Unpacking and Measuring Urban Complexity Evidence from amenities in Paris

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Unpacking and Measuring Urban Complexity
Evidence from amenities in Paris

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Abstract : In this paper, we argue that a complexity-driven systemic perspective of urban life can be characterized through the consumption practices of people that interact within urban spaces, and that such a characterization can uncover relevant information for planners. We propose a granular analysis of commercial amenity networks within cities and adapt a measure of economic complexity to aptly reduce these networks. This yields the *Amenity Complexity Index* (ACI), which is the focus of this work. The ACI is interpretable in terms of consumption practices and of place characteristics, both from a macro city perspective and from a place-based granular perspective. The dynamic illustration of our complexity measure in Paris helps demonstrate ways in which the ACI can enrich our understanding of cities and of the transformative systemic challenges they face. Ultimately, this work proposes a measure and an accompanying interpretation of urban complexity based on commercial amenities that paves the way for novel analyses of the causes and effects of urban transformations, of urban policies, and of the wellbeing of dwellers.

Keywords: complexity, amenities, cities, consumer, transformations
JEL Code : R11, C81

Introduction

In the New York of the 50's, Robert Moses was a legendary city planner. Jane Jacobs (1961) was one of its most ardent opponents and one of the first to eminently outline the limits of top-down approaches to apprehend cities. Her work has since inspired modern planning literature to increasingly outline the systemic and bottom-up nature of urban issues, sometimes within complexity frameworks (Batty & Marshall, 2012; Boonstra & Boelens, 2011; Moroni, 2015; Rauws et al., 2016). Infrastructure, housing, job markets, innovation, education, health, are all a part of deeply interrelated dynamics between all types of agents with their respective objectives, and are difficult to observe in practice. Adequately informing urban decisions is thus very tricky. Still, the view of cities as complex systems has come a long way in theorizing these dynamics, in part through interdisciplinary inspirations (Allen, 1997; Anderson, 1972; Batty, 2000; Krugman, 1996). Modern understandings of self-organization (Moroni et al., 2020) and of flows (Batty & Cheshire, 2011) provide systemic explanations of the way

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cities emerge and evolve. Empirical contributions have also leveraged mathematics-inspired complex systems (Batty, 2001) to explain human organization.

In this paper, we add to the ongoing trend of interdisciplinarity in urban planning. We bring forward evolutionary economic geography and the paradigm of economic complexity and show how it can further uncover and explain issues within cities as systems through the empirical tools it provides.

The paradigm of economic complexity : A network-based approach

We focus on the modern network-based interpretation of economic complexity in evolutionary economic geography spheres (C. A. Hidalgo et al., 2007; C. A. Hidalgo & Hausmann, 2009). This recent development has gained a lot of traction over the past decade (Balland et al., 2022; C. A. Hidalgo, 2021). In the same way systemic approaches to planning go against orthodox views of cities, economic complexity has come as a reaction to traditional approaches to growth (Balland et al., 2022; C. A. Hidalgo, 2021). It is also heavily focused on the importance of systemic interrelations. In economic complexity, the quasi-infinite hidden interactions between interrelated economic agents lead to emergent and constantly out-of-equilibrium systems that evolve non-linearly. In practice, economic complexity supports the idea that "Growth, development, technological change, income inequality, spatial disparities, and sustainability are the visible outcomes of hidden systemic interactions" (Balland et al. 2022). This is akin to what planning has adopted as a form of self-organization (Krugman 1996).

However, one key difference between economic complexity and systemic approaches in planning is how the former has revolved around providing empirical methods to reduce the dimensionality of complex interactions. The premise is that one cannot predict outcomes through agents' interactions in a *genotypic* way, that is, through the information contained within the processes, because these interactions are too complex. Economic complexity literature takes a *phenotypic* approach by apprehending and measuring systemic interactions from the perspective of what can be observed[2], that is, by focusing on observables. Reducing the dimensionality of observables through a network perspective can help characterize processes that would otherwise be too complex. The reduction of systemic interactions and interrelations in the field of economic complexity can be tightened down to two related but separate movements : Relatedness measures and Complexity measures.

Both of these measures are deeply intertwined. They rely on the concept of a product space, or network, in which countries, regions and cities all operate (C. A. Hidalgo et al., 2007). Measuring the *relatedness* between products in that space provides information about how similar these products are in the inputs, knowledge and routines they require to be produced (C. A. Hidalgo, 2021). The combinations in places of localized events or attributes influences the likelihood of related events or attributes entering. These combinations can contribute to explaining path-dependent evolutions at various spatial scales (Boschma, 2017; Frenken et al., 2007; Neffke et al., 2011). The *Economic*

[2] Very recently, Economic Complexity has starting exploring issues *genotypically* through the deduction of *phenotypic* tools (Balland et al., 2022)

Complexity Index, a measure of places' leverage within the same product space, is the measure we translate to cities' amenities and is the focus of this paper.

The Economic Complexity Index

Economic complexity assumes that all products are not equal within the product space ; Their position in the space will depend on what kind of knowledge they require. Measuring a countries' economic complexity is measuring the leverage it has in the product space, and thus its ability to generate future growth in a more complete way than traditional growth models based on aggregate inputs and total factor productivity (Balland & Rigby, 2017; Hausmann et al., 2014; C. A. Hidalgo, 2021; C. A. Hidalgo & Hausmann, 2009). In economic complexity, differences in outcomes are due to the distinct kind of goods countries are able to produce. C. A. Hidalgo and Hausmann (2009) (HH hereafter) presented a first version of the *Economic Complexity Index*. They argue that what countries are able to export relative to the rest of the world is representative of their relative knowledge. In practice, this index is an applied spectral method that solves a reduction of the global export network of countries and products, and that thus does not require prior assumptions about the relative positions of goods or of countries. Through this, it assigns a given complexity index and rank to every country and every product. HH assume that products that are non-ubiquitous (that are rare, exported by few countries) and that are produced in diverse countries (that export many different & rare products) require a rich set of enviable capabilities, and therefore a higher level of knowledge. In practice, the complexity of countries (the *Economic Complexity Index*) is reflective of the complexity of its products, and vice versa. The philosophy and the strength of results yielded by the *Economic Complexity Index* have granted it a strong stand in the modern economic geography discourse, both methodologically and in its very flexible applications (Balland et al., 2022; C. A. Hidalgo, 2021).

In the following paper, we argue that the economic complexity paradigm is suited to address systemic planning-oriented issues. Using economic complexity to granularly understand cities is also the focus in the work of Juhász et al. (2022), where they interpret a complexity index of neighborhoods' amenities as indicative of socio-economic mixing, and relate it to urban segregation.

In our contribution, we translate economic complexity's product space into a strictly commercial amenity space to uncover market-driven consumption patterns. We apply this space at a granular level using a 15-minute walking radius from buildings to amenities. We present a specific adaptation of the economic complexity index, the *Amenity Complexity Index* (ACI), to reduce places' commercial amenity spaces. Using a consumption-focused framework, we find that the ACI is a powerful tool to uncover urban dynamics through its underlying segregation of places, of commercial amenities, and of consumers. We argue that, through market dynamics, separating places through their commercial amenities is ultimately akin to separating them through their non-commercial amenities, and that the ACI can thus be interpreted as an estimation of overall place attractivity.

First, we unpack the usefulness of using commercial amenities to analyze cities, and present a framework upon which to build commercial amenity networks. Second, we present a methodology for computing the complexity of amenities and of their places. Third, we build interpretations of our complexity measures and illustrate them through a multi-year application on the city of Paris. We conclude by opening up a research agenda by offering scholars and policy makers ways through which ACI can be related to various indicators in order to reveal hidden urban patterns, and explore ways in which it can be leveraged to understand cities in the context of systemic urban transformations.

1- The commercial amenity space

Commercial amenities and urban transformations

"Cities must attract workers on the basis of quality of life", (Glaeser et al., 2001). In the same way differences in outcomes between cities are driven by their amenity space in Glaeser et al. (2001), we postulate that different outcomes between cities' places[3] are also driven by their amenity space ; And that commercial amenities are an apt reduction of that space from a systemic standpoint.

The way we define commercial amenities is akin to the first type of amenity Glaeser et al. (2001) outline and refer to as "services and consumer goods"[4]. Current important discourse regarding urban transformations through the lens of the demand for cities (Florida et al., 2023), overtourism and place alienation (Diaz-Parra & Jover, 2021), and transnational gentrification (Sigler & Wachsmuth, 2016 ; Sigler & Wachsmuth, 2020) are to various degrees all intertwined with commercial amenities. We claim that commercial amenities are the heart of the underlying processes that motivate these transformations. They are both factors and outcomes of urban transformations through their provenance from and effect on flows of people. With adequate tools, commercial amenities can teach us about urban dynamics and the modern challenges cities are facing[5].

Kaufmann et al. (2022), in their dive into the scaling of urban amenities, go beyond commercial amenities and elect to include public services. This is also the case in the ongoing work of Juhász et al. (2022), where they compute the economic complexity of amenities and districts, and relate it to urban centrality and visitor diversity. We elect to exclude aesthetics, public services and speed (Glaeser et al., (2001)'s other urban amenity types) from our framework. First, commercial amenities are more objectively observable than the others. Speed (or accessibility) is difficult to define in an objective way. Aesthetics even more so, and the few noteworthy attempts (Naik et al., 2014) have been limited in scope. Second and more importantly, commercial amenities depend relatively weakly on top-down planning efforts. Urban planners can somewhat control their locations through licensing and land use,

[3] In the context of this paper, "places" can be seen as sub-city level divisions of space

[4] For the purpose of this paper, commercial amenities are defined as market-oriented goods and services that imply physical economic interactions between private individuals and suppliers. Online retail is not a part of the framework, neither are non-profits.

[5] The digital transformation of cities and e-commerce, and the way in which they can replace physical commerces, are out of the scope of this paper.

but commercial amenities will only ever survive if they have adequate consumption and a sustainable business model. Their existence requires market coordination that comes as a result of many codependent interactions and interrelations that lead to consumer presence rather than of conscious planning decisions, and thus they are best suited to the systemic analysis we engage in. Thirdly, and just as importantly, excluding amenities more dependent on planners allows us to approach them exogenously. Public goods and services as well as accessibility modifications affect the ability a place has to attract different types of consumers, and they are part of the systemic process ; They are however under more control. Confronting these other amenities to a unifying measure of the basket of commercial amenities as an exogenous variable is an essential part of potential applied research. It could help planners to uncover the impact of their decisions on places' consumer attraction and on its transformations, and to adapt accordingly.

This effort is not the first attempt at using commercial amenities as proxies for ongoing urban transformations. It is clear that commercial amenities are intertwined with other place characteristics of interest to people. Glaeser et al. (2018) find that leveraging commercial amenities using Yelp data can help predict gentrification, albeit with caution regarding causal interpretations. Couture & Handbury (2020) find that non-tradeable service amenities play an important role on location choices of college graduates. Recent tourism-oriented literature has also been investigating links between commercial amenities and changes in the composition of local demand (Particularly short-term rental literature, Basuroy et al., 2020; Ioannides et al., 2019; A. Hidalgo et al., 2023). However, most current applications either aggregate different types of amenities or select specific amenities, like restaurants, and discard potentially important information about the whole picture. Juhász et al. (2022) avoid this by also leveraging economic complexity methodology in Budapest. Despite common methodological roots, we provide a different reading of the ECI in this paper that we argue is closer to urban transformation frameworks. We propose a data-driven methodology to unearth patterns of complex commercial amenity co-locations, and provide a framework in which to interpret these patterns.

Laying the foundations of the commercial amenity space

In order to better understand why and how different commercial amenities co-locate in the way they do, we must first understand how suppliers of these amenities come to choose their locations. In other words, we need to understand how the amenity space is built. C. A. Hidalgo et al. (2020) show that using relatedness is relevant towards understanding urban commercial amenity spaces from an evolutionary perspective. We deviate from this approach and take a consumer-motivated perspective to explain the amenity space. The following section elaborates on the links between different agents in the commercial amenity space, and on the hidden systemic interactions behind observed commercial amenity locations. Assuming that they are profit-driven, commercial amenities require consumers to be sustained. Their location will therefore depend on the availability of individuals willing to consume them and on the aggregation of these individuals in places (Waldfogel, 2008), or at least on their anticipation of their presence. This is the key behind most economic approaches to consumption, from Hotelling's most basic models (Hotelling, 1929) to those that rely on complementarity across supply. Of course, reality is complex. Different amenities require different levels of consumer availability as well as the availability of different consumers, as different people enjoy different commercial amenities.

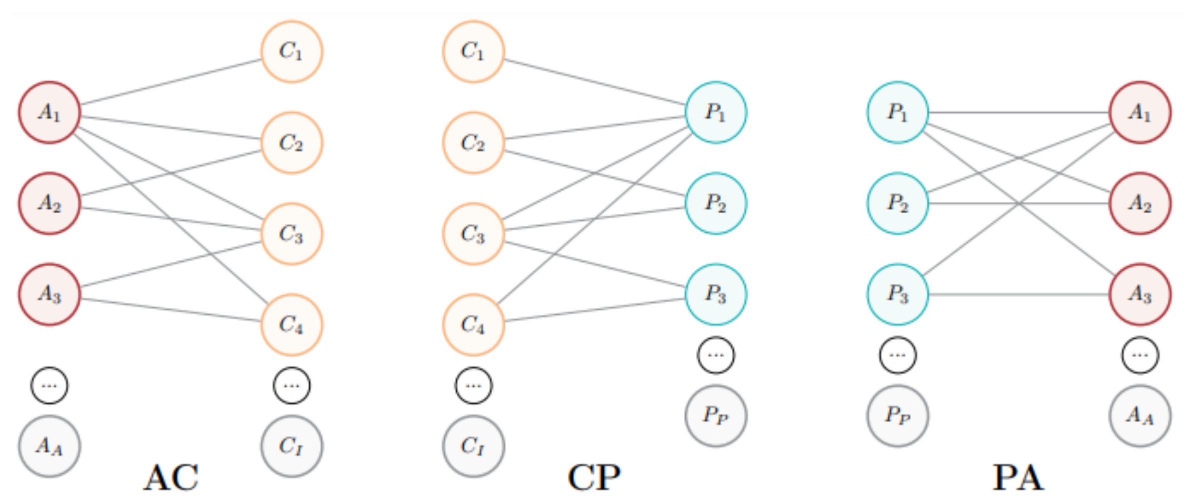
But what is it that makes people consume different amenities ? This very broad question can find answers in various fields, often by attempting to understand peoples' preferences. In our setting, grasping the mechanisms behind individual preferences is not necessary, and we do not need to take an epistemological stance on consumer choice (see Hands, 2010 for a perspective) or rationality. We accept preferences for amenity consumption holistically and abstractly as a result of individuals' income, cultural influences, perceived identities, status, tastes ; Overall, as a result of what would be an unquantifiable *habitus* in a sociological framework (Bourdieu, 1977). Later in this paper, we attempt to characterize the groups of people behind different amenities' consumption. To that aim, we argue that a strong common characteristic to people that consume similar commercial amenities is how much they consume as a whole, as a function of both their spending power and their will to spend it on commercial amenities. This ties in to the idea of budget constraints in consumer choice theory – there is strong empirical evidence that spending power is linked to observed differentiated consumption (two examples of which are Jackson, 1984; Aguiar & Bils, 2015) –, and to the idea that economic capital is intrinsically linked to *habitus* (Bourdieu, 1987).

