The Policy Implications of Economic Complexity

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Abstract

In recent years economic complexity has grown into an active field of fundamental and applied research. Yet, despite important advances, the policy implications of economic complexity remain unclear. Here I organize the policy implications of economic complexity in a framework grounded on 4 *Ws*: *what* approaches, focused on identifying target activities and/or locations; *when* approaches, focused on when to time support for developing related and unrelated activities; *where* approaches, focused on the geographic diffusion of knowledge; and *who* approaches, focused on the role played by agents of structural change. The goal of this framework is to clarify the policy implications of recent work in economic complexity and to facilitate its continued use in regional and international development efforts.

Keywords: economic complexity, economic policy, structural change
JEL: O11, O25, O33, R11, R58

Introduction

In less than two decades, economic complexity grew from a handful of papers into an active field of research (Hidalgo, 2021). Today, scholars and practitioners use economic complexity methods to explain variations in diversification patterns (Bustos et al., 2012; Hausmann et al., 2014; Hidalgo et al., 2007; Jara-Figueroa et al., 2018; Neffke et al., 2011; Neffke and Henning, 2013), economic growth (Chávez et al., 2017; Doğan et al., 2022; Domini, 2019; Hausmann et al., 2014; Hidalgo and Hausmann, 2009; Koch, 2021; Lo Turco and Maggioni, 2020; Ourens, 2012; Stojkoski et al., 2016; Stojkoski and Kocarev, 2017), inequality of income and gender outcomes, (Barza et al., 2020; Basile and Cicerone, 2022; Ben Saâd and Assoumou-Ella, 2019; Chu and Hoang, 2020; Fawaz and Rahnama-Moghadamm, 2019; Hartmann et al., 2017), and sustainability (Can and Gozgor, 2017; Dong et al., 2020; Dordmond et al., 2020; Fraccascia et al., 2018; Hamwey et al., 2013; Lapatinas et al., 2019; Mealy and Teytelboym, 2020; Neagu, 2019; Romero and Gramkow, 2021). In fact, economic complexity methods are increasingly common in policy reports and national development strategies (Balland et al., 2018; Hausmann et al., 2011; Mealy and Coyle, 2021; Montresor and Quatraro, 2019) and have been used to justify the creation of several data observatories by ministries of economy or production, or by national innovation or statistics agencies in Mexico, Chile, Brazil, Peru, and Estonia, among other places ("DataChile," 2018; "DataMéxico," 2020; "DataViva," 2013; "Eesti | Data Estonia," 2018; "ITP Producción," 2021; Simoes and Hidalgo, 2011). But despite these advances, the policy implications of economic complexity can remain unclear. This is due in part to the rapid growth of the field, and also, due to the fact that—as an interdisciplinary endeavor—economic complexity builds on network science and machine learning methods that are uncommon in economic geography, international development, and science, technology, and innovation studies. The goal of this paper is to help fill this gap by reviewing past attempts to bring economic complexity into practice and organizing them in a framework that integrates multiple approaches.

Before diving into the framework, we need to define economic complexity, both as an academic field and as a collection of methods. In brief, economic complexity is the use of network science and machine learning techniques to explain, predict, and advice changes in economic structures. The focus on economic structure is motivated by work showing that these structures explain and predict important macroeconomic outcomes, from economic growth to reductions in the intensity of greenhouse gas emissions and income inequality (For a recent review see: (Hidalgo, 2021)). But economic complexity is also a peculiar field, in that it involves contributions from scholars from a wide range of disciplines, from the physicists and computer scientists who have pushed the development of machine learning and network science techniques, to the economic geographers, innovation scholars, and development economists that use economic complexity methods in their empirical and applied work.

But what explains the rise of this discipline? Economic complexity techniques have become popular because of their ability to work with fine grained data in ways that preserve the identity of the elements involved and their patterns of interaction. They provide a non-aggregative approach that allows a more nuanced understanding of economic structures without having to rely on coarse categories, such as changes from "agriculture" to "manufacturing" or from "manufacturing" to "services." These methods resonate with recent advances in economic theory that focus on the accumulation and diffusion of specific "chunks" of non-fungible knowledge. These advances have provided an empirical counterpart to the qualitative theories of knowledge accumulation advanced in evolutionary economic geography (Boschma, 2005; Boschma and Frenken, 2011; Nelson and Winter, 1985) and to the formal models used in endogenous growth theory (Aghion and Howitt, 1992; Romer, 1990; Solow, 1956; Weitzman, 1998).

