information required to describe the state of the system deviation from the schedule (de Leeuw et al, 2013). We posit that whereas smart cities and big data increase structural complexity, they have an opposite effect on operational complexity. In the following sections, we analyze in depth this issue.

3.4.1. Smart cities vs. structural complexity

The implementation of big data in SCM activities does not necessarily imply more efficiency (Miller and Mork, 2013). Indeed, smart cities and big data tend to increase structural complexity, because they amplify the amount of information necessary to monitor the state of the system. Furthermore, Browne and Gomez (2011) argue that delivering in urban areas increase the amount of information to be considered during logistics planning (e.g. delivery windows, routing and vehicle capacity have to be defined according to regulatory restrictions). Urban supply chain restrictions can be divided in internal (e.g. delivery windows, fixed routes, maximum vehicle load) or external (e.g. congestion charge, low emission zones, speed limits). Additionally, these restrictions have important interactions among them. For example, the definition of customer delivery windows cannot be separated from the parking restrictions that apply at the customer’s premises (Browne and Gomez, 2011). Therefore, these restrictions tend to increase the structural complexity. In a coupled system, such restrictions could jeopardize the efficiency and flexibility, because when coupling is tight, events in one part of the system affect other parts in unpredicted manners (Skilton and Robinson, 2009). Thus, unless firms completely redesign their distribution networks, an increased structural complexity could increase costs and decrease flexibility. In addition, the complexity of interactions between so many heterogeneous automated systems may generate more mobility problems that solutions. For example, the use of self-driving vehicles may incentive urban displacements, increasing traffic jams (Rudin, 2014).

3.4.2. Smart cities vs. operational complexity

Alternatively, smart cities and big data can lower operational complexity by reducing the system uncertainty or the deviation from the schedule. For example, the mobility patterns of consumers throughout the day can be tracked and combined with other sources e.g. credit cards transactions, pictures posted on social networks, government and open data bases. This may support the development of a "heat map" with geographically displayed information such as density of commercial transactions, average expenses, consumption location, etc. Just like a doctor examines a magnetic resonance image to make a brain diagnosis, managers will be able to analyze heat maps of consumer mobility to plan distribution strategies, or fine-tune inventory level (Martinez and Rodriguez, 2012). This is especially relevant for stores that are supplied several times a day. From an information processing view, organizations aim at systematically improving decision-making to reduce uncertainty (March and Simon, 1958). In supply chain design, for example, such information can be useful to plan the location and distribution strategies of "nanostores" (i.e. to fit the mobility patterns of consumers during the day). Another potential development is the synchronization of deliveries with consumer's location data obtained through mobile phones. Moreover, electronic sensors in trucks or other modes of transportation can provide critical data such as real-time position, temperature, vibration or humidity, which is especially useful for perishable products. Finally, smart traffic systems can be combined with smart parking to provide additional data to improve routing of deliveries.

Furthermore, there are several potential sources of data that may contribute to reducing transportation operational complexity, using mainly citizens input. For example, CivicReady[3] is an emergency management portal and a public data base that provides accurate emergency-related information such as road closings, severe weather warnings, travel alerts and health alarms (Cohen, 2014). Moreover, new physical devices can also provide access to information from the environment. For example, the city of Boston is testing smart sensors such as barcodes and RFID tags integrated into street elements that enable routing applications (New Urban Mechanics, 2014).

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[3] www.civicplus.com

Although network structure (e.g. density, centralization, complexity) helps understand some aspects of how smart cities and big data interact with SCM, it is also important to consider the mechanisms used by the focal firm to govern interactions within the network. More specifically, the concept of social embeddedness (Granovetter, 1985) posits that firms are embedded in dynamic networks of social relationships, which are constantly shaping their expectations and behaviors. Thus, network governance mechanisms should also be taken into consideration in this study, because they can be understood as behaviors molded by the smart city environment. This issue is discussed in the next section.

3.5. How smart cities and big data interact with governance mechanisms

A critical aspect of the interaction between smart cities, big data and supply networks is network governance i.e. the set of mechanisms that supports cooperation among organizations (Alvarez et al, 2010). In particular, we borrow from the organization design literature the notion of formal (Gulati and Singh, 1998; Dekker, 2004) and informal (Jones et al., 1997; Powell, 1990) governance mechanisms.

Formal governance mechanisms rely on control systems through which organizations structure their interaction in an explicit manner (Gulati and Singh, 1998; Dekker, 2004). They can include command structures, incentive systems, standard operating procedures and documented dispute resolution procedures (Alvarez et al, 2010) and are often based on hierarchical controls (Gulati and Singh, 1998).