However, for now, we set out a framework with fewer assumptions, where consumers have different spending power, different preferences for commercial amenities and different preferences for places based on all of their amenities (including but not limited to commercial ones). Here, commercial amenity presence in places comes as a result of the sufficient presence of consumers that are willing to consume them (Waldfogel, 2008).

To accommodate this framework, we borrow economic complexity' network representations of underlying interactions (C. A. Hidalgo et al., 2007). Take a consumer-amenity matrix $\boldsymbol{AC}$ with A rows (commercial amenity types) and I (consumers) columns where $\boldsymbol{AC}_{a,i}$ is equal to the amount consumer i is willing to spend on amenity type a. The row sums of this matrix is the overall spending power of consumers, and their preferences define how they allocate that spending across different columns. Conversely, the column sums of the matrix are supply-side revenue, provided consumption is realized. For the purpose of visual clarity, let us simplify this perspective by assuming binary relationships between individuals and types of amenities, where $\boldsymbol{AC}_{a,i} = 1$ when i is willing to spend a unit of income in a and $\boldsymbol{AC}_{a,i} = 0$ otherwise. This caps per-amenity consumer spending to 1 unit of income in a way that is not reflective of the real world, but it is not an assumption we keep beyond visualizations. We illustrate matrix $\boldsymbol{AC}$ with a bipartite network in **Box 1**.

Parallelly, the same individuals distribute their spending in different places within the. Where they consume depends on place characteristics that throw us back to the consumer city (Glaeser et al., 2001). Amenities in a broad sense, including unobserved non-commercial ones, play the role of place characteristics that would motivate demand similarly to how characteristics of goods motivate consumption in consumer preference frameworks (Lancaster, 1966). Accessibility to a place for a consumer likely influences these links strongly, and urban planners have relative control upon them. We note a consumer-place matrix $\boldsymbol{CP}_{i,p}$ with *I* consumers in rows and *P* places in columns. Different links between consumers and places do not all hold the same value in regard to consumption allocation, but once again for visual simplicity, we binarize ***CP*** into 1 when a given consumer can spend a single unit of spending in a place and to 0 otherwise. A network representation of ***CP*** can be found in **Box 1**. ***CP*** is a representation of the demand for consumption in places.

Box 1 gives a visual representation of a third matrix $\boldsymbol{PA}_{p,a}$, where places *p* share edges with amenity types *a* when *a* is present in *p*. ***PA*** is the commercial amenity space and it is observable with data. For simplicity's sake, we assume that all different amenity types require the same level of revenue in a place to be present in it. We set the level of required revenue to 2 in this example. If at least two units of relevant consumption are found in *p*, then presence in *p* is sustainable for *a*. The observed commercial amenity space ***PA*** is a function of the hidden relationships between consumers and amenity types (***CA***) and between consumers and places (***CP***) : When *a* has a high enough number of relevant consumers in *p*, it can open up shop.



***AC :** Network of individual consumers and commercial amenities. Consumers C_i share an edge with Amenity A_a if they allocate consumption to it.*
Here, A_1 is a necessary amenity. All consumers allocate money. In practice, this amenity is likely to be essential to everyday life, like a supermarket for example.
C_3 has the highest spending power and shares it equally between all three of the presented amenities.
C_2 and C_4 both have the same spending power, but they have different preferences.

***CP :** Network of individual consumers and places within cities.*
Consumers C_i share an edge with Place P_P if the place is attractive enough for them to spend income there.
In this specific example, P_1 is frequented by everyone. In practice, P_1 is likely to be central, providing access to various amenities in a way that is accessible to all the consumers.
C_3 spreads her spending the most across the city, while C_1 only spends in P_1.
C_2 and C_4 both provide consumption opportunities in two different places.

***PA :** Network of commercial amenities and places within cities. Amenity types A_A share an edge with Place P_P if they are observed to be present in the place. We argue that **PA** comes as a result of subnetworks **AC** and **CP**.*
Amenity type A_1 is present in all 3 Places because it is desired by all consumers, and all 3 places host at least 2 consumers.
A_2 is not present in P_3 because C_2 is missing from P_3. A_3 is not present in P_2 because C_4 is missing from P_2.

Box 1 : Network visualizations of the coordination processes behind commercial amenity consumption

The ***PA*** matrix is what we can observe with data. It is also what Juhász et al. (2022) and C. A. Hidalgo et al. (2020) observe. Edges between places and amenity types signal the availability of a sufficient amount of relevant consumers (that are willing and able to consume it) in a place.

The networks presented in **Box 1** are voluntarily oversimplified views of reality. Still, they suffice to perceive consumption in cities from a systemic standpoint. Interactions between and among all agents are permanent, and small changes can have large and non-linear ripple effects. Let us play out a made-up scenario to demonstrate these ripple effects. A planner decides to replace a parking lot with a park in city center P_1. This might make the place less accessible to suburban consumer C_2 for whom it will be a lot more costly to drive there, but encourage C_4 to spend a larger share of her time there because she finds it more desirable. As a result, C_2 visits P_3 instead. Parallelly, C_4 now meets up with her friends in P_1 instead of P_3. With time, A_3 will be lacking available revenue in P_3 because of C_4's absence, and its presence will not be sustainable in the long term. The changes in place habits of these consumers and of the commercial amenity-mix distribution could in turn impact other places' relative ability to attract consumers. In fact, this scenario can not be fully played out as the multiplicity of agents and interactions will never leave enough time to reach an optimal situation. This is inherent to complex systems : they are permanently emerging and out-of-equilibrium. Attempting to fully grasp the process of places' emergence within cities through their characteristics alone is quasi-impossible. Yet the commercial amenity mix of places tell us about a number of different things that can influence both the presence of consumers and their spending habits. In its most holistic interpretation, the amenity space contains information about flows and interactions, ranging from supply and demand dynamics, to top-down zoning, to specialization, to quality of life, to overall atmosphere. The problem we seek to solve in this paper is to determine what it is that differentiates places in their consumption structures, as these consumption structures can be representative of important situations and phenomena.

Economic complexity methodology is particularly well-suited to solving network-driven problems and to unlocking hidden underlying patterns. Leveraging the full information of the observable network in ***PA*** is important, because if it can help us uncover the profiles of places and amenities, and if we can associate these profiles to profiles of consumers, it can help understand changes within cities on a broader scale (Florida et al., 2023; Sigler & Wachsmuth 2016). In the following section, we present an adaptation of the *Economic Complexity Index* to places and to their commercial amenities as a way to summarize the observable network ***PA*** while preserving information over ***AC*** and ***CP***. We then explore its possible interpretations through an application in Paris. We leverage the network to determine, by location and amenity mix similarities, a continuous and uni-dimensional typology of places and commercial amenities. Within the framework we just explained, we argue that this typology is representative of underlying differences in consumers, by their preference for places and for amenity types. After that, we seek to unravel interpretations of place and amenity type complexities while illustrating the index's application in Paris.

2- Measuring Places' and Amenities' Complexity

Understanding the ECI

Economic complexity has given economists information-preserving ways of summarizing productive structures. The flexibility of these principles has been thoroughly explored in the last few years of evolutionary economic geography research, as Balland et al. (2022) and C. A. Hidalgo (2021) aptly summarize. After having presented the groundbreaking work of C. A. Hidalgo & Hausmann (2009) (*HH*) and explored the ECI's interpretations, we will discuss its conceptual and practical challenges in the amenity space and propose a specification for the *Amenity Complexity Index* (ACI).

HH explain differences in complexity for countries as emanating from sets of productive capabilities that determine which goods a country is capable of exporting. The ECI is meant to reduce a bipartite network (like ***PA*** in **Box 1**) that can be represented in a binary matrix $\boldsymbol{M_{c,p}}$ with $\boldsymbol{M_{n,p} = 1}$ where country *n* is linked to product *p* and $\boldsymbol{M_{n,p} = 0}$ otherwise. It does so in a Singular Value Decomposition-like way that preserves information well and is agnostic about the complexity of both products and industries (C. A. Hidalgo, 2021). In their original work, *HH* presented the *Method of Reflections (MOR)* as a way of estimating country (ECI) and product (PCI) complexity indexes. The *MOR* uses an average-based iterative algorithm that uses countries' diversity and products' ubiquity (or non-rarity) as initial conditions. Diversity, noted $\mathbf{K_{n,0}}$, is number of industries each country is linked to : $\mathbf{K_{n,0} = \sum_a (M_{n,a})}$. Ubiquity $\mathbf{K_{p,0} = \sum_n (M_{n,p})}$ is the sum of countries each industry is linked to. The MOR interacts ubiquity and diversity measures over *i* orders, with $i \in \{1,\dots,I\}$ and *I* being the order at which $\boldsymbol{K_{n,i}}$ (ECI) and $\boldsymbol{K_{p,i}}$ (PCI) are stable. It defines the ECI $\boldsymbol{K_{n,i}}$ and the PCI $\boldsymbol{K_{p,i}}$ simultaneously as :

$$K_{n,i} = \frac{1}{K_{n,0}} \times \sum_p (M_{n,p} \times K_{p,i-1}) \tag{1}$$

$$K_{p,i} = \frac{1}{K_{p,0}} \times \sum_n (M_{n,p} \times K_{n,i-1}) \tag{2}$$

HH originally argued that $\boldsymbol{K_{n,i}}$ was a generalized measure of diversification or of ubiquity depending on the parity of the iteration, but these interpretations have since been mathematically disproven (Kemp-Benedict, 2014). In fact, it was proven that the *MOR* converges towards estimations of two specific fixed points, as demonstrated in (Caldarelli et al., 2012; Hausmann et al., 2014; Kemp-Benedict, 2014). Using a square similarity matrix ***W*** between countries (products) weighted by their diversity (ubiquity), that is,

$$W^N = \frac{1}{K_{c,0}} \times \frac{M \times M^T}{K_{p,0}} \tag{3}$$

$$W^P = \frac{1}{K_{p,0}} \times \frac{M^T \times M}{K_{n,0}} \tag{4}$$

They show that the eigenvectors $\boldsymbol{\nu}^{C}[2]$ and $\boldsymbol{\nu}^{P}[2]$ associated with the second largest eigenvalues of $\boldsymbol{W^N}$ and $\boldsymbol{W^P}$ correspond to the fixed points estimated by the *MOR*'s iterations. It is then standard practice to normalize the $\boldsymbol{\nu}^{C}[2]$ and $\boldsymbol{\nu}^{P}[2]$ by subtracting them by their means and dividing them by their standard deviations, yielding the ECI and the PCI as it is now used. Although the intrinsic ties between products' and countries' complexities remain, complexity can no longer be thought of as a "generalized measure of diversity" (*HH*). Interestingly, the eigenvector procedure has however opened up new, clearer interpretations than those at high orders of the initial *MOR* (C. A. Hidalgo, 2021; Mealy et al., 2019). Eigenvectors tell us about how different countries (or products) are from each other, both in sign and in magnitude. Here, they are a way of separating observations into groups based on $\boldsymbol{M_{n,p}}$ that minimizes between-group dissimilarities and maximizes within-group similarity (Mealy et al., 2019), and that best explains the structure of $\boldsymbol{M_{n,p}}$. At a fundamental level, complexity is a way of assigning numbers to observations that tell us how similar or dissimilar they are to each other, based on $\boldsymbol{M_{n,p}}$. Consequently, $\boldsymbol{\nu}^{C}[2]$ and $\boldsymbol{\nu}^{P}[2]$ are equivalent to -$\boldsymbol{\nu}^{C}[2]$ and -$\boldsymbol{\nu}^{P}[2]$ respectively. Typically, readability encourages the association of high scores with higher knowledge in economic complexity – But the inverse would be just as valid[6].

We use the standard (C. A. Hidalgo, 2021) normalized eigenvector method on our amenity-place network, and we reiterate the relativity of complexity because it is paramount to interpreting our indexes. There is nothing absolute about low or high complexity values. A highly complex place is however similar to other highly complex places and very dissimilar to low complex places as based on the amenity[7] network. It helps to imagine complexity measures as positions on a line that simply indicate how close observations are to each other. Our intuition is that (dis-)similarities yielded by complexity can be interpreted through the consumption-driven lens of our theoretical framework. Having provided a basic understanding of what the ECI means, let us now focus on the challenges that are specific to the amenity space in building the network.

Amenity complexity's conceptual and practical challenges

Two separate dimensions have to be articulated to define each place's amenity-mix ; Space, that is, what a place is, and what intensity (amenity count) is enough to justify binary adjacency between places *n* and amenity types *a* in $\boldsymbol{M_{n,a}}$.

Defining places

Existing network-driven amenity literature evacuates the spatial problem by using predefined administrative boundaries (Juhàsz et al., 2022) or clustering amenities (C. A. Hidalgo et al., 2020). We seek an alternative definition of places that would *(1)* allow for heterogeneity within administrative boundaries that are not intrinsically relevant to consumption, *(2)* be respectful of the urban landscape, and *(3)* provide continuity across space.

All three of these issues can be solved by considering practitioner-defined spatial coordinates as the centers of spaces, while allowing for overlapping places and with a large enough number of places. The downside of this added granularity is it might require more work to clean the data (which is already a problem at non-granular country levels, see C. A. Hidalgo, 2021) and to select appropriate global space. In practice we find that using residential buildings as the center of places strikes a good balance between granularity and practicality, solving (1) by filtering out *à priori* non-urban places better than gridded points would, and providing a better solution to (2). We call $\boldsymbol{c}$ the cutoff used to define

[6] In that -$\boldsymbol{\nu}[2]$ and $\boldsymbol{\nu}[2]$ are interchangeable to reconstitute $\boldsymbol{W}$ using their associated eigenvalue $\boldsymbol{\lambda}[2]$, because $\boldsymbol{\lambda}[2](-\boldsymbol{\nu}[2])(-\boldsymbol{\nu}[2])^{T} = \boldsymbol{\lambda}[2]\boldsymbol{\nu}[2]\boldsymbol{\nu}[2]^{T}$. These inversions are common in software implementations of the ECI/PCI. Balland (2017) inverts $\boldsymbol{\nu}^{P}[2]$ if it is correlated to ubiquity for example. However, if $\boldsymbol{\nu}^{P}[2]$ or $\boldsymbol{\nu}^{C}[2]$ is inverted, the other should also be.

[7] Hereafter, "commercial amenities" are referred to as just "amenities" unless explicitly specified otherwise.

places around buildings, with $c < d$ the distance between buildings, allowing for the introduction of spatially correlated places (solving (3)). Amenities are a part of a building's place when they are within c of it. Both the metric used to define c (e.g. meters or minutes) and the value of c depend on the practitioner's understanding of local context. A general rule of thumb is that c should define sizes of places in a way that is as close as possible to how place-goers envision them in a homogeneous way across the city. Having defined places and c, we focus on how to binarize the links between places and their amenity types.