The ability of economic complexity methods to advance this non-aggregative view comes from two key concepts (Hidalgo, 2021): the idea of relatedness (Hidalgo et al., 2018, 2007), which is simply the use of recommender systems (Maes, 1995; Resnick and Varian, 1997)—a common machine learning method—to explain activities that a location will enter or exit in the future, and metrics of economic complexity (Hausmann et al., 2014; Hidalgo and Hausmann, 2009), which apply dimensionality reduction techniques (e.g. PCA, SVD) to specialization matrices to estimate the value of a country or region's ensemble of activities, from products (Hidalgo and Hausmann, 2009), to industries (Chávez et al., 2017; Fritz and Manduca, 2021), and patents (Balland et al., 2018).

Relatedness metrics help formalize the idea of path dependencies by anticipating the probability that a location will enter or exit an economic activity (Hidalgo et al., 2018, 2007) (e.g. probability that Austin, TX will increase its patenting activity in "IPC G11C 5/14: power supply arrangements for information storage"). Relatedness has thus opened a more pragmatic approach to industrial policy where recommendations are tailored to each activity and location. This has helped pushed development advice away from stereotypical global champions (e.g. A.I., green energy, biotech, etc.), which not all regions are capable to compete in.

Complexity metrics help provide measures of the value or sophistication of an economic structure. This is validated by their ability to predict future economic growth (Chávez et al., 2017; Doğan et al., 2022; Domini, 2019; Hausmann et al., 2014; Hidalgo and Hausmann, 2009; Koch, 2021; Lo Turco and Maggioni, 2020; Ourens, 2012; Stojkoski et al., 2016), and explain geographic variations in inequality, (Barza et al., 2020; Basile and Cicerone, 2022; Ben Saâd and Assoumou-Ella, 2019; Chu and Hoang, 2020; Fawaz and Rahnama-Moghadamm, 2019; Hartmann et al., 2017), and emissions (Can and Gozgor, 2017; Dong et al., 2020; Dordmond et al., 2020; Fraccascia et al., 2018; Hamwey et al., 2013; Lapatinas et al., 2019; Mealy and Teytelboym, 2020; Neagu, 2019; Romero and Gramkow, 2021). This has made economic complexity metrics a target in efforts of structural upgrading. During the last decade, these results have been validated by dozens of independent studies showing the applicability of these methods across a wide range of geographic scales (neighborhoods, municipalities, cities, regions, and countries) and activities, from urban amenities and research areas to patentable technologies and product exports (Balland and Rigby, 2017; Bandeira Morais et al., 2018; Barza et al., 2020; Boschma et al., 2015; Chávez et al., 2017; Chu and Hoang, 2020; De Waldemar and Poncet, 2013; Felipe et al., 2012b; Fritz and Manduca, 2021; Guevara et al., 2016; Hartmann et al., 2017; Hidalgo et al., 2018; Jara-Figueroa et al., 2018; Koch, 2021; Kogler et al., 2013; Lo Turco and Maggioni, 2020; Lyubimov et al., 2017, 2018; Ourens, 2012; Poncet and de Waldemar, 2013; Romero and Gramkow, 2021; Sbardella et al., 2017; Stojkoski et al., 2016; Zaldívar et al., 2019).

It is thus not surprising that economic complexity methods have enjoyed rapid adoption among policy practitioners. This is due to a number of reasons. First, on the demand side, complexity approaches speak directly to a frustration that runs deep among many policymakers, especially in developing countries. These are policymakers who have grown tired of development advice that is either too abstract or too unspecific (e.g. level the playing field, improve institutions, adopt best practices, etc.). Development practitioners, particularly in Latin America, Asia, the Middle East, and Africa, have long had the intuition that economic structures matter, and that doubling down on their current patterns of comparative advantage (raw minerals and agriculture) may not be the best long-term strategy. Yet, this intuition was at odds with the economic consensus of the 80s, 90s, and early 2000s, which pushed developing countries to focus on their current sources of comparative advantage and reform their institutions instead of working to develop new sources of it. This frustration was accentuated by the fact that many of those who followed the advice, and engaged in the recommended institutional reforms, failed to reap much of the benefits, especially when they adopted reforms as a short-term signaling strategy (Andrews, 2013). This frustration was reinforced by a lack of sector specific approaches that could satisfy the demand of those looking to promote structural transformation. This combination of forces explains why economic complexity has grown quickly among those looking for sector specific approaches to economic development.