Informal governance mechanisms are characterized by relationships rather than by bureaucratic structures (Jones et al., 1997; Powell, 1990). They include information sharing, values, culture, and social norms (Alvarez et al, 2010). According to transaction cost theory and the concept of bounded rationality, complex transaction contracts will always be incomplete (Williamson, 1983), so informal mechanisms may be needed in order to decrease transaction costs of monitoring and coordination (Kale and Singh, 2009). They may include self-regulation, combined with moral perspectives (Schmoltzi and Wallenburg, 2012). Similarly, Jones et al (1997) argue that ties between organizations serve as social mechanisms of control. Although usually considered as a complementary governance mechanism, they can be the main form of governance when formal controls are complicated (McEvily et al, 2003).

3.5.1. Smart cities vs. formal governance mechanisms

Some supply relationships are highly specified or rigidly controlled (i.e. formal), while others are poorly defined and ambiguous (i.e. informal) (Skilton and Robinson, 2009). *Formal governance mechanisms* are based on standards, contracts, formalized processes, and control systems (Alvarez et al, 2010). Formalization is often associated to coupling. A supply network is tightly coupled when product, processes and performance standards are well defined. In slackly coupled relationships, information exchange is difficult (Skilton and Robinson, 2009). Smart cities and big data are often associated to coupled relationships and formal governance mechanisms. For example, the FAMILY Loyalty program of IKEA recognizes all consumer purchasing channels (e.g. catalogs, clickstream data from the web or store visits), and processes this data to give benefits to its members accordingly. Also, the Intelligent Operations Centers (IOC) allow a formal control system that uses analytics to manage traffic patterns and optimize routes (IBM, 2013).

In addition, the interaction between smart cities, big data and formal governance mechanisms can be better understood under the theoretical lens of innovation diffusion (Rogers, 2003) and the information processing view (Wu et al, 2013). Whereas innovation diffusion claim that specific characteristics of the technology determine IT adoption, the information processing view posits that both organization and its environment influence it (Melville and Ramirez, 2008). Therefore, the adoption of smart city and big data techniques is driven simultaneously by the demand of firms in the network and the supply of new technologies. Similarly, adaptive structuration theory (AST) is used to analyze how changes in information technology affects supply chain evolution (Lewis and Suchan, 2003). It predicts an adaptive iteration between new technologies and the system (Holweg and Pil, 2008) through formal structures that emerge as organizations interact with these technologies (Orlikowski, 1992). This is consistent with Alvarez et al (2010), who posit that formal mechanisms tend to be adopted in dynamic and unstable circumstances. Social embeddedness can also help understand this interaction. Embeddedness is the process of becoming part of a structure. It can be characterized by the strength of the social ties of a firm with its immediate social context, aiming at support and mutual collaboration (Sarkis et al, 2011). In the context of smart cities, social embeddedness is leveraged through formal ICT-enabled initiatives such as open data bases and urban operating systems (Manville et al, 2014). For example, the city of Boston has launched Street Bump, which is a mobile app that collects data about driving “smoothness”. For example, citizens may use Street Bump to record road obstacles, which are identified using special electronic devices and located using its GPS. This app can provide users with real-time information that can be used for better routing of deliveries (New Urban Mechanics, 2014).

3.5.2. Smart cities vs. informal governance mechanisms

Informal governance mechanisms are based on more intangible elements such as values, culture, social norms and relationships (Alvarez et al, 2010). According to Pilbeam et al (2012), informal mechanisms are implemented when there is a stable context and trust between the parties. In the case of smart cities, the context is still evolving rapidly, and long-term collaboration is incipient. Moreover, according to a study from the European Commission, more than two-thirds of smart city projects in Europe are in the planning or pilot testing phases (Manville, 2014). Therefore, informal governance mechanisms in smart cities settings are apparently not as important as formal ones. However, informal governance mechanisms such as culture or social norms could play a role in facilitating citizen input to smart apps (e.g. Open311).

All the examples provided confirm the important influence of technology on smart cities implementation. Nevertheless, the resource-based view (RBV) posits that firms should base their competitiveness on resources that are valuable, rare and hard to imitate (Barney, 1991). Thus, the simple adoption of a freely available technology per se (e.g. big data) will not induce a long-term competitive advantage. Instead, IT should be complemented with a firm's existing resources (Ray et al, 2005), e.g. culture and relationships. Similarly, Rudin (2014) argues that there is an urgent need to move away from the techno-determinism that surrounds discussions about mobility innovation. The extent to which these concerns are taken into consideration may determine the success of projects related with smart cities.