Defining places' amenity-mixes

Computing the ECI requires a binary matrix. The problem of binarization is equivalent to finding the best way of reducing a bipartite weighted network $O_{n,a}$, that holds the number of amenities of type *a* in place *n,* into $M_{n,a}$, a matrix of 0s and 1s. $O_{n,a}$ can be viewed as a weighted bipartite network between places and amenities where weights are discrete counts. We argue for a methodology wherein $M_{n,a}$ is defined through a simple measure of presence as follows :

$$M_{n,a} = \begin{cases} 1 & \text{if } O_{n,a} \geq 1 \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

We therefore deviate from the Balassa index (Balassa, 1965) of *Revealed Comparative Advantage* (RCA), a standard in economic complexity (C. A. Hidalgo, 2021) which Juhász et al. (2022) also use for amenities in Budapest (results using RCA in Paris remain close but are noisier, see **Appendix 2**). First, we argue that count data are not comparable from one amenity type to another, nor from one specific amenity to another within a type. A restaurant has different implications to a places' economic interactions and different relative importance in the network when it can seat ten people compared to when it can seat one hundred, which we have no way of observing. Because there is reason to believe both different types of amenities and different places will have different size patterns, defining a binary matrix in a relative way is likely to be skewed – On top of being sensitive to thresholds. Conceptually, attracting consumption is not about the relative strength places have in hosting amenities, it is about their absolute strength, and we therefore emancipate this framework from specialization and diversification. Second and opting for an absolute definition, the difference between consumers being attracted to a place because of a commercial amenity, or the evidence a commercial amenity can be sustained in a place, is never bigger between two discrete values of count than it is between 0 and 1. There is more to be learned about places' amenity-mixes through the absolute absence of amenity types than through any given relative intensity of presence as long as amenity types are defined granularly enough. When amenity types are missing, we are absolutely certain there is no consumption for their type in a place.

Altogether, a presence-based binarization of the network is both the most agnostic and the most straightforwardly related to consumer habits. Having obtained our binary matrix $M_{n,a}$, we propose a way of applying the ECI to places and their amenities.

The Amenity Complexity Index

To determine our *Amenity Complexity Index* (ACI), we follow the particular specification of green complexity found in Mealy & Teytelboym (2022), but we do so for different reasons. Using very granular places (i.e large *N* in $\boldsymbol{M_{n,a}}$) comes with potential drawbacks we seek to mitigate through this specification. First, the level of hardware needed to compute $\boldsymbol{W^N}$ (the place similarity matrix based on $\boldsymbol{M_{n,a}}$ in (3)) grows fast enough with *N* that building-level indexes rapidly becomes impossible. Thankfully, as demonstrated by Mealy et al. (2019) in their supplementary materials, a place's ACI $\boldsymbol{\nu}^N[2]_n$ corresponds to the average of the *Amenity-Type Complexity* (TCI, our equivalent of the PCI) of the amenities it is associated to in $\boldsymbol{M_{n,a}}$. Therefore, the ACI can be deduced through $\boldsymbol{\nu}^A[2]$ and $\boldsymbol{M_{n,a}}$ by summing the TCI of present amenities and dividing this sum by the place's diversity and we can spare ourselves from computing $\boldsymbol{W^N}$.

We want our amenity data to be as granular as possible, i.e, not to exclude amenity types based on a scarcity threshold as can sometimes be the case in economic complexity (C. A. Hidalgo, 2021). The downside of this is that it makes our place indexes susceptible to outliers and quasi-random noise induced by amenity suppliers' imperfect market decisions and granular places. Considering places have very different market sizes and diversities ($\boldsymbol{K_{n,0}}$), and that some are very small, distortions brought by extreme TCI values in a place with low diversity would automatically make it an outlier if we defined the ACI as an average of TCIs.

We therefore opt for a specification of ACI that is additive regarding the TCI of present amenities, similarly to Mealy & Teytelboym (2022) for countries' green complexity :

$$ACI_n = \sum_a (TCI_a \times M_{n,a}) \qquad \textit{(6)}$$

Where $TCI = \frac{(\nu^A[2] - \underline{\nu}^A[2])}{\sigma(\nu^A[2])}$, a normalized version of $\boldsymbol{\nu}^A[2]$ the second largest eigenvector of $\boldsymbol{W^A}$ (equivalent to $\boldsymbol{W^P}$ in equation (4)). The TCI measures the (dis)similarity between amenity types based on a component that best explains the differences across $\boldsymbol{M_{n,a}}$ while being agnostic about what that component might be in the real world. The ACI therefore does not directly measure places' similarity, but it gives an aggregation of their amenities' (dis)similarities. We are measuring the ability of places to accumulate amenities associated with complex places, *not* their similarity to complex places - although the two are strongly correlated (**Appendix 2**). For that reason, the ACI should be treated as a measure of the bias towards lower or higher TCI values of its amenities.

Understanding the ACI in the real world consequently depends on providing meaning to the component behind $\boldsymbol{\nu}^A[2]$. This component represents what most differentiates commercial amenity types given their absence/presence within the network. This also means ACIs and TCIs are not comparable across cities, and to make them comparable, we would need to treat all sub-city places as part of the same amenity space with complicated implications (Discussed in **Appendix 1**).

In the following section, we unpack the meaning of place and amenity complexity through a consumption-based approach, and along with an illustration of the index in Paris. We then use our findings to lay the ground for understanding how the ACI and the TCI can be used in future research.

3- Interpreting Amenity Complexity : An illustration in Paris

In this section, we propose interpretations of both the TCI and ACI and confront them to a dynamic empirical application in Paris. Because market-driven amenity presence depends on the presence of consumers, the separation of amenities through the TCI is a one-dimensional separation of underlying consumption patterns. We call complex consumers those that are associated with complex consumption, and non-complex consumers those that are associated with non-complex consumption. We defend the idea that the amount of spending people are able and willing to dedicate to amenities is strongly connected with their consumption preferences, and that as such, differences in consumer complexity tend to imply differences in relative spending power. The ACI, as an aggregation of places' TCIs, therefore tends to reflect places' biases towards consumers with low (high) spending power. Because high-spending consumers can pay premiums for goods and services, they have more leverage on the presence or absence of amenities by being present themselves. The ACI thus informs us on which places have overall characteristics that are attractive to complex (high spending) consumers. It can be interpreted as a measure of observed place (un)attractivity for consumption, and changes in ACIs changes can be interpreted as changes in relative (un)attractivity.

We illustrate these interpretations by an application of the ACI methodology to the city of Paris, both as a proof of concept and to further explain our framework. We provide tools for interpreting the TCI and the ACI and we demonstrate that the ACI is insightful as an indicator of ongoing urban transformations in the Parisian case. Paris is a particularly interesting use-case of the ACI for multiple co-dependent reasons. It is a large city in which multiple activity hubs coexist. There is no single place to which everyone would go to consume and we can therefore compare the evolution of different hubs. Paris is also still one of the leading world tourist destinations, and an international destination for world class business congresses and fairs. On top of this, France is very centralized in its qualified job market for economic and administrative centers of decisions. Overall, it is a place that experiences large, global and diverse flows of people that are willing and able to consume. The amenity space is therefore very rich and our index is less likely to be threatened by noise. Let us first present our dataset and our binary matrix $\boldsymbol{M_{n,a}}$, representing the place-amenity network.

Data

A strong argument for the study of Paris is the quality of available data. We leverage BDCOM data from the Paris Urbanism Agency[8]. BDCom is an on-field survey-based documentation of retail and private commercial services in Paris that is carried out every 3 years, the objective of which is to provide an exact, exhaustive and detailed view of Parisian commercial businesses. We have access to data in 2014, 2017 and 2020. Unlike Google Places (used notably in C. A. Hidalgo et al., 2020; Juhász et al., 2022; Kaufmann et al., 2022) or OpenStreetMap data, BDCom is independent of users and of businesses, and its repeated surveys provide a dynamic perspective on the data. This is key if we want to be able to unlock ongoing urban transformations. On top of this, BDCOM's documentation of market-oriented amenities into categories is a lot more detailed than that of off-field alternatives or of public business registries that tend to group together amenities with poor substitution properties. In a perfect world, amenities would be grouped into types in a way that is indistinguishable to consumers. This is an unattainable standard in the real world, but BDCom's hundreds of registered types gets close. Its categories are also focused on commercial amenities and tend to be better divided. For example, a 5-star hotel does not serve the same purpose as a 1-star hotel does. Likewise, designers' clothes shops are different from generalist clothes shops. These are the kinds of subtleties that give BDCOM an advantage over alternatives. We use 202 separate amenity types that are listed in the **Appendix 5**, along with their corresponding TCIs.

Spatial aggregation - Building the binary matrix

Using official data (namely a BDNB[9] aggregation of BDTOPO[10] data) and following the methodology set out in Section 2, we set the coordinates of each Parisian residential building[11] as the center of places. These building-centered spatial units can be aggregated up later on to include socio-economic data at the census level, and it should be clear that buildings as the center of places serve no interpretative purpose beyond their practicality to efficiently grid out the city.

From these building coordinates, we use the Pereira et al. (2021) adaptation of the Conveyal R5 routing engine[12] along with different *OpenStreetMap* street networks for each year[13] to compute a travel time matrix of itineraries by foot between all buildings and all amenities. We use cutoff ***c = 15 minutes***[14] to determine $\boldsymbol{M_{n,a}}$. $\boldsymbol{M_{n,a}}$ is therefore a binary matrix with roughly 168,000 rows (55,985

[8] https://www.apur.org/fr
[9] https://www.data.gouv.fr/fr/datasets/base-de-donnees-nationale-des-batiments/
[10] https://geoservices.ign.fr/documentation/donnees/vecteur/bdtopo
[11] The handful of buildings outside of the ring road have a hard time finding itineraries towards the inside, and we therefore exclude them
[12] https://github.com/conveyal/r5
[13] For our index to be robust against changes in the city landscape, we use historical street network data corresponding to each year provided by Geofabrik
[14] With a walking speed of 4km/h

residential buildings observed in 3 different years[15]) and 195 columns in which cells hold a value of $M_{n,a}$ = 1 when an amenity type is within 15 minutes of a building.

We use $c = 15$ as a starting point, but **Appendix 3** provides evidence that the ACI is not extremely sensitive to c. The initial use of a 15-minute cutoff stems from growing literature around the 15-minute city (Moreno et al. 2021; Khavarian-Garmsir et al. 2023; Pisano, 2020) and appears to be a good compromise for the city of Paris that will be large enough to uncover spatial trends for the index, but small enough that we do not artificially over-homogenize the city. **Figure 1** gives the reader an idea of how much space the 15-minute radius represents and of how amenity-dense Paris is. It also serves to remind her of the amount of spatial autocorrelation in the data : One should imagine a continuum of buildings between the two selected points. As such and by design, an amenity type that appears only once in the data may belong to multiple thousands of places.

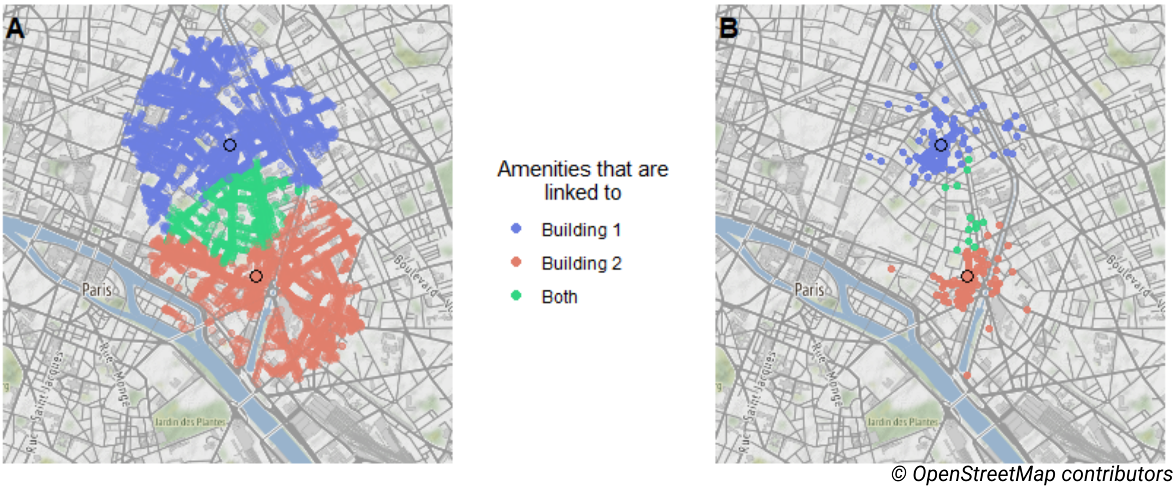


Figure 1 : Visual representations of 2 buildings' amenity spaces in 2020, and of how these spaces can overlap. Map **A** shows all amenities within a 15-minute walk for the buildings ($O_{n,a}$), while Map **B** shows only those that are the closest of their type to the building ($M_{n,a}$).

Complexity and consumers

In this subsection, we evaluate key properties of the ACI and of the TCI and relate them to our initial consumption framework. To unpack this with data, we start by looking at the complexity of amenities to better grasp how they are separated. We then relate the ACI to diversity and to average ubiquity.

[15] We compute complexity on a matrix of grouped observations for results to be comparable across years because complexity is always relative to the global network it is constructed from. Grouping the data allows for better comparisons across time. This makes our interpretations of change rely on the relatively weak assumption that consumer preferences for different amenity types are homogeneous between 2014 and 2020.

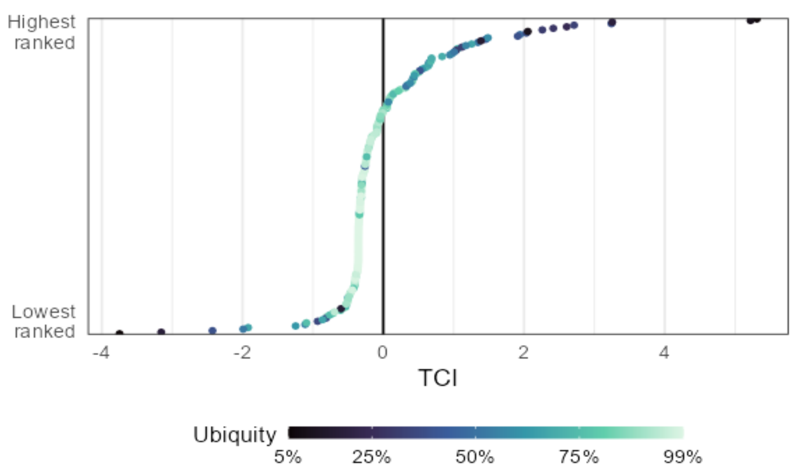
Different amenities for different consumers

The complexity of places is a function of the complexities of the amenity types they host, and vice versa. The separation between amenity types operated by the TCI is dependent on where amenities are found – Or where they are not found (Paris is an amenity-dense city, and $M_{n,a}$ is 80% filled). Amenities that are less ubiquitous (more rare) provide more information about places' complexities and are more likely to be strongly separated from the rest. **Figure 2.A** shows a sample of the 15 most divisive amenity types in each direction, that is, with the highest and lowest TCIs.