Today, the policy impact of economic complexity methods can be seen in reports focused on Smart Specialization in Europe (Balland et al., 2018; Deegan et al., 2021; Foray et al., 2009; Hassink and Gong, 2019; Montresor and Quatraro, 2019), China's special economic zones (De Waldemar and Poncet, 2013; Kahn et al., 2018; Zheng et al., 2016), Mexico's Smart Diversification strategy (Economía, 2021), or papers calling to upgrade manufacturing in the United States (Karsten, Jack, 2022). Today, it is not uncommon to hear experts across the world debate about the need to upgrade, sophisticate, or complexify an economy, which is how the ideas of economic complexity are seen in the mainstream. We can find these concepts on reports and studies focused on the economies of China (Chen et al., 2017; Dong et al., 2022; Ferrarini and Scaramozzino, 2015; Gao et al., 2017; Gao and Zhou, 2018; Guo and He, 2017; He and Zhu, 2019; Zhu et al., 2020), Mexico (Chávez et al., 2017; Pérez Hernández et al., 2019; Zaldívar et al., 2019), Russia (Lyubimov et al., 2017, 2018), Brazil (Britto et al., 2016; Dordmond et al., 2020; Gala, 2017; Jara-Figueroa et al., 2018; Swart and Brinkmann, 2020), Uruguay (Ferreira-Coimbra and Vaillant, 2009), Turkey (COŞKUN et al., 2018; Erkan and Yildirimci, 2015; Hartmann, 2016), and Paraguay (González et al., 2018). These ideas are also in efforts focused on the economic structures of developed nations, such as the United States (Balland and Rigby, 2017; Boschma et al., 2015; Essletzbichler, 2015; Farinha et al., 2019; Fritz and Manduca, 2019; Lo Turco and Maggioni, 2020; Rigby, 2015), Canada (Wang and Turkina, 2020a, 2020b), Australia (Reynolds et al., 2018), Italy (Basile et al., 2019; Cicerone et al., 2020; Innocenti and Lazzeretti, 2019a, 2019b, 2017; Stafforte and Tamberi, 2012; Tullio and Giancarlo, 2020), and the United Kingdom (Bishop and Mateos-Garcia, 2019; Mealy and Coyle, 2019).

On the context of modern industrial policy, economic complexity methods provide a strong complement to mission-oriented policy approaches (Mazzucato, 2018; Savona, 2018), which aim to rally innovation across multiple sectors by focusing on concrete missions. Mission-oriented policies acknowledge the need to consider absorptive capacity (Cohen and Levinthal, 1990), yet, they lack a quantitative methodology to estimate the absorptive capacity of a location across multiple sectors. Economic complexity approaches, however, are a means to provide these estimates. Without them, grounding mission-oriented policies may be difficult in a world where electoral ambitions can push missions into unfeasible territories.

Yet, despite this success, economic complexity can remain confusing for scholars in some academic circles. This can be explained in part by some key epistemological differences. Traditional approaches to economic development focus on identifying specific causal factors, and then using them as potential levers in policy interventions (Kleinberg et al., 2015). Complexity approaches are based instead on variables that capture combinations of factors. A useful analogy here is to think of propensity or risk scores in medicine. Consider an indicator for a patient's propensity to heart disease. The indicator will produce a score by combining multiple factors (age, tabacism, body weight, diet, sex, etc.). Some of these factors can potentially be intervened (e.g. diet, tabacism) but others cannot (e.g. age). That propensity score can be used to predict the risk of heart disease, but the score itself is not a causal factor (these are age, diet, tobacco, etc.). In a similar way, a relatedness or complexity index estimates a "risk" or "potential" to enter an activity or to experience economic growth that results from a combination of factors. But unlike in the heart disease example, relatedness and complexity provide propensity scores for systems where the exact factors and their combinations are unknown. Take relatedness. Relatedness approximates the propensity that a location enters or exits an activity by looking at the co-location of similar activities. Whether these activities collocate because they share labor, knowledge, supply chains, infrastructure, or customers is irrelevant. Relatedness approximates their combined forces as long as this propensity expresses itself in a repeated pattern of colocation. This works even when the balance between these forces change, since co-location patterns will adapt accordingly. Thus, the policy implications of economic complexity are not about increasing relatedness or complexity, as if they were single causal factors, but about using these metrics as strategic indicators for the propensity of a location to enter and exit specific economic activities or to generate inclusive, green, growth. They belong to what some recent authors have called prediction policy problems (Kleinberg et al., 2015).

Putting this epistemological discussion aside, it is safe to say that, despite the widespread adoption of economic complexity methods, there is limited clarity or consensus on how these methods should be used in practice. In fact, many efforts to put these methods into practice can be ad-hoc or may even build on naïve interpretations of the possible policy implications. In the following pages, I review and organize efforts to bring economic complexity ideas into practice in a framework that is explicit about the strength and shortcomings of different approaches. I organize this summary around four simple albeit fundamental questions: *what*, *when*, *where*, and *who*. Going forward, I call this the *4Ws* or the W^4 approach to economic complexity policy.

1. What

What efforts are the most common way to bring economic complexity ideas into practice. They focus on either identifying the activities that geographies could diversify into (Balland et al., 2018; Hausmann et al., 2014), or the geographies that are most suitable to the development of an activity.