4. CONCLUSION

In this study, we draw on organizational theories to posit an integrative framework relating smart cities, big data, supply networks characteristics and governance mechanisms. Several studies have analyzed IT innovation adoption in supply chains (Patterson et al, 2004; Wu et al, 2013), but to the best of our knowledge, there has been no study focused on smart cities. Moreover, we argue that the concept of smart cities by itself has limited potential to support new SCM configurations. Nevertheless, when it is combined with big data initiatives, the impact on SCM can be significant. More specifically, smart cities may provide firms with the necessary infrastructure to leverage big data initiatives. Furthermore, the proposed framework is used to depict potential impacts on different SCM issues.

The main theoretical implication of this study is the notion that the relationships between smart cities, big data and supply networks cannot be described simply by using a linear, cause-and-effect framework. Accordingly, we have proposed an integrative framework that can be used in future empirical studies to analyze smart cities and big data implications on SCM.

This study has several managerial implications. First, it suggests that smart cities and big data alone have limited capacity of improving SCM processes, but combined they can support improvement initiatives. Secondly, we posit that, despite potential benefits, smart cities and big data can suppose some novel obstacles to effective SCM. Lastly, from a strategic perspective, new competitors could take advantage of both opportunities and restrictions, and launch new competing business models. The proposed integrative framework helps managers to identify and react to these threats from an OM perspective.

This study raises some interesting lines of research. Firstly, according to adaptive structuration theory, when new information flows are implemented in line with the interests of the lead firm, the other members of the supply chain are forced to rely on buffers to protect themselves against potential information gaps (Holweg and Pil, 2008). To what extent this phenomenon also applies to a smart cities and big data context is still unknown.

Secondly, more than thirty million networked sensors are present in transportation, automotive, and several retail sectors, and this figure is increasing thirty per cent a year (Manyka et al, 2011). The potential impacts of such increased process visibility on several industries, especially those based on information asymmetry, should be further explored.

Thirdly, drawing on Manville et al (2014)'s distinction between "top-down" or "bottom-up" smart cities implementation approaches, a potential research line could focus on the implications of firms proactive and reactive strategies. More specifically, it would be interesting to investigate under which condition firms should take the lead or adopt a more conservative approach with respect to smart cities.

Moreover, there is the risk that over reliance on big data implies that practices are implemented based on what firms *can* measure, instead of what they *should* measure. A typical example is the focus on implementing smart sensors and all kinds of physical devices in urban areas, without a prior analysis of the real user needs or how this information will be used. In other words, the increase in structural complexity and operational load may incentive firms to neglect exploring other approaches not based on "hard" data. Further research should be developed in order to consider how this affects operational performance, and to contrast alternative approaches to tackle this issue.

Another potential line of research is the role of brokers and "structural holes" (e.g. lack of ties among network nodes) in the smart cities implementation. When ties among network members are information exchanges about better integrating outputs, structural holes will have a negative impact on performance. Alternatively, when such ties correspond to information with respect to other network members interactions with a third party (e.g. price), structural holes will have a positive impact on performance (Borgatti and Li, 2009). Thus, it remains to be verified how structural holes affect smart city implementation and performance.

Furthermore, it remains to be investigated to what extent different country contexts affect smart cities-big data implementation and its impact on SCM. In particular, our study challenges the current governmental view (Department for Business Innovation & Skills, 2013), by placing firms and logistics providers as key drivers of this process.

Lastly, researchers should investigate to what extent smart cities and big data shift the power structure within supply networks. Smart cities and big data may have a significant role in altering power distribution within supply networks, for example by providing firms with critical data on consumption patterns. According to a study by McKinsey Global Institute, big data will provide enormous opportunities for firms that are in the middle of large information flows, that process millions of transactions or that interface with large number of consumers (Manyka et al, 2011). Under this scenario, large retailers could use this data to better fit distribution strategies and detailed customer segmentation, increasing margins and streamlining processes. Moreover, it will provide a mechanism for the transit operator to both buy and sell data, as well as to publish open data for use by 3rd parties (Rudin, 2014). To examine how this will affect power relations within supply networks seems to be an auspicious research line.

In a nutshell, this study has contributed to expand knowledge on SCM by providing an integrative framework of supply networks in a smart cities and big data context. We contribute to the literature by setting the ground for future research on this area, and also by providing future research directions for academics and practitioners interested on this increasingly important issue.

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Figure 1. Integrative framework: Smart cities-Big data and supply networks