Figure 2.A : Top 15 (**left**) and Bottom 15 (**right**) amenity types by their complexity (TCI), along with their ubiquity (*U*) as a share of total places covered (*see* Appendix 5 for a full list).

Rank	*Name*	*U (%)*	*TCI*	*Rank*	*Name*	*U (%)*	*TCI*
1	Luxury general food > 300 m².	9.57	6.103		...		
2	Tourist hotel - Palace	15.36	5.494	188	DIY	90.53	-0.544
3	Tourist hotel with 5 stars	49.22	2.999	189	Nurse's office	95.07	-0.545
4	Department store	30.25	2.995	190	Sale of pets	52.92	-0.591
5	Coffee shop	44.22	2.801	191	Moving / Storage	87.49	-0.666
6	Large cultural multispecialist	38.49	2.488	192	Tattoo - Piercing	80.38	-0.727
7	Ticketing - Booking shows	42.5	2.454	193	Telecommunication in store	83.7	-0.779
8	Smile Bars	15.88	2.334	194	DIY and home equipment rental	83.41	-0.792
9	Sale of coins and medals	42.58	2.06	195	Youth Hostel	53.09	-0.822
10	Haute couture - Designers	62.23	1.856	196	Discount store	68.44	-0.904
11	Gambling	53.85	1.81	197	Sale of automotive equipment	79.53	-0.962
12	Sale of erotic items and sex shop	51	1.524	198	Ambulances	74.94	-1.612
13	Concert hall	64.88	1.269	199	Discount supermarket	66.59	-1.94
14	Philately	47.53	1.251	200	Technical control of the car	53.96	-2.301
15	Sales room	42.1	1.226	201	Specialized supermarket	25.64	-3.138
	...			202	Hypermarket	7.66	-4.919

Figure 2.B : TCI values[16], ranks and ubiquities (as a share of places covered) of amenity types



[16] As a reminder, there is not much point in reading these values alone. The fact most amenities are negative does not mean most of them are biased towards lower spending power in an absolute sense. However, the bulk of amenity types is closer to non-complex amenities than to highly-complex amenities in how they are present across the city.

A qualitative look at **Figure 2.A** reveals patterns that drive amenity-type complexity. On the right hand side, we find goods and services that are either cheap, associated to primarily residential use, and/or to what consumption economists might call *inferior* goods[17]. On the left hand side, amenities with the highest TCIs are strongly associated with tourism, high prices and margins, leisure, and could be qualified as *luxury* goods. The presence of coffee shops at the top is also interesting : Bantman-Masum (2020) uses them as a witness for ongoing (not tourism-led) transnational gentrification in Paris. In **Figure 2.B**, we see that as amenities tend to be less ubiquitous they tend to be more informative of complexity and more distinctive of each other. We also see that at a very aggregate level, more ubiquitous amenity types tend to be less complex. The separation it presents, which we can also attempt to perceive qualitatively through **Figure 2.A** (or Appendix 5 with the example of food stores), is the basis for defining the complexity of places.

In economic complexity, the separation of products is thought to be made through their sophistication, that is, how difficult they are to produce. In our context, the presence of (non-)complex market-driven amenities is a reflection of the presence of (non-)complex consumers, both because amenities need the right consumers to be sustained and because they attract consumers that desire them. Understanding the TCI and the ACI requires us to understand what it is that motivates the complexity of consumption, that is, peoples' propensity to co-consume different amenity types. Although the answer is necessarily intricate, we argue that consumers' spending power is intrinsically linked to their complexity, hence to how amenities are able to co-locate and to how the TCI separates them.

First, as a direct factor. For given preferences, people might allocate more to leisure-oriented amenities when they have more ability and will to spend. This specific example is consistent with Engelian frameworks of consumption where income-driven preferences for leisure and diversity are found (Jackson, 1984; Table 2 in Aguiar & Bils, 2015). Second, as a confounder of possible social, cultural, and other consumption determinants that are difficult to quantify alone. In Paris specifically, consumers' residential status (that is, whether or not they are a resident) could be a relatively important determinant because non-residents are likely to consume different amenity types than residents do. However, tourists also come with a lot of spending power allocated to amenities relative to residents for the short time they are present, and separating consumers by spending power will tend to separate tourists from residents. The ties between culturally or socially differentiated consumption practices and peoples' ability to spend are not a groundbreaking idea either, and they fit into a Bourdieu-indulging view of economic capital associated with *habitus* (Bourdieu, 1987), which determines consumption practices. In fact, what determines consumption preferences is likely a set of deeply interrelated factors. We argue that, as a single characteristic, peoples' spending is as strong a representative differentiating characteristic of that set as any.

Moreover, we are not trying to directly infer spending power levels from our indicators.. Instead, we are unveiling tendencies within places' and amenities' consumer patterns. Thus these operational

[17] In an Engel-like framework, *inferior* goods are those for which consumption goes down as income goes up

confoundings between spending power and other characteristics are a strength rather than a weakness. They can help us characterize consumption in a broad way that allows for more flexibility of the indicator across different cities with different local contexts. Complex amenities are consumed by complex consumers, and consumer complexity is strongly related to spending power one way or another – But it does not necessarily come *as a result* of spending power. In the following, we evaluate the underlying structure of places' amenities in Paris to consolidate our understanding of how complexity separates places, and of what is associated with complex consumers.

Diverse places, rare amenities

Places' diversity ($\boldsymbol{K_{n,0}}$) and average ubiquity ($\boldsymbol{K_{n,1}}$) are key characteristics of the amenity presence network, and they could help unravel consumption patterns driving the ACI. The two leftmost panels in **Figure 3** tell us that places' biases towards complex amenities slightly go up with *(1)* how many different amenity types they have, and with *(2)* how rare their amenities are.

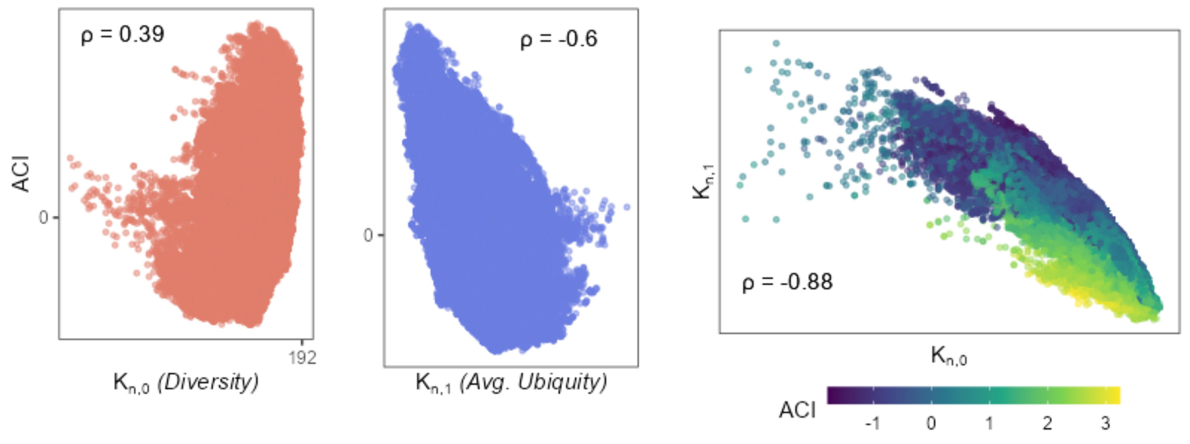


Figure 3 : Diversity, ubiquity and Complexity of places with *c = 15* in all 3 studied years. More diverse places tend to have a lower average ubiquity of amenity types, and the ACI is a mixture of both of these measures. Spearman correlations are shown within each plot.

Our interpretation of the relationships between complexity, $\boldsymbol{K_{n,0}}$ and $\boldsymbol{K_{n,1}}$ is the following. Because the TCI is normalized around 0, some amenities contribute negatively to the ACI and *(1)* is not down to our aggregation method. As such, *(1)* is also not representative of a diversity in consumer complexity within places, because the more consumers are different, the more they push TCI (and ACI) values in different directions. Let us explore a spending power-led complexity component. More complex neighborhoods are biased towards a subgroup of consumers that has a preference for diversity, either at the individual level (consumers preferring to split their consumption) or at the aggregate level (the subgroup consists of consumers with different consumption practices). Either way, attributing the consumer type dichotomy to spending power would be consistent with Engelian empirical work on the income elasticity of demand (Jackson, 1984; Table 2 in Aguiar & Bils, 2015), as long as there are more amenities for which demand goes up with spending power than there are *inferior* amenities in our dataset. Our implicit assumption is that either consumers have a preference for diversity that gets revealed as their spending power goes up, either they have more available choice, or both of these statements are true.

Conversely, *(2)* does not mean that there are less complex consumers than non-complex consumers. Instead, it implies that complex consumers tend to consume goods and services that are more rare. This also fits the spending power framework for the same reasons *(1)* does. Rare and complex (*luxury*) amenities tend to agglomerate with each other in complex places, whereas there are fewer rare and non-complex (*inferior*) amenities and they agglomerate less together. Thus, on the one hand non-complex places are those that host a few non-complex (and less ubiquitous) amenities along with highly ubiquitous amenities. On the other hand, complex places are those that host more highly complex (and less ubiquitous) amenities along with more average-to-highly ubiquitous amenities.

The rightmost quadrant of **Figure 3** echoes an inverse relationship between the diversity of places and the average ubiquity of their amenity types that is highlighted for countries and exports in Hausmann and C. A. Hidalgo (2011). Their intuition is that countries have a preference for diversification, that is, that they will produce non-sophisticated ubiquitous goods on top of sophisticated rare goods whenever they can. This network characteristic hints at nestedness, a concept that emanates from almost century-old ecosystemic analyses of species in biology (Hausdorf and Hennig 2003) and that is relevant to evolutionist thinking. The hint at nestedness holds conceptual ground within a framework of spending power by a simultaneous extension of *(1)* and *(2)*. In practice, nestedness could heavily depend on how granularly different amenity types are defined ; The more there is a balance between the number of *luxury* and of *inferior* amenities, the less the network will tend to be nested. Our intuition is that amenity networks should be nested (as is the case here and in Juhász et al. (2022)) because of the economic intuition of aggregate subgroup preferences for diversity. Either way, **Figure 3** makes it clear that the places most biased towards hosting complex amenities are those that are simultaneously diverse and host rare amenities.

Keeping in mind the definition of place complexity as a uni-dimensional separation of consumers based on a set of characteristics (of which spending power appears to be dominant), we provide a short complexity-driven analysis of Paris that should help appreciate the concept in more concrete terms and demonstrate its ability to outline ongoing urban transformations.

Results in Paris

In this section, we present how the ACI can help unlock consumption structures in a broader way. We propose that, as an indicator that is intrinsically linked to local consumers' spending power, the ACI is therefore intrinsically linked to the attractivity of both commercial and non-commercial amenities (examples of which are nature, accessibility, public services, or aesthetics), or of place characteristics. We illustrate this with map-based approaches to Parisian complexity, and leverage our dynamic data to show how the ACI can be a valuable proxy for ongoing urban transformations. Then, we use place-based data related to local consumption and place characteristics to cement our indicator as reflective of consumer and place typology.

Complexity in space

To help elucidate the distribution of complexity and its evolution, we look at the ACI in Paris through a qualitative spatial analysis. Prior knowledge of local context is key to making the best out of the indicator, and mapping is a good place to start. **Figure 4** maps the spatial distribution of the mean complexity rank throughout the observed period (**A**) and the difference between the 2020 ACI and the 2014 ACI for every place (**B**).

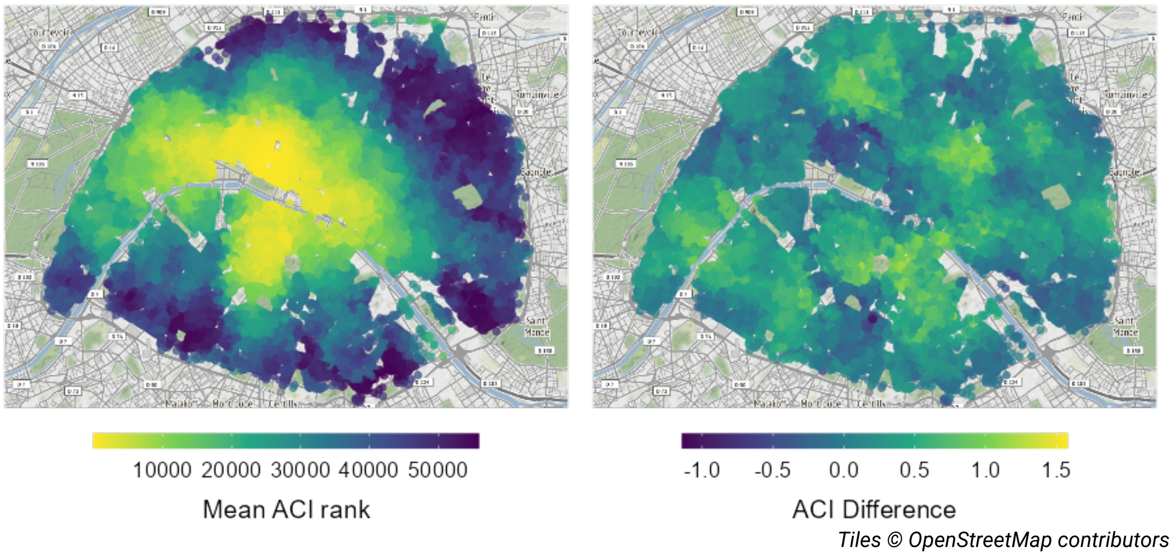


Figure 4.A : Map of the mean ACI rank in Paris in 2014, 2017 and 2020

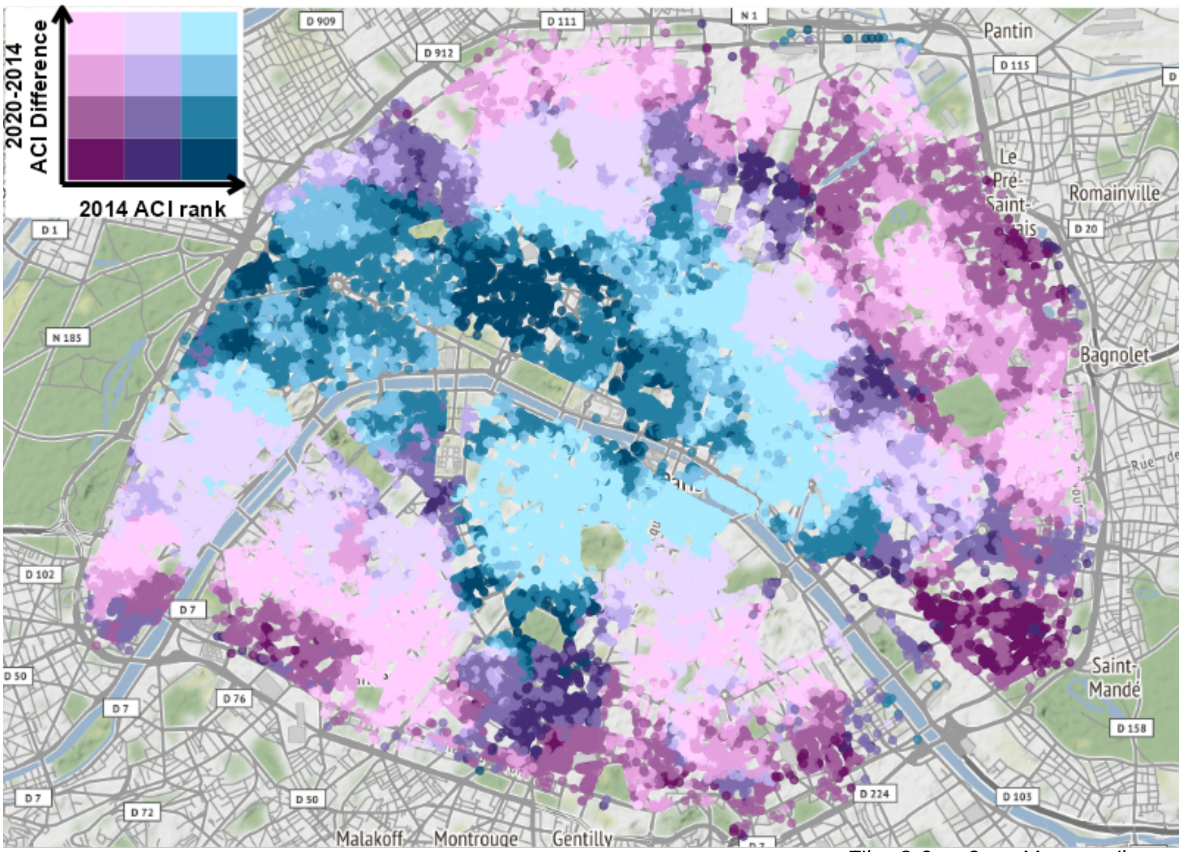
Figure 4.B : Absolute change in ACI over the observed period (2020-2014)