What approaches use relatedness metrics to recommend the activities that an economy should target and complexity metrics to assess the potential value of each entry or exit.

The standard way to implement *what* approaches is to use a relatedness-complexity diagram (Figure 1 a), like the ones in introduced in the 2011 edition of the Atlas of Economic Complexity (Hausmann et al., 2014).*

For a location (e.g. a country, city, or region), relatedness-complexity diagrams compare the relatedness of that location to different activities (x-axis) and the complexity of each activity (y-axis). Here we consider the case for locations, but a similar case can be made for activities (e.g. Figure 1 c).

We can think about complexity-relatedness diagrams in terms of four quadrants (Figure 1 a). The top-right quadrant (high-complexity and high-relatedness) shows activities that are both desirable and accessible. We call this the *"let it be"* quadrant, since it is a quadrant in which diversification is feasible and desirable. The top-left quadrant (high-complexity and low relatedness) shows activities that are desirable but less accessible. We call this the *"wish you were here"* quadrant, since diversification into activities in this quadrant is difficult yet desirable. The bottom-right quadrant (low-complexity and high relatedness) shows activities that are accessible but unattractive. We call this the *"long road ahead"* quadrant, since it shows activities where diversification is feasible, but that are not too attractive in terms of complexity. Finally, the bottom-left quadrant (low-complexity and low-relatedness) shows activities that are neither desirable nor accessible. We call this the *stuck in the mud* quadrant.

* This diagram has recently gained popularity thanks to work using it in the context of Europe's smart specialization strategy (Balland et al., 2018)

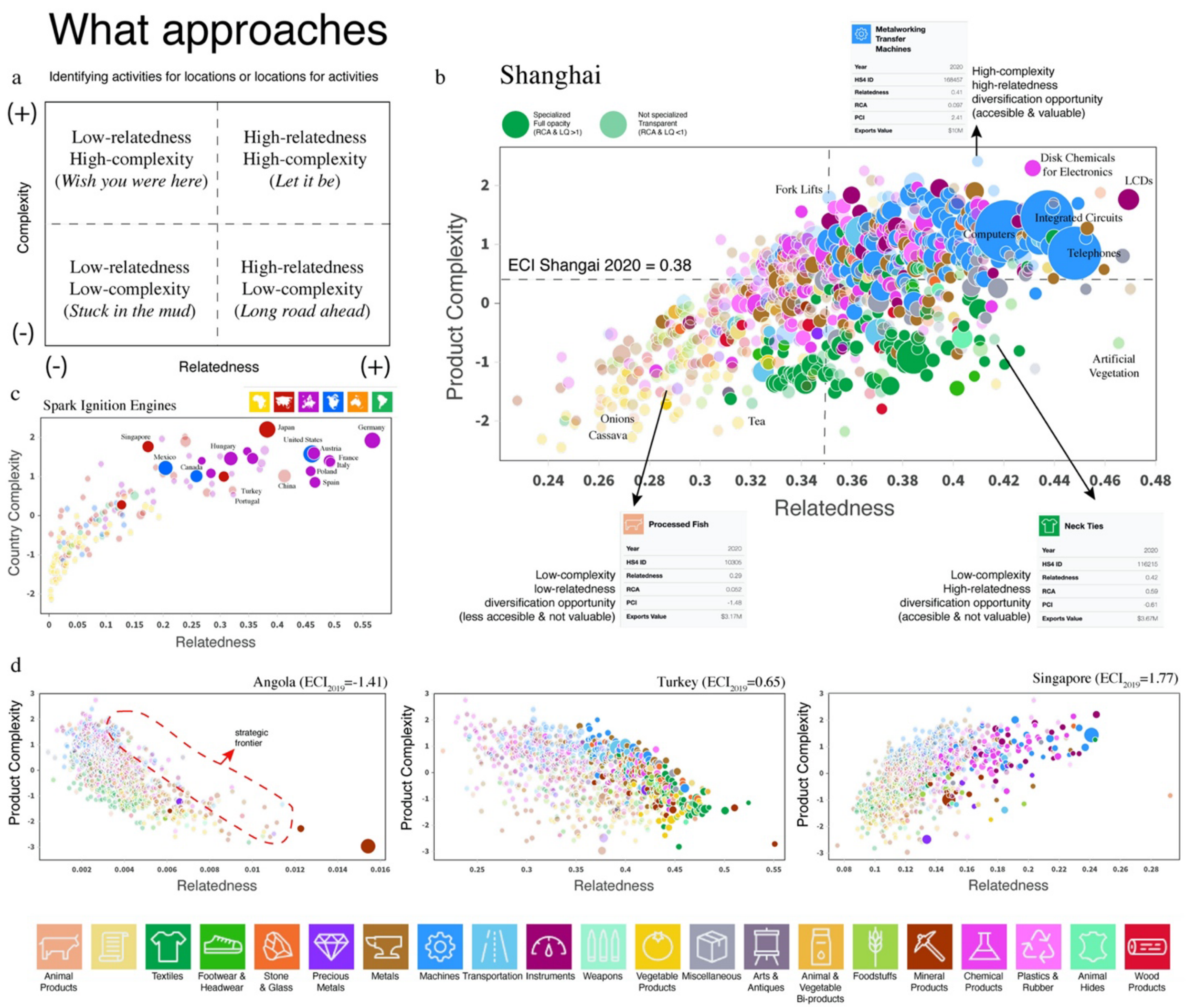

Figure 1 What approaches. (a) schematic explanation of the quadrants of a relatedness-complexity diagram. Relatedness-complexity diagrams for (b) Shanghai exports, (c) spark ignition engines, (d) Angola, Turkey, and Singapore.

Figure 1 b uses export data from Shanghai to highlight products in the various relatedness-complexity quadrants. Products that Shanghai is exporting with comparative advantage (Shanghai is specialized in) are shown in full opacity. Products that Shanghai is not specialized in are shown with 50% transparency. Since Shanghai is a complex economy (ECI=0.38), there are almost no products in the low relatedness high complexity quadrant. In fact, for Shanghai most products are located in the high relatedness-high complexity quadrant. That means Shanghai is in a very attractive structural position because its natural diversification opportunities (highest relatedness products) are also high complexity (and high income) activities.

When applied to activities (products, industries, technologies), the relatedness-complexity diagram can be used to recommend suitable locations for the production of an activity. Figure 1 c shows a relatedness-complexity diagram for Spark Ignition Engines (using 2019 international trade data). The chart shows that spark ignition engines are a product related to Germany, France, and the United States, who are already specialized in them, but also, they are related to China and Turkey, who are not currently specialized in it (RCA<1). Thus, the diagram suggests that China and Turkey are two countries with a high potential to develop comparative advantage in spark ignition engines in the future.

Relatedness-complexity diagrams, sometimes referred to as the "diversification opportunity spectrum" or "diversification frontier," are an exploratory tool that people can use to identify diversification opportunities that are both feasible (high relatedness) and attractive (high complexity). This diagram can of course be modified by choosing different metrics of relatedness (e.g. using machine learning to estimate the probability of entry and exit) and alternative metrics of complexity or economic value, such as the market growth for an activity, its current market size, or the income of current competitors. An example of this can be found in a report prepared for the government of the Dominican Republic in 2011, which included several metrics of value, such as an activity's global market size, its growth potential, and whether the global market in an activity was growing or shrinking (Hausmann et al., 2011). Such modifications, however, do not change the qualitative goal of the approach: identifying activities for potential upgrading that are feasible and attractive.

1.1. Using Relatedness-Complexity Diagrams in Practice

Using relatedness-complexity diagrams in practice requires understanding both the concepts behind these diagrams and the empirical patterns described by the data. While in principle, an activity or an economy can locate in any quadrant, in practice, the non-random nature of economic development implies recurring shapes and patterns in the data.

One well-known pattern is the reversal of the correlation between product complexity and relatedness observed for different levels of economic complexity (Figure 1 d)(Pinheiro et al., 2021). At relatively low levels of complexity (e.g. ECI < 0), economies exhibit a strong negative correlation between relatedness and complexity (as is the case for Angola in Figure 1 d). That means economies are more related to low complexity activities. In this case, the *let it be* quadrant is empty and the diagram is mostly populated in the other three quadrants. This pattern implies a tradeoff, since it means that for low complexity economies the most feasible activities are unattractive (low complexity) while the most attractive activities (high complexity) are hard to develop (low relatedness). In this case, "what" approaches recommend focusing in a strategic frontier focused on the highest complexity activities for a given level of relatedness (area encircled by red dashed line). But as we will see later, there are important considerations that escape what approaches and involve timing the strategic development of unrelated activities ("when" approaches).

For more complex economies, the negative correlation between complexity and relatedness weakens and eventually reverses (case of Turkey & Singapore in Figure 1 d). At the reversal point, economies are more related to complex activities (case of Singapore in Figure 1 d). Advanced economies, therefore, are in a much more favorable strategic position, since for them, the most attractive activities are also those that are most feasible. For these economies, the frontier is not one of identifying compromises, but one of rapid catchup or innovation.