Having a central position is an important factor to welcoming complex consumers. In an inland city like Paris, being further away from the city's ring road is positively correlated to being more complex. This is consistent with urban central place theory (Christaller, 1966), with previous attempts to map human activity in cities (Zhong et al. 2017), and with Juhász et al. (2022)'s implementation of amenity complexity, where they find a direct link between geographical centrality and amenities' complexity. Central location is however not the only explanatory factor of complexity in space from a practical standpoint, and the distribution of complexity in **Figure 4.A** is not homogeneously decreasing from a point in the center to the periphery. Very complex places in the center-West tend to be hotspots for traditional tourism and international brands ; On top of being well located, they offer aesthetically pleasing architecture (*Champs-Elysee*), are safer than peripheral alternatives, host museums (*Le Louvre*) and monuments (*Arc de Triomphe, Palais Royal, Opéra Garnier)*, and are not too far away from the river banks of *La Seine*. We argue that, like other non-commercial amenities of consumer city thinking (Glaeser et al., 2001) that include aesthetics and public goods and services, accessibility induced by central locations is a desirable trait of places that suits the idea of a spending-power based complexity framework. In fact, consumers endowed with spending power end up consuming in the places they enjoy because they have more leverage in where market-driven amenities are located. On the flipside, non-complex consumers, that is, those with lower spending power, concentrate their consumption in places that are left over, because they have comparatively little ability to pay premiums for goods and services and therefore little leverage in amenity location.

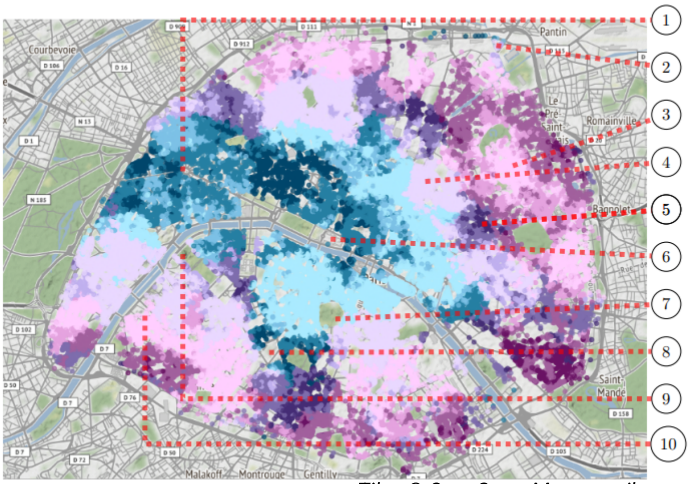
On this basis, the ACI can be interpreted as an indicator of economically *revealed* (in the sense of Samuelson, 1948) place attractivity. Attractivity is not universally defined across consumers, and different people might prefer different things. Still, under the assumptions of TCI separation being strongly linked to spending power and of spending power granting leverage, the ACI yields the place preferences of those with more spending power. While this interpretation seems to fit well in Paris from a qualitative look at **Figure 4.A**, it begs the question of how places come to be attractive through time. Paris has had time, throughout history, to develop place attractiveness in ways that can make it akin to path-dependent phenomena. It is notable that the "*rive droite*", the part of the city that is north of *La Seine*, is a lot more complex than the other side. This echoes the historical development of the city that already had its trade, its economic activity and its population development focused on the *rive droite* throughout the Middle Ages, with the south side of the river hosting convents and universities. These universities were however located in the bright part of the *rive gauche* (South of the Seine), and strong levels of complexity on that side appear to struggle to break the old city boundaries.

However, the role of urban centrality (and of other non-commercial amenities) is a lot less obvious as a feature of complexification in **Figure 4.B**. Central (and complex) places have not necessarily been getting more complex between 2014 and 2020. In fact there is no visible indication of a self-reinforcing process of complex (and non-complex) places in the observed period, nor of a polarization of outcomes. Some relatively central places have gone up, but not those that are the most complex. Specifically, the Western traditional tourism hotspots do not appear to be gaining in complexity. Parallely, some initially less attractive places in the periphery have been catching up.

Figure 5.A combines the 2014 level of complexity and changes in complexity into a single map in order to further unlock spatial patterns, and show how the ACI can be related to ongoing urban transformations.



Tiles © OpenStreetMap contributors



Tiles © OpenStreetMap contributors

↑ **Figure 5.A**: This map combines the initial level of 2014 ACI and the ACI evolution into a single map. Darker colors denote ACI shrinking and brighter colors denote ACI growth. Different hues denote different tertiles of 2014 complexity. Different brightnesses divide growth into 4 different groups, where the darkest are shrinking, the second darkest are stable, and the 2 brightest are growing at different speeds.[18]

← **Figure 5.B** : Numbered pointers to illustrate examples in the text

There is a lot to unpack from this map. The first element is a confirmation that there is no clear pattern of complex places becoming relatively more complex in time than non-complex places (Spearman ρ = −0.13), or else the blue parts would be very bright. While self-reinforcing processes of complexity have almost certainly played a role historically, they do not seem to be at play in the observed period.

[18] With ΔACI_n the 2020-2014 difference in ACI in place *n* and σ the standard deviation of ACI differences :
Shrinking (dark) if $\Delta ACI_n < -\sigma/2$; Stable (moderate) if $-\sigma/2 \leq \Delta ACI_n \leq \sigma/2$; Growing (bright) if $-\sigma/2 \leq \Delta ACI_n \leq \sigma/2$; Growing strongly (very bright) if $\Delta ACI_n > \sigma$

Among average-to-highly complex places (Purple and Blue), there has been a shift of complexity towards the East and the North. Center-west places, the more traditional tourist center that expands from the city's main intra-travel transport hub *Châtelet-Les-Halles* and the nearby *Louvre* museum (Pointer **[6]** in **Figure 5.B**) westwards to the city's periphery, have either stagnated or decreased in complexity between 2014 and 2020. This darker-to-moderate blue area includes important landmarks like the *Louvre* Museum (**[6]**), the *Palais Royal*, *Concorde* square, the *Champs-Elysée*, the *Arc de Triomphe* (**[1]**) and the *Palais Garnier* Opera. These remain some of the city's most complex places in 2020 (See Figure 6), but they are being caught up to by places in multiple other neighborhoods. We notice a large semi-circle of strengthening complexity around the Eastern side that extends roughly from the *Canal St-Martin* (**[4]**) to just past the *Luxembourg Gardens* (**[7]**) into the *Quartier Latin*. Although Paris is a tourism-oriented city as a whole, what opposes this semi-circle the most to those that are shrinking (or stable) in the Centre-West is the fact that these are not traditionally as tourism-oriented as the places that are losing out. They host landmarks that can be visited, but they are also places with strong local implementation that include Universities, important nightlife and theaters. The peaks in complexity gains on the *rive droite* are located just North of *Le Marais*, around the *Canal Saint-Martin* (**[4]**). It is clear that some of these rapidly complexifying places are disproportionately prone to urban transformations and gentrification. This is especially credible on a transnational scale for the city of Paris, in general ways explained by Sigler and Wachsmuth (2020).

The *Canal Saint-Martin* (**[4]**) is a perfect example of lifestyle-driven gentrification, even if it is not necessarily only transnational. Changes in consumption we observe through amenity complexity are backed up by a gentrification sentiment that has been ongoing for years and is expanding in space, enough so to earn the neighborhood a gentrification-linked nickname in *Le Parisien*[19]. A case study by Bantman-Masum (2020) uses a specific area at the junction between the 4th and the 11th district that is just south of the Canal to better understand ongoing commercial gentrification through the example of coffee shops.

The map alone cannot tell us if these places' complexity growth is due to tourists visiting them instead of traditional western hotspots (to a de-concentration of central complexity). However, despite the lack of polarization of complexity at a macro city-wide scale, neighboring places could be polarizing relative to each other. In fact, while the spatial distribution of complexity is quite continuous (**Figure 4.A**), we find stark contrasts in complexity growth on the outward edges of some strongly complexifying places. A great example of this is the shrinking of complexity in places at the junction between *Belleville* and *Folie-Méricourt* (**[5]**). This dark area is stuck between the complexifying *Canal Saint-Martin* (**[4]**) and the *Village Jourdain* (**[3]**).

Jourdain (**[3]**) is a historically lower-income neighborhood that has been in the process of "*accelerated*" gentrification in recent years. Communities within that atmospheric neighborhood describe it as an "*Enclosed area*" with an "*invisible frontier*" to Belleville in the press[20], motivating the

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[19] "[...] like in the southern area of the canal Saint-Martin (10th district), which is already known as «Boboland»"
Le Parisien, 2021
https://www.leparisien.fr/paris-75/paris-le-quartier-populaire-louis-blanc-nouveau-boboland-12-01-2021-8418662.php
"*Boboland*", or land of the "*Bobos*", a pejorative word for bourgeois-bohemian types

[20] "In Paris, the path of a neighborhood that has become a « village »", Le Monde, 2020

concept of the *Jourdain Village*. We learn from the same article that the *Jourdain Village* (**[3]**) brand is an asset to real estate agents to differentiate the neighborhood from others in the area. From a consumption standpoint, it is plausible that the area around pointer **[5]** is struggling to attract outsiders with high spending power precisely because of its proximity to the attractive *Canal Saint-Martin* (**[4]**) and *Village Jourdain* (**[3]**).

The ACI can be attached to real-world meaning, historical path dependencies and perceptions of local communities and development in an extensive way. The post-industrial development around *Porte de Pantin* (**[2]**), the separation of consumption created by the *Luxembourg Gardens* (**[7]**) and the *Montparnasse Station* (**[8]**), the lack of complexity around the *Eiffel Tower* (**[9]**), and the rejuvenation around the new mall in *Beaugrenelle* (**[10]**) are just some examples of the ability ACI measures can have to go hand in hand with local knowledge to better understand narratives surrounding urban situations and urban transformations.

The ACI and the TCI could help objectivize some of these narratives, but we must reiterate that complexity and attractivity are the result of centuries of systemic evolution. The scale of (de)complexification over such a short period of time will therefore seldom be paradigm-shifting. Despite this, viewing complexity through a macroscopic lens provides insight over cities' evolutions in a way that is less sensitive to noise and to slow evolution. To do so we present the distributions of the ACI in Paris, their evolution, and relate them to a more general view of cities as complex systems of places.

The distribution of Complexity

Here, we explore ACI coherence within cities. In other words, we look at the distribution of complexity, which yields information over how segregated consumers are based on their sophistication, and thus of how *revealed* attractivity is distributed. Policy-makers directly or indirectly affect this through planning strategies, but it is also the result of market forces, laissez-faire, and centuries of historical developments.

Looking at how these distributions change over time (ideally over long windows) is a good indicator of how much more or less centralized a city is becoming in its ability to attract consumption. **Figure 6** plots the Amenity Complexity Index distributions in Paris for the 3 years in which we have data. Here, indexes are relative to complexity in other places and over all years (because we constructed the global network in a time-exclusive way[13]).

As consumers with higher spending power have more leverage in commercial amenity location, policies that affect how non-market characteristics of places are distributed across cities necessarily affect attractivity as measured by the ACI. This is the case of intended efforts to change how accessible different places are, which the Paris-embraced 15-minute city concept is a part of (Khavarian-Garmsir et al., 2023 ; Pozoukidou & Chatziyiannaki, 2021). But it is also intertwined with an infinity of unintended and sometimes hidden phenomena that affect panels ***AC*** and ***PA*** of **Box 1**. For example, paradigm

https://www.lemonde.fr/m-perso/article/2020/09/11/a-paris-itineraire-d-un-quartier-devenu-village_6051874_4497916.html shifts like that of short-term rental platforms are likely to have changed how attractive different places are for tourists to consume. These potential shifts would all be reflected by complexity : The relative concentration or dilution of complexity reflects the relative homogeneity of places in their ability to attract consumers with high spending power. The ambivalence of homogeneous or heterogeneous attraction effects fits into important, broader discussions about urban transformations and how we want to live in cities.

In Paris specifically, we notice that places have slowly moved away from lower complexity towards higher complexity over time. This is true for every complexity decile, but it seems primarily driven by the leftmost (non-complex) peak flattening rightwards. Places are, in general, slowly gaining more ability to attract complex consumers who tend to be higher-spending. On the other hand, the most attractive places are less segregated from the rest in 2020 than they were in previous years. In concrete words, it seems that places' ability to attract high-spending biased amenities is gradually becoming less concentrated than it used to be, with the possible ambivalent effects mentioned above.

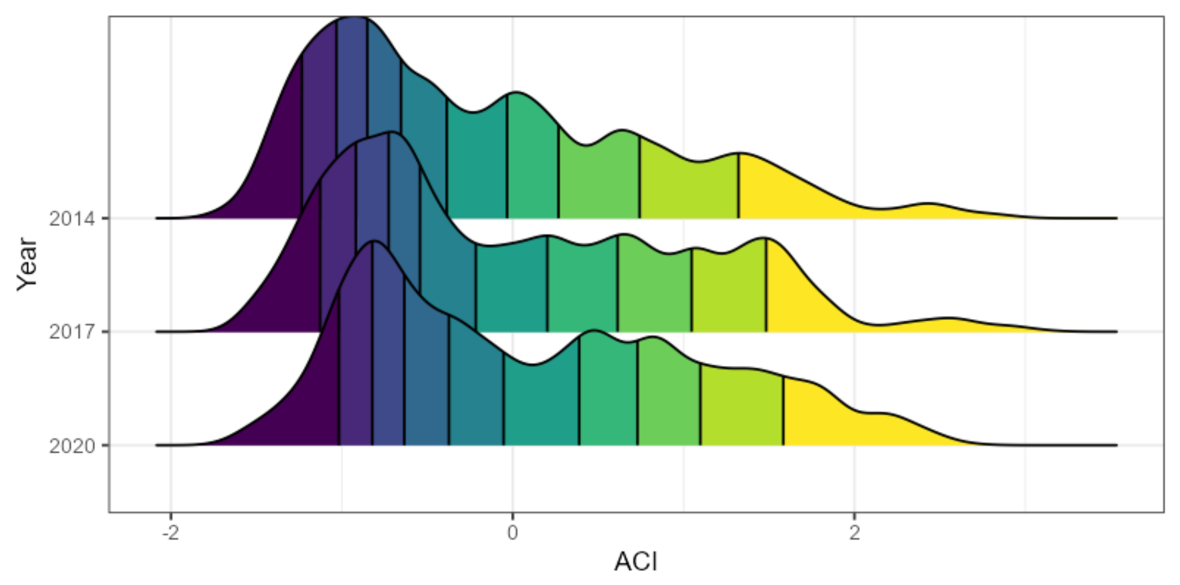


Figure 6 : Density distributions of the ACI in Paris in 2014, 2017 and 2020, colored by decile.

This is however an average result that has to be moderated by its size, and qualitative spatial analysis (such as that in **Figure 5.A**) should help the practitioner understand these changes. For example, the leftward move of the most complex places between 2014 and 2020 can likely be put down to traditional tourism hotspots comparatively losing out in high-spending consumption. The reader should also keep in mind that changes in commercial amenity structures over just 6 years are unlikely to be paradigm-shifting alone. They are a part of slow ongoing processes that take decades, to unfold.

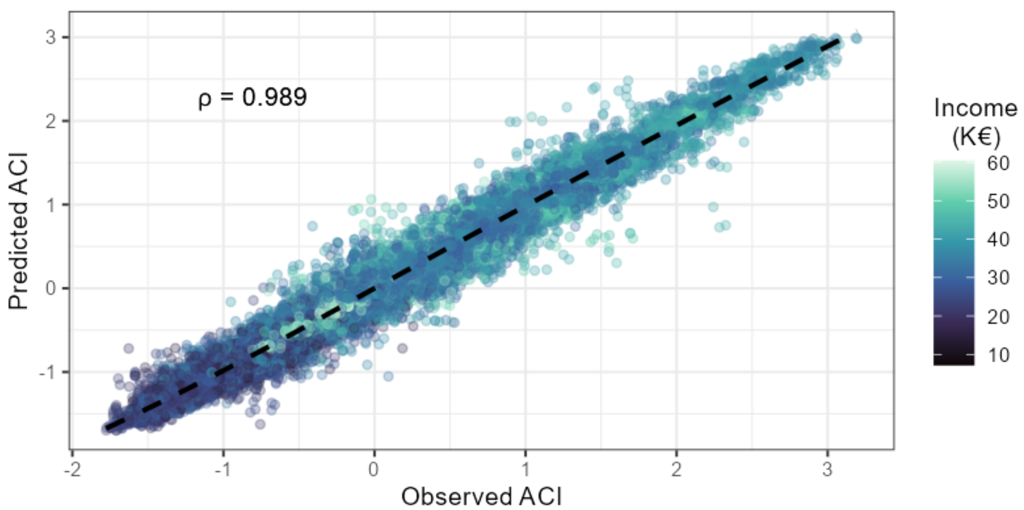
This section has related amenity and place complexity to patterns in consumption that are related to local consumer characteristics (most importantly, to spending power), and that are themselves motivated by place characteristics. As such, the ACI can come as a witness of these place characteristics, and its changes as a witness of how places' transformations are received by consumers. To further cement the idea that the ACI depends on and influences place and socio-demographic variables, we naively relate the ACI to other observables that should contribute to explaining edges in ***AC*** and ***CP*** (see Box 1), that is, variables that should characterize places' local demand. The ACI correlates well to a number of different socio-demographic variables, but seldom in a linear way and often in combination with others. Using the Wright and Ziegler (2017) implementation of random forests algorithms (Breiman, 2001), we show that proxies for local place and demand characteristics are apt at predicting the ACI. We use the share of primary residences built before 1919, the median income of the place's census tract, the gini coefficient of income in the census tract, the share of dwellers aged 25 to 39 and a measure of nearby short-term rental visits (see **Appendix 4** for data explanation).

As shown in **Appendix 4**, the mean squared prediction error on out-of-bag observations is 0.0174, which is about 1.7% of a standard deviation of the ACI. The model's variables therefore offer excellent predictions of the ACI. Random forests are not linear at an aggregate level, and they do not assign overall coefficients nor signs to variables, that is, we could not have predicted the ACI without the prior knowledge of how the ACI related to these variables through training. However, these models can still assign importance measures based on how much prediction accuracy is lost when the variables' values are randomly permuted. These measures outline how impactful a variable is within the model and are presented in **Figure 7.B,** along with the spearman correlation of the variables to the ACI. For example, on average, the R-squared only decreases by 0.15 when year dummies are randomly permuted in a tree, as opposed to 0.79 when the Gini coefficient of income is permuted. Features however combine in ways that are difficult to quantify to yield high complexity values ; For example, the share of 25-to-39 year olds among primary residents is negatively correlated to the ACI, but it could very well contribute positively in higher-income places that have older buildings in the random forest setting. The contribution of this regression to our paper is mainly to demonstrate that the ACI is representative of elements that constitute a place and its consumers, even if these elements are intrinsically complex and impossible to generalize individually.

To add to our regression and to double check that we are not overfitting our data, we train the same random forest model on a subset of 70% of the data. The other 30% are then used solely for prediction purposes, the results of which (plotted in **Figure 7.C**) confirm that our predictor is very accurate. Moreover, **Figure 7.C** also makes the point of a non-linear relationship between census tracts' median incomes and their places' ACI values. A place with richer residents does not systematically equate to more complex consumption (that is, richer people do not necessarily spend more on commercial amenities), but combinations between median income and other variables are useful towards finding complex consumption, as evidenced by the figure.

Figure 7.A : Importance of different variables within the random forest model (using the full data), correlations of the same variables to the ACI, and random forest model characteristics.		
	Feature Importance† for predicting the ACI	*Spearman correlation to ACI*
Median income	0.38	0.53
Gini coefficient of income	0.79	0.71
Share of primary residencies built pre-1919	0.58	0.73
Short-term rental nights spent	0.38	0.51
Share of 25-39 year olds	0.24	−0.09
Year dummies	0.15	∅
† *Permutation importance*		

Figure 7.B : Random forest prediction results on a test subset of places, and tested places' actual ACI values. The dashed line is a loess fit of actual observed ACI values against predicted values. Observations are colored by income to outline the imperfect positive relationship it has with the ACI.



All things considered, we propose that the ACI and the TCI are measures that can amplify researchers' understanding of cities because they directly reflect local demand and indirectly reflect unobservable (or difficult to observe) place characteristics. Under their broadest interpretations, they are measures of *revealed* place and amenity attractivity, because people who are able and willing to spend more on amenities are segregated by our methodology and have more leverage in shaping amenity landscapes. These interpretations require stronger assumptions about what separates people in their consumption (here, ability and willingness to spend), and they might hold more or less weight depending on local context. Still, even the narrower interpretations of ACI and TCI as segregations of consumers (regardless of what segregates them) can provide important information over the subjective attractivity of different people for different place characteristics. There are many ways these consumption patterns could be used, some of which were outlined in this section. In the following section, we briefly discuss how the ACI can be related to other data and methods to provide novel, systemically motivated perceptions of urban situations and dynamics.

4- Discussion and research agenda

Future research could use the ACI and its dynamics as a proxy for urban transformations, the specific type of which depends on what is deemed to segregate consumers. The ACI itself is representative of place consumption structures, and it can help decipher what motivates attractivity of different types of consumption towards different place characteristics. Likewise, it would be worth exploring what changes in these structures mean to cities as systems. The ACI could thus help answer important questions :

What kind of path dependency is place-based consumption built upon? Who are those that are changing city paradigms, and what attracts them? How much power do planners have in making places deviate from their consumption path dependencies? How does the distribution of various public goods and services relate to place demand, and to changes in place demand? What is the impact on consumption structures of different planning decisions and cultural shifts? How do changes in consumption structures affect people, and who do they affect? These questions, just like those this paper began with, can be of particular interest to researchers and policy-makers that are seeking to make cities better places to live in. The ACI alone cannot provide straight answers to them, but it can help enrich our perception of these issues, especially if it is combined with prior knowledge and other data.

Prior knowledge of the city of Paris was dispersed throughout Section 3 to illustrate and help interpret the ACI, but such analysis could be a lot more extensive. For example, a historian's eye on maps would likely provide different and enriching insights that could help unlock the origins of specific path dependencies in consumption structures. In Paris specifically, medieval and early republican organizations of city life could easily be related to patterns found in ACI maps (**Figure 4** and **Figure 5.A**). It is probably not a coincidence that the *Palais-Royal*, a 17th-century royal residence that neighbors the *Louvre*, is at the heart of the cities' most complex modern places. It was likely established there as a part of path dependency in place attractivity for rich and sophisticated individuals and has reinforced that path dependency. What defines the characteristics of places, and thus their economic activities, depends on century-long processes of institutional and individual decision-making. Different processes in different places are likely to have led to very different contemporary consumption structures. The ACI could be used as a lens through which to analyze different urban systems relating to different historical developments (for example, between European and North American cities, Glaeser et al., (2001)).

Historical analysis is important to comprehend current structures, but policy-makers might have a preference for relating the ACI to its causes and to effects they seek to enhance or mitigate. On the side of causes, many might be outside of planners' control. The example of the COVID pandemic comes to mind as a hot topic for transformations in city structures (Florida et al., 2023), and relating lockdown policies and COVID-driven shifts in consumption practices to changes in ACI structures could be an interesting path to explore. Labor-related phenomena such as digital nomadism, the general rise in working from home or from everywhere, and potential AI-induced job market shifts are also all elements that should affect the distribution of complex consumers within cities. The ACI could also add to short-term rental (STR) literature that explores associations between modern mass tourism and various urban transformations. In this context and in the wider context of gentrification, the ACI could perhaps be used as a proxy to observe ongoing transformations that stem from STR.

In an even more applied sense, we could study place complexity from a policy evaluation perspective. For example, regulation aimed at limiting STR often implicitly seeks to limit ACI changes within certain places (Robertson et al., 2023) under the assumption that tourists and residents have different needs. Our methodology provides a measurable approach for evaluating these efforts. Modern planning issues like chrono-urbanism and the 15-minute city (Khavarian-Garmsir et al., 2023; Moreno et al. 2021) also imply changes in amenity structures for which the ACI could provide insight. Chrono-urbanism is conceptually about the control of flows. In the same way flows constitute cities and their places as systems (Batty & Cheshire 2011), the interpretation of ACI as a measure of consumer flows is not unfounded. The ACI of a place could be seen as a combination of residents' and non-residents' consumption practices. Chrono-urbanism, by limiting the flows of non-residents across places, would make the importance of residents' consumption capacity greater – perhaps with unwanted effects on the distribution of amenities and of the ACI. For a concrete example, the ACI could be used in combination with accessibility changes (bike lanes, transit, parking space) and public service presence to uncover the intended and unintended effects of policy efforts.

When and where possible, relationships between various indicators and the ACI will always be grasped better over longer periods of time. One drawback of the ACI is that it is not dependent on actual consumption within places, but rather on how suppliers believe they can coordinate with consumers based on these suppliers' imperfect information. The market for retail goods and services is also far from frictionless. Suppliers of amenities might over or underestimate possible consumption, they might be resilient and take too long to close when they should or might miss market opportunities. Consumers are not omniscient or perfectly rational either. In the short-term, the observed place-amenity network is therefore a polluted representation of the hidden networks that motivate our understanding of the ACI. Further borrowing principles of evolutionary economic geography, the pollution we speak of could be paired to what Boschma and Lambooy (1999) refer to as "chance". Commercial amenities' locations are probabilistic rather than deterministic for given stable states of optimal location choices.

This is not a huge problem for the analysis of a static ACI over a city (as in **Figure 4.A**) because commercial amenity locations depend on centuries of adjustments, and suppliers with suboptimal locations are unlikely to sustain a profit over long periods of time. In other words, actual ACI levels and ranks are unlikely to be far off their stable states given optimal location choices. However, for changes in ACI over shorter periods of time, the risk of "chance" misallocating a supplier is a lot higher. Because of this, it could be hard to tell whether an event or an intervention actually shifted these places' stable state in some cases. The wider the spatio-temporal range of the data and the denser the city is with respect to its commercial amenities, the less noise is a threat and the better ACI will be able to help assess ongoing transformations.

We also claim that the ACI is not a normative assessment of place quality as a whole. Unlike the consensus on regions, cities and countries in the context of growth-defining economic complexity (Balland et al. 2022), a place being more complex is not always a good thing. Complexification can often come along with inequality, and we want to insist on the fact that enhancing it should not be a policy objective within itself because effects are likely to be ambivalent. Nevertheless, there could be ways in which complexity is made normative to accommodate given objectives. Mealy and Teytelboym (2022) use economic complexity-inspired methodology with a custom list of green products to evaluate countries' ability to transition towards these products. In the same way, we could define an objective (for example, avoiding place alienation caused by tourists and lifestyle migrants (Diaz-Parra & Jover, 2021)) and select specific amenity types that are linked to it (those seeked by tourists and lifestyle migrants) to evaluate if and what places are likely to transition towards (places at risk of alienation) given their current commercial amenity setup. This example is part of a broader set of economic complexity tools that can work hand in hand with the ACI and the TCI to evaluate or anticipate outcomes in a normative way.

5 - Conclusion

Measures of complexity are notoriously difficult to analyze in absolute terms, and they need to be connected to underlying intuitions. In the case of the ECI, these intuitions are grounded in evolutionary growth modeling (Balland et al. 2022. In this paper, we presented a setting upon which to measure the complexity of places and a guide to measuring it that is specific to commercial amenities. We leveraged the network-based framework of Economic complexity and related it to systemic urban thinking. We then derived the ACI and the TCI through a specific adaptation of the ECI and proposed them as segregators of places and amenity types that rely on the consumers that visit them (for places) or that consume them (for amenities). Complex consumers that spend in complex places visit them for an infinitely broad, and unobservable, ensemble of characteristics of which market-driven amenities are a part of. Because commercial amenities are market-driven, the relative presence of amenities complex consumers enjoy is therefore a sign of these consumers' relative presence. In a holistic way that is typical of complexity thinking, place complexity thus tends to estimate how much complex consumers are attracted to places. It can be a way of evaluating the overall quality of (mostly unobservable) place characteristics, as revealed by these consumers' preferences.