The observation that more complex economies are in a more favorable position may seem intuitive, or even naïve, until we notice that complexity and income are not perfectly correlated. In fact, it is the mismatch between complexity and income what help us predict future economic growth (Hidalgo and Hausmann, 2009). Consider Peru and South Korea. Back in 1973, Peru had an income per capita that was twice that of South Korea, and also, about four times the capital per worker. It also had a similar level of education (measured in years of schooling). But in 1973 South Korea was a more complex economy than Peru. Recall that ECI is measured relatively to the world average, so an ECI=0 means that a country is on the average of the world, and an ECI of 1 means a country is one standard deviation to the right of the world average. In 1973 South Korea had an ECI=0.86 and Peru had an ECI=-0.8, meaning that South Korea was 1.66 standard deviations more complex than Peru. Thus, back in 1973, complexity tells us that South Korea was in a better position for subsequent structural change than Peru, even when it had half the income and a quarter of the capital per worker. This would be a hard conclusion to make using traditional aggregates (which are blind to the structural information available in the specialization matrices used to estimate variables such as relatedness and complexity).

The reversal of the correlation between relatedness and complexity has therefore been proposed as an explanation for middle-income traps, since it is a pattern that differentiates between high- and low-complexity middle income economies. Those that succeed at crossing the chasm (e.g. Japan in the 70s, South Korea in the 80s and 90s, etc.) were relatively high complexity economies compared to those that have not (e.g. Peru, Algeria, etc.).

Another empirical pattern that is also important to keep in mind is the fact that relatedness is a stronger predictor of entries for low complexity economies (Pinheiro et al., 2021). This may wrongly lead us to conclude that low complexity economies should focus primarily on related activities, but as we will see in the next section, this argument is flawed, since betting all development efforts on related activities can be shown to be a mathematically suboptimal diversification strategy. This is related to the idea that focusing too much on relatedness may overspecialize economies and risk technological lock-in (Boschma et al., 2012), trading off short-term adaptability for longer term evolvability. These fears of lock-in have pushed recent research to focus on unrelated diversification (Boschma and Capone, 2015; Zhu et al., 2019, 2017). But since unrelated diversification is empirically infrequent (Pinheiro et al., 2021), this research often finds weaker statistical results (smaller size effects). Nevertheless, it involves interesting findings. For instance, Boschma and Capone (Boschma and Capone, 2015) find that relatedness is a stronger predictor of diversification in economies with more coordinated forms of capitalism (but find a size of effect that is about 1/10 to 1/3 that of relatedness alone). Similarly, Zhu, Wang, and He (Zhu et al., 2019) find that the introduction of high-speed rail reduces the effects of relatedness, inducing more path-breaking development, but with a size effect that is again about 1/10 to 1/5 that of relatedness.

Overall, the moral of this section is that using relatedness-complexity diagrams in practice requires going beyond the theory, since it involves knowing about the empirical regularities observed in these diagrams when applying them to multiple locations and/or activities.

1.2. Limitations of *What* approaches

What approaches attempt to identify diversification opportunities using measures of relatedness and complexity. While these approaches are expected to beat chance, they may still be somewhat naïve, since economic context is only partially captured by data on the geography of economic activities. Moreover, these approaches involve a classic example of the tension between positive and normative philosophy that often permeates policy discussions. What is "natural" (philosophically positive) for developing economies is to enter more related activities. But that may be undesirable (negative from a normative perspective), since following relatedness may lock-in these economies in low complexity activities. At the same time, what is desirable for these same economies—upgrading their productive structure—may be unnatural given the inertial force of relatedness. That's why the policy implications of economic complexity need to go beyond efforts to identify sectors to enter or locations to target.

What approaches epitomize the dream of a pragmatic, machine-like industrial policy. They are built on the idea of a "*neutral*" tool that avoids the *"biases"* of political influence. But it is also an approach that needs improvement. While the ability of relatedness to predict economies entering new product exports, industries, research areas, and patentable technologies, has been widely documented (Hidalgo et al., 2018), it is important to keep in mind that statistical significance can be large even when size effects are small. *What* approaches beat chance, but are unable to remove it from the equation. They tell us about changes in probability, not certainties, and if used naively can lead us astray. The fact that economies enter related activities—on average—still means that they will fail many related diversification attempts. *What* approaches, therefore, are far from the end of the path. They provide at best a limited first glimpse of the promise of these methods. A promise that will largely remained unfulfilled, if we were to stop here. To move ahead, we need to flesh-out their limitations in search for complementary approaches.

2. When

When should an economy attempt to enter related or unrelated activities? How much should an economy invest in related and unrelated diversification attempts? How should this calculation change as an economy climbs the complexity ladder? While *what* approaches focus on what activities to target, when approaches tell us about when to target related and unrelated activities.