This makes it a good observable proxy for place attractivity that future research could leverage to understand the emergence of systems within cities, of urban transformations, and how to adapt planning strategies to local objectives.

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Appendix 1 : Discussing Methodology

Cutoff definition

For cutoff ***c***, we could also have applied a cutoff on the mean distance to an amenity type instead of on minimum distance ; This would have also been an alternative to the presence-based binarization of $M_{n,a}$. The downside of this is we would once again have been evaluating places relative to others, and we would have opened ourselves up to important spatial distortions.

Pre-defining the importance of amenity types and how far it is acceptable for them to be, i.e to have different cutoffs for different amenity types is another way to go. In this paper, we want to be able to deduce the same idea in a data-driven manner, which is allowed for by the spatial continuity of our observations. If an amenity is everywhere, then it has come to be everywhere because of market dynamics that mean it is important to everyone, i.e, it is *necessary*. The assumption is that if an amenity needs to be closer than others, then it will be more ubiquitous in the data. The reader should however understand that other methods could have merit, especially in settings where types of amenities and spatial units are defined with a lower granularity. Moreover, spatial-autocorrelation is paramount for our method to be valid, and cutoffs ***c*** = 0 (in the case of administrative boundaries for example) should be avoided.

Accessibility to places

It could have been tempting to weigh amenity presence by place accessibility in the binary matrix. However, this would go against the systemic philosophy of our approach. The distribution of commercial amenities depending on accessibility is a voluntary feature of the ACI as a holistic measure. Accessibility is part of what makes places attractive to consumers and should impact the ACI. This does not stop future practitioners from weighing ACI values by their accessibility if they want to isolate specific effects.

Defining space, and alternatives to distributions

The city of Paris allows us to establish distributions like those in Figure 4 without too much distortion because it is quite homogeneous in its density and in its buildform, that is, there are few to no places where there is no market for commercial amenities altogether. Correctly defining the spatial extent of the global commercial amenity network is paramount to getting suitable results. Ideally this paper's methodology is used on well-defined, dense urban spaces. In practice, these can be difficult to find. It is key to have homogeneity across areas and, when it can be done, not to break chains of spatial-autocorrelation. Other cities, because of their natural structures or because the extent of the global network of amenities is harder to define, might be prone to having distribution-distorting outliers. In such cases, using ranks of ACI instead of raw ACI values can be a better option to visually map complexity and to confront it to different variables. For Paris specifically, we find the same upward trend in complexity at mean, median and quartile levels with rank data as we do with raw data, and rank is very strongly correlated ($\rho = 0.98$) to ACI values.

Appendix 2 : Alternative binary network definitions

The ACI as we define it in this paper uses a simple presence indicator to determine whether an amenity is within a place or not. Standard economic complexity applications use the RCA (or Balassa index), that is defined as follows :

$$RCA_{n,a} = \frac{O_{n,a}/\sum_a O_{n,a}}{\sum_n O_{n,a}/\sum_n \sum_a O_{n,a}}$$

$$M_{n,a} = \begin{cases} 1 & \text{if } RCA_{n,a} \geq R* \\ 0 & \text{otherwise} \end{cases},$$

Where $\boldsymbol{O_{n,a}}$ is the amenity count matrix and $\boldsymbol{M_{n,a}}$ is the binary matrix used to compute the ACI. One relevant question that often dismissed in the literature (see the supplementary materials in Mealy et al., (2019) for a counterexample) is the selection of *R**, the binarization threshold. The practical consensus is to use *R* = 1*, which means that place *n* has a comparative advantage in amenity type *a* if its share of amenity type *a* is larger than *a*'s average share of the global market. Beyond the issues surrounding count data and how difficult they are to compare (see **Section 2**), this threshold is difficult to relate both to consumer and supplier behaviors, and changing it can make the measures noisy. The left panel of **Figure 9** shows that ACIs measured through different RCA thresholds overall correlate quite strongly to presence-based ACI measures (the lowest Spearman correlation for the RCA-defined ACI to the presence-defined RCA is close to 0.9). *R* = 1* is however the threshold furthest away from what we consider to be the more conceptually grounding presence-based indicator (which is equivalent to *R* = 0*), and given the movement on the graph, threshold selection will have a clear impact on the ranking of some places.

In **Figure 10**, we find similar spatial trends in RCA-driven ACI measures as those found in **Figure 5**, but also notice the index as a whole is considerably more noisy than with a presence-based indicator.

A second alternative in the methodology could have been to apply the ACI in an ECI-like way, as an average of TCIs instead of as their aggregation (*ACI'*). We see in the right panel of **Figure 9** that these two measures are in fact very close[21]. The Spearman correlation between the measures is 0.99, with many points overlapping on the plot. We also see that, naturally, The less diverse places are, the more *ACI'* deviates from our ACI. Our conceptual grounding is that the more amenities a place has, the more information we have over which direction (non-complex or complex) that places' consumers tend towards. Fewer amenity types should not necessarily equate to lower complexity ; The fact different types of consumers disproportionately visit a place should define high or low ACIs. On top of this, an

[21] It should be noted that the measures are inverted if they are correlated to $\boldsymbol{K_{n,1}}$ in order to keep their interpretations comparable. The inversion of eigenvector values' signs bears little meaning beyond interpretation ; The TCI is still separating the amenities based on the same underlying component, that component itself is simply inverted. See Note 6 for a demonstration. Complexity is about ordering amenities by their relative similarities, and they can interchangeably be ordered from top to bottom or bottom to top while keeping the same *relative* positions. By ordering them according to correlation to ubiquity, we make the implicit assumption that there are more rare high spending-power amenities than there are low ones, but using any other indicator that relates to the practitioner's interpretation is just as valid as long as it is used consistently.

aggregation method is more resilient towards lower quality data (that can be inherent to the dataset or result from poor routing between buildings and amenities).

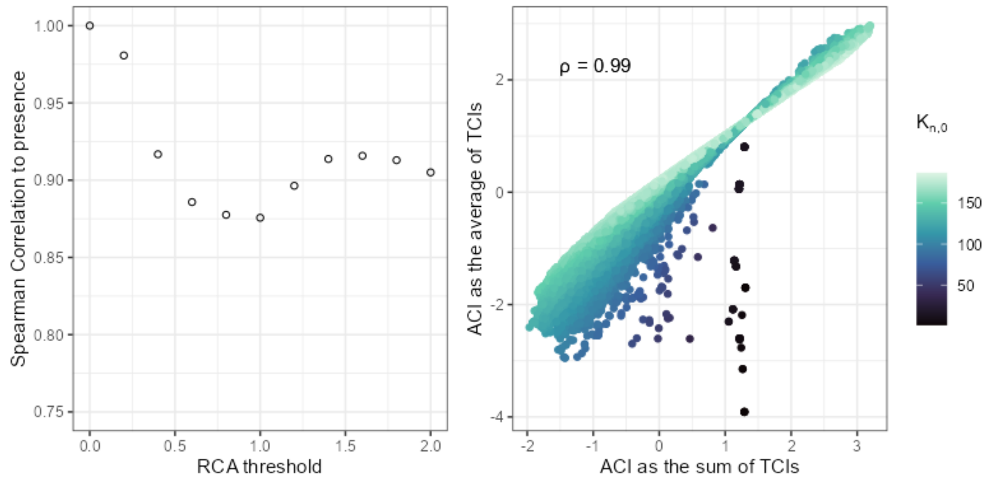


Figure 9 : Correlations between our presence-based ACI measures and ACI measures that use RCA to define $M_{n,a}$, at given thresholds R* (0.2 increments) (**left**) ; Relationship between the ACI as a sum of TCIs and the ACI as an average of TCIs (**right**), colored by diversity.

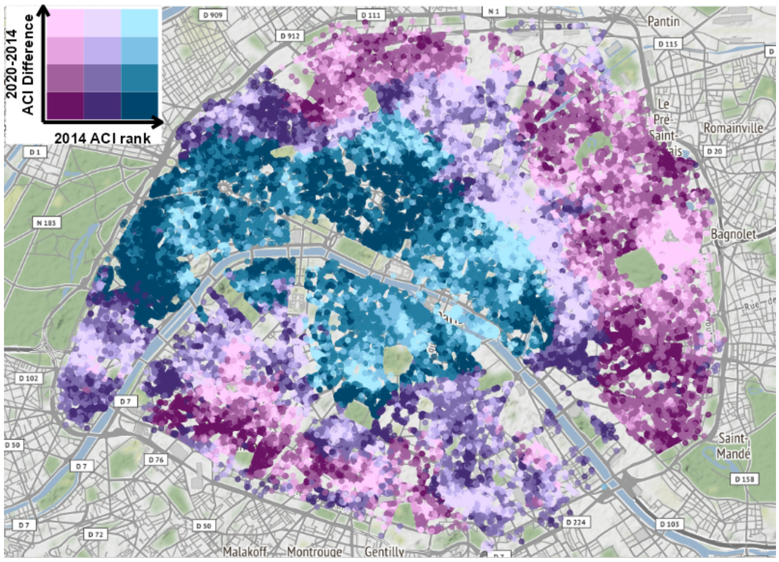


Figure 10 : Level and evolution of ACI ranks (2014) and levels (2020-2014) using a RCA with R* = 1 to construct the binary network. To be compared to **Figure 6.A**.

Appendix 3 : Sensitivity to cutoff selection

Figure 11 shows the equivalent of **Figure 6.A** for different selections of ***c***, the cutoff in minutes used to determine the size of places. We find that our indicator is not overly sensitive to cutoff selection in order to determine overall spatial patterns beyond ***c = 7***. The cutoff selection issue is akin to finding a balance between a measure that segregates places enough through their patterns in order to flatten out noise (which is predominant in low cutoffs), but that also allows for heterogeneity within close places (which can get lost in larger cutoffs). In our example of Paris, we use a cutoff ***c = 15*** to define places.

Figure 12 shows changes in TCI ranks for given cutoffs. Baring small differences, changes in the selected cutoff beyond ***c = 7*** should also not have large bearings over the overall separation of amenities.

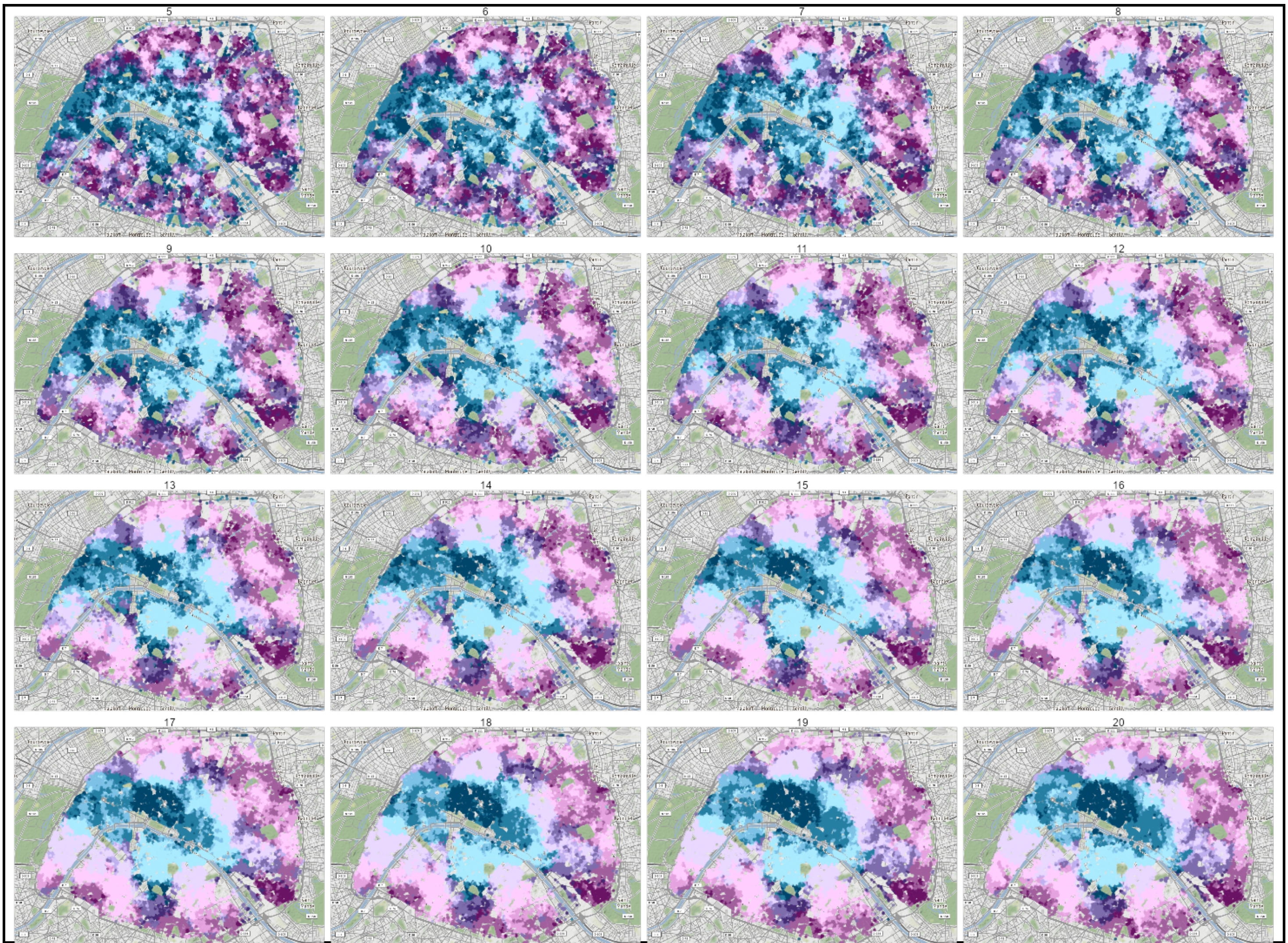
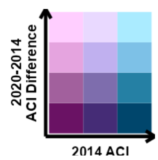


Figure 11 : ACI level and change between 2014 and 2020 in Paris.
These maps are replications of **Figure 6.A** for different values of cutoff ***c***, with the value for ***c*** noted above each map.



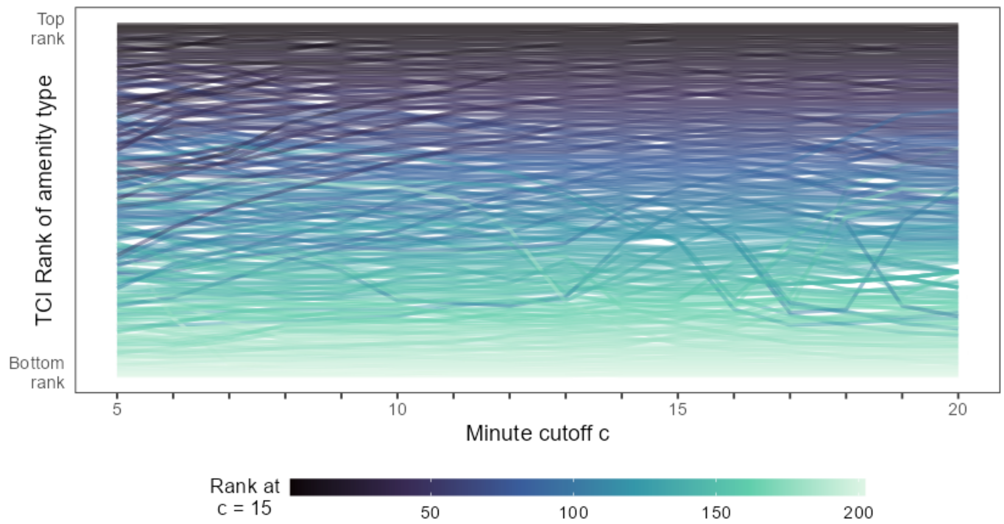


Figure 12 : The evolution of TCI ranks throughout different cutoffs ***c***, and how they compare to the ranks at ***c = 15***. Every line is a given amenity type.

Appendix 4 : Random Forest regression

Table 1 : Data sources and justification of variable selection in the random forest regressions

		Median Income	Gini Coefficient of Income	Share of housing built pre-1919	Share of 25-to-39 year olds	STR reservation days within 500 meters
Variable		*Median Income*	*Gini Coefficient of Income*	*Share of housing built pre-1919*	*Share of 25-to-39 year olds*	*STR reservation days within 500 meters*
Data source		*INSEE*	*INSEE*	*INSEE*	*INSEE*	*AirDNA*
Dataset name		*"Revenu disponible"*	*"Revenu disponible"*	*"Logement"*	*"Population"*	-
Date of data associated to ACI values in	2014	*2014*	*2014*	*2014*	*2014*	*2014 → 2015*
	2017	*2017*	*2017*	*2017*	*2017*	*2016 → 2018*
	2020	*2020*	*2020*	*2019*	*2019*	*2019 → 2021*
Granularity[22]		*Census tract*	*Census tract*	*Census tract*	*Census tract*	*Building*
Reason for selection		*Link to spending power insofar as people are willing to consume, possible association to desirable neighborhoods*	*The idea of diverse places yielding desirable atmospheres. People who are more into social mixing could have stronger consumption habits.*	*Aesthetically pleasing, desirable places. Especially in Paris.*	*Young active people are less likely to have high income. But they could also proportionally allocate more income to amenity consumption*	*Short-term rental tourists, like tourists, have a high willingness to spend, thus a high spending power. Their ability to shape place landscapes is already an important planning subject.*

Table 2 : Random Forest Model Characteristics (Using the full dataset)

Observations*	Number of Trees	Max depth	Features at each split	Minimum samples per split	**R-squared**
163,693	500	∅	3	1	**0.982**

**Observations exclude about 5,000 places with unknown median income or gini of income data because of low-population census tracts*

[22] *There are 992 census tracts in Paris, called "IRIS". Spatially interpolating census-level data to obtain place-level granularity using Kriging methods yields even better random forest estimates – That is, our models do not "overfit" on census tracts. Interpolating data however makes our models less transparent and straightforward, so we opt for keeping them at a census level.*

Appendix 5 : TCI Values

The BDCom data we use originally has over 220 amenity types. We remove various wholesale amenities ; B2B businesses ; non-selling offices and workshops ; empty, under construction, stocking and equipment premises ; Prefecture ; and unemployment offices. We also aggregate two variables that were otherwise overgranularized. “Car related” aggregates all combinations of car dealerships, garages, and fuel pumps when they are found together. Car dealers and service stations that do not offer any other services are left independent. Likewise, “Motorbike related” aggregates simple motorbike repairs and motorbike repairs that are also dealers.

We obtain the following list of 202 commercial amenities, ranked by their TCI values. U is the presence rate of each amenity, that is, its ubiquity divided by the total number of places (throughout all 3 years). Paris is an extremely amenity-dense city, and the overall presence rate is around 80% even with this very granular dataset. The more an amenity type is present across places, the less information it holds, and therefore the less extreme its TCI will be.

A good way to illustrate the separation yielded by the TCI is to check for ubiquitously needed characteristics that can be consumed through different amenities for different people. In the table of amenities below, we highlight stores related to grocery shopping. The link between non-ubiquity and information gained over the amenity is clear, and it is also clear that there is an important spending power pattern associated with their separation.

Table 3 : List of amenity types used to compute complexity along with the share of places they cover, ranked by their TCI

Rank	*Name*	*U*	*TCI*	*Rank*	*Name*	*U*	*TCI*	*Rank*	*Name*	*U*	*TCI*
1	**Luxury general food > 300 m²**	9.57	6.103	69	Photocopies	96.36	-0.151	136	Shoe repair - "Minute" repair (keys, heels...)	99.98	-0.281
2	Tourist hotel - Palace	15.36	5.494	70	Sale of living room and bedroom furniture	97.98	-0.157	137	Laundry - Pressing	99.99	-0.281
3	Tourist hotel with 5 stars	49.22	2.999	71	Patisserie	98.39	-0.17	142	Workshop in the store	99.99	-0.281
4	Department store	30.25	2.995	72	**Specialized grocery store**	80.91	-0.176	142	Asian caterer	99.99	-0.281
5	Coffee shop	44.22	2.801	73	Leather goods - Travel items	98.31	-0.177	142	Butchery - Butchery	99.99	-0.281
6	Large cultural multispecialist	38.49	2.488	74	Furniture sales and multi-specialists	98.3	-0.179	142	Bookstore	99.99	-0.281
7	Ticketing - Booking shows	42.5	2.454	75	Roaster - Tea and coffee retailer	98.17	-0.183	142	Brasserie - Continuous restaurant with tobacco	99.99	-0.281
8	Smile Bars	15.88	2.334	76	Women's shoes	98.61	-0.188	142	Clothing alterations	99.99	-0.281
9	Sale of coins and medals	42.58	2.06	77	Parapharmacy	96.85	-0.192	142	Laundromat	99.99	-0.281
10	Haute couture - Designers	62.23	1.856	78	Thrift store - Clothes sale - Depot-sale	98.8	-0.198	142	Beauty institute - Thermal and thalasso activities	99.99	-0.281
11	Gambling	53.85	1.81	79	Specialist in a sport	95.98	-0.199	142	General building work (electricity, plumbing, painting, insulation...)	99.99	-0.281
12	Sale of erotic items and sex shop	51	1.524	80	Sale of tableware - Household utensils - Art of the table	98.5	-0.2	142	Bank - Savings Bank	99.99	-0.281
13	Concert hall	64.88	1.269	81	Hardware and drugstore	98.98	-0.203	148	European Restaurant	99.99	-0.281
14	Philately	47.53	1.251	82	**Organic food store**	98.48	-0.204	149	Brasserie - Continuous catering without tobacco	100	-0.281
15	Sales room	42.1	1.226	83	Framing - Sale of paintings - Posters	98.36	-0.206	152	**General food <120m²**	99.99	-0.281
16	Generalist Sport	59.14	1.201	84	Smoke-free bar or café	99.15	-0.215	152	Pharmacy	99.99	-0.281
17	Cabaret - Dinner and show	73.73	1.148	85	Computer self-service - Cybercafé	88.02	-0.219	152	Optician	99.99	-0.281
18	Pop-up store†	20.18	1.082	86	Furniture craftsmanship (upholsterer, cabinetmaker...)	99.18	-0.225	152	Real estate agency	99.99	-0.281
19	Ice cream shop	78.54	1.024	87	Coffee - Tobacco	99.13	-0.226	154	Seated fast food	99.99	-0.281
20	Aparthotel	74.05	0.873	88	Telephony (Major operators + resellers)	99.24	-0.226	155	Bakery - Pastry shop	99.99	-0.281
21	ATM (not linked to a bank)	68.81	0.825	89	School / extracurricular courses (Acadomia...)	98.59	-0.228	156	Traditional French restaurant	99.99	-0.281
22	Engraving	69.38	0.785	90	General household equipment	99.26	-0.234	157	Hairstyle	99.99	-0.281
23	Men's shoes	81.87	0.782	91	Second-hand goods - *Brocante*	97.2	-0.239	158	Asian restaurant	99.99	-0.282
24	Sale of video games (+ video game room)	71.32	0.734	92	Sale of toys and games	99.4	-0.24	159	Cultural and leisure activities courses (pottery, dance...)	99.95	-0.282
25	Exchange office	80.91	0.727	93	Mixed shoes	99.26	-0.241	160	Insurance	99.97	-0.282
26	Sale of religious articles	79.57	0.629	94	African restaurant	79.26	-0.242	161	Sale of frozen products	99.94	-0.283
27	Binding and finishing	77.42	0.573	95	Sale of hearing aids	99.01	-0.245	162	Creamery - Cheese factory	99.7	-0.284
28	Other venue	64.21	0.558	96	Fishmonger's	98.84	-0.249	163	Sale of fruits and vegetables	99.93	-0.285
29	Sale of old books - Autographs	80.5	0.478	97	Fabrics - Textile - Haberdashery	99.36	-0.249	164	Veterinarian	99.84	-0.286
30	Garden center - Nursery	58.44	0.449	98	Service station	96.01	-0.253	165	Sale of medical articles - Prostheses and orthopedic insoles	95.53	-0.287
31	Discotheque and private club	82.6	0.433	99	Car rental	98.89	-0.254	166	Household appliance specialist	92.47	-0.288
32	Costume or accessory rental - Leisure	74.68	0.427	100	Maghreb restaurant	99.02	-0.256	167	Driving school	99.89	-0.288
33	Generalist household	81.06	0.39	101	Fashion jewelry - Fashion	99.68	-0.257	168	Pet grooming and equipment	95.93	-0.289

	appliances - Radio - TV - Hi-Fi				accessories						
34	Childcare	82.47	0.368	102	Stationery - Office Supplies	99.56	-0.257	169	Sale of records, cassettes, CDs, DVDs	81.23	-0.291
35	Sale of luminaries	89.04	0.351	103	Men's Ready-to-Wear	99.69	-0.26	170	Multi-sports hall	99.53	-0.292
36	Watches	84.89	0.35	104	Sale, repair, rental of bicycles / electric bikes	95.85	-0.26	171	Sale of newspapers	99.63	-0.298
37	West Indian restaurant	64.27	0.334	105	Repair of electrical or electronic items	97.2	-0.262	172	Personal services (cleaning, help for the elderly...)	99.11	-0.302
38	Other world restaurant	88.81	0.321	106	Tourist hotel with 2 stars	99.72	-0.264	173	Dental office	99.59	-0.305
39	Cinema	86.75	0.271	107	Tobacco	99.72	-0.267	174	Funeral homes	97.75	-0.306
40	Graphic arts materials - Creative leisure	77.91	0.247	108	**Regional and foreign specialty food products**	99.81	-0.267	175	Tanning salon - Solar / UV	90.42	-0.309
41	Tourist hotel with 4 stars	91.49	0.237	109	Physiotherapist's office	99.78	-0.268	176	Radiology Center	96.89	-0.318
42	Sale of cameras	72.94	0.213	110	Tourist hotel with 3 stars	99.83	-0.268	177	Home delivery of food dishes	99.33	-0.319
43	Sale and manufacture of bridal wear	88.29	0.187	111	Perfumery - Beauty products	99.84	-0.27	178	Sale of computer equipment	98.02	-0.321
44	Games room or club	71.31	0.156	112	Medical analysis laboratory	99.86	-0.272	179	Printing	94.85	-0.322
45	Custom tailor	92.58	0.131	113	Chocolate - Confectionery	99.87	-0.274	180	Bazaar	99.18	-0.33
46	Buy - Sell gold	91.83	0.091	114	Sale of electronic cigarettes	99.8	-0.275	181	Carpentry - Glazing - Mirrors	96.52	-0.34
47	Household linen	94.01	0.074	115	Massage parlour	99.9	-0.277	182	**Curbside grocery pickup✝**	22.38	-0.358
48	Shopping and express mail	68.22	0.035	116	Delicatessen - Catering - Delicatessen	99.93	-0.278	183	Car dealer	94.21	-0.373
49	Radio - TV - Hi-Fi Specialist	92.46	0.025	117	Ready-to-wear Mixed	99.95	-0.278	184	Motorbike related	97.27	-0.395
50	Video Club (Cassette and DVD rental)	57.41	0.006	118	Art Gallery	99.91	-0.278	185	Temporary employment agency	87.03	-0.441
51	Floor and wall coverings	95.97	-0.036	119	Watches - Jewelry	99.91	-0.278	186	Car related	97.72	-0.452
52	Sale of kitchen and bathroom furniture	95.86	-0.044	120	Nail care	99.93	-0.278	187	Motorcycle dealer	85.31	-0.473
53	Sports - Clothing and footwear	96.45	-0.055	121	Locksmithing	99.95	-0.279	188	DIY	90.53	-0.544
54	Rapid development - Photo film sale	95.21	-0.064	122	Travel and tourism agency - Airlines	99.96	-0.279	189	Nurse's office	95.07	-0.545
55	Bimbeloterie - Souvenirs	94.71	-0.065	123	**Monoprix**	98.83	-0.28	190	Sale of pets	52.92	-0.591
56	Central and South American restaurant	89.62	-0.066	124	Other physician assistant activity - Speech therapist	99.97	-0.28	191	Moving / Storage	87.49	-0.666
57	Children's shoes	91.46	-0.066	125	Professional training courses (languages, computers...)	99.89	-0.28	192	Tattoo - Piercing	80.38	-0.727
58	Theater	93.74	-0.076	126	Florist	99.98	-0.281	193	Telecommunication in store	83.7	-0.779
59	Jewelry	95.84	-0.082	127	Specialized gym	99.98	-0.281	194	DIY and home equipment rental	83.41	-0.792
60	Tourist hotel with 1 star	84.29	-0.101	128	Retail trade of beverages	99.98	-0.281	195	Youth Hostel	53.09	-0.822
61	Ready-to-wear Lingerie	97.42	-0.102	129	Indian, Pakistani and Middle Eastern restaurant	99.99	-0.281	196	Discount store	68.44	-0.904
62	Antiques	96.89	-0.112	130	Women's ready-to-wear	99.99	-0.281	197	Sale of automotive equipment	79.53	-0.962
63	Discount telephony and accessories (no particular brand)	97.62	-0.119	131	Newspaper kiosk	99.98	-0.281	198	Ambulances	74.94	-1.612
64	Tourist hotel without star	93.84	-0.12	132	Medical practice	99.98	-0.281	199	**Discount supermarket**	66.59	-1.94
65	Children's clothing	97.83	-0.128	133	**Classic convenience store**	99.98	-0.281	200	Technical control of the car	53.96	-2.301
66	Manufacture and sale of musical instruments	90.97	-0.131	134	**Classic supermarket**	99.98	-0.281	201	**Specialized supermarket**	25.64	-3.138
67	Studio of photographic reports	95.55	-0.136	135	Fast food standing up	99.99	-0.281	202	**Hypermarket**	7.66	-4.919
68	Tea room	97.99	-0.144								

✝ Grocery curbside pickups and pop-up stores were new additions to the 2020 database. They are absent from all places in 2014 and 2017.