When approaches were introduced recently by Alshamsi et al. 2018 (Alshamsi et al., 2018) (expanded theoretically in (Waniek et al., 2020)). Unlike most work on relatedness, which tends to be statistical, Alshamsi's work is theoretical. It starts by accepting relatedness as an empirical reality and then builds models to explore the question: what is the optimal strategy to diversify an economy?

Using both stylized and numerical models, Alshamsi et al. (2018) show that, under relatively general conditions, strategies focused purely on relatedness (targeting the most related activity) are suboptimal diversification strategies. That is, they show that to diversify an economy faster you should not always target the most related activity. This result may seem counterintuitive, but it is also good news, since it provides both, a strong mathematical argument against the idea of focusing solely on relatedness, and also, opens a door to a portfolio-based view of complexity policy, where strategies look to balance efforts to enter related and unrelated activities.

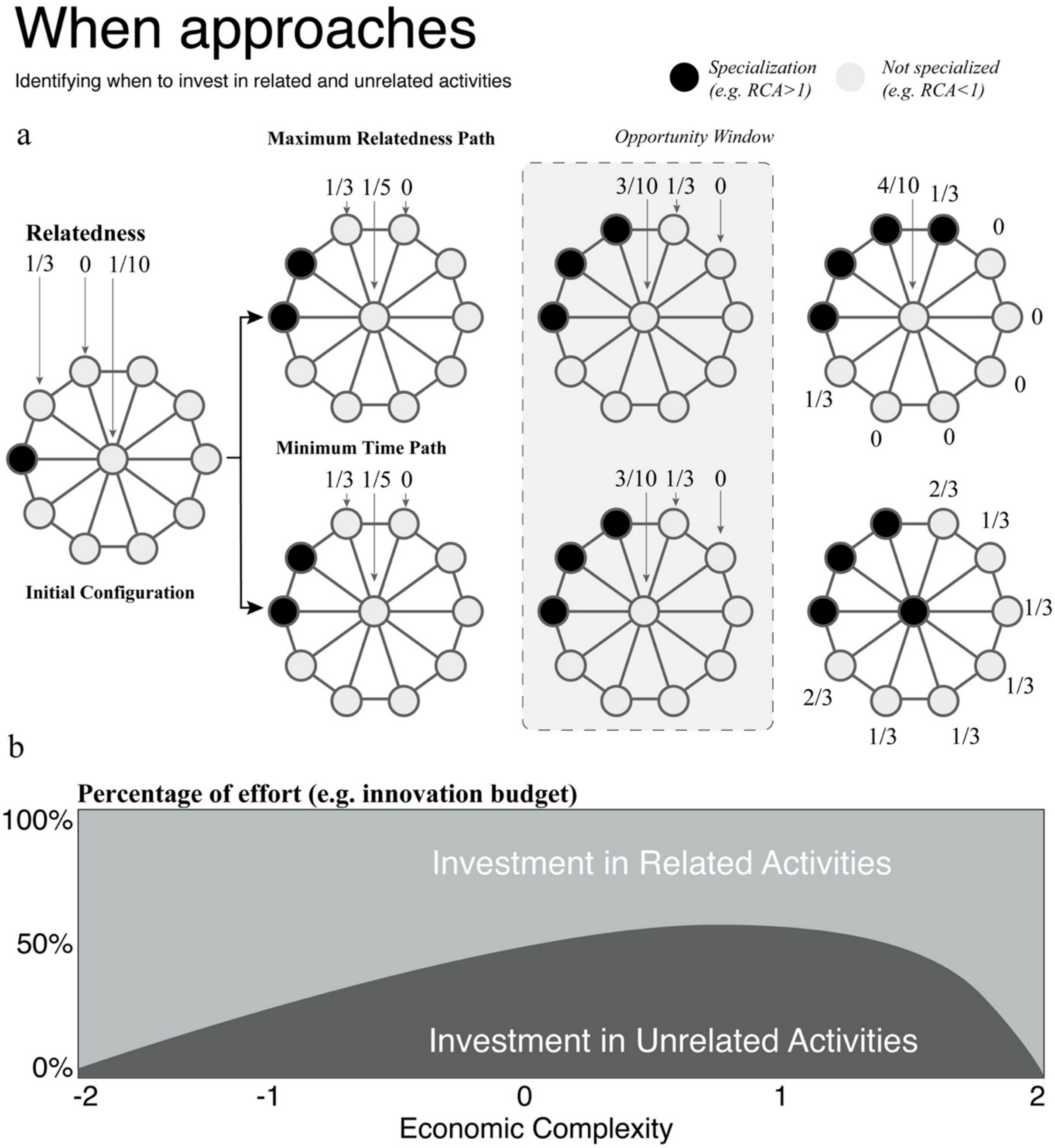

Figure 2. When approaches. **a** Illustration of the toy-model used by Alshamsi et al. 2018 to show that diversification strategies focused on maximizing relatedness are technically suboptimal. **b** Schematic of a development strategy that varies the level of investment in related and unrelated depending on an economy's level of economic complexity.

We can get the intuition behind Alshamsi et al.'s 2018 main result in Figure 2 a. Consider a network of related activities (e.g. a product space, technology space, or industry space) that looks like a wheel, with a central node (a hub) and a ring of peripheral activities.

Now consider an economy with a pattern of specialization on that network, represented by the darkened nodes. Since relatedness is an estimate of the chance that an economy enters a new activity, it is intuitive to think that diversification will be the fastest when we maximize the probability of success of each step (top path). That is, when we always pick the highest relatedness activity. The problem with this intuition is that relatedness is not a static quantity. In fact, changes in relatedness ripple through the network as an economy enters a new activity. So, thinking only one move ahead (picking the highest relatedness product) is not the optimal strategy. In fact, instead of targeting activities by simply maximizing relatedness, we should also consider the change in relatedness induced by each successful entry event (bottom path). This implies entering the central node in that network a bit earlier, when it is relatively unrelated (1/5), because unlike the nodes in the periphery, the hub can accelerate subsequent diversification events. Thinking multiple moves ahead implies targeting activities that are relatively unrelated (low probability of short-term success), but that are strategically connected and can enhance future diversification events. These are activities that link distant parts of the product space, research space, or technology space.

This result has three important implications. First, it pushes us to think about relatedness not only in terms of its present value, but in terms of its time derivative. Second, it also implies key timing considerations, providing the motivation for strategies focused on *when* to target related and unrelated activities. Finally, it also implies the need for a portfolio-based thinking, with different levels of support for related and unrelated activities.

The timing consideration relates to the ideas of opportunity windows and leapfrogging (Lee and Malerba, 2017; Malerba and Lee, 2021), since targeting an unrelated activity is only beneficial during a relatively narrow fraction of the development process. Targeting an unrelated activity too early, may lead to failed attempts and wasted resources. But targeting an unrelated activity too late, misses the opportunity to benefit from its spillovers (or from a short-lived cost advantage).

This relates to the need for a portfolio-based strategy focused on balancing support for related and unrelated activities.

For instance, consider a national innovation agency that splits its budget into "two" buckets[†]. One bucket is for supporting the development of related activities, which can be managed using *"what"* approaches. These are activities that the economy should be in a good position to enter. The second bucket is reserved for investing on more unrelated diversification attempts. Yet, these riskier investments are not random. They involve activities that can act as hubs connecting to more distant parts of the product, industry, or technology space.

"When" approaches also tell us that the relative size of these two buckets is dynamic. In fact, their relative size should adapt to an economy's level of complexity (Figure 2 b). The size of the bucket for unrelated activities should be relatively large at an intermediate level of development, when the window of opportunity to enter unrelated activities is open and incomes are relatively low. Missing that window of opportunity could leave an economy with a relatively high income, but in a poor structural position. That is a challenging combination, since it represents a state of relatively low capacity without a price advantage.

Today, *what* strategies dominate the current use of complexity methods in policy, but *when* strategies may be the key for economies stuck in the middle-income trap (Bank, 2017; Felipe et al., 2012a). *When* approaches imply that the development model that may have brought these economies to middle income status may fail to push them past the chasm. In fact, it is countries with relatively high income and low complexity that are at risk of getting stuck at middle income and high inequality.

There is also some empirical evidence supporting the idea that targeting the most related activities may be suboptimal, and hence, supporting the general idea of "when" approaches. Using data on European projects, (Uhlbach et al., 2017) find that, compared to unfunded projects, funding contributes more to the probability that a region will enter a technology for regions that are intermediately related to the technology. Regions that are already related to the technology enter with a similar probability whether funded or not.

[†] In fact, the explanation is easier assuming two buckets, but it is technically a continuous.

But to upgrade their productive structure, countries, cities, and regions need knowledge. So, the next approach focuses on how knowledge moves across space, and how communication and transportation technologies can help "bend" space. We call these *where* approaches.

3. Where

One of the best-known facts about economic geography is the notion that knowledge diffusion decays with geographic distance. Unlike the relatedness and complexity approaches that emerged in the late 2000s (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009), this fact can be traced back to the 80s and 90s (Jaffe, 1989, 1986; Jaffe et al., 1993), as it developed in parallel with the knowledge turn in growth theory (Aghion and Howitt, 1992; Romer, 1990, 1986). At first, researchers used patent citation data to show that knowledge spillovers decayed with geographic distance (Audretsch and Feldman, 2004, 1996; Jaffe et al., 1993). Subsequent literature provided a relational turn, by showing that this decay was explained primarily by the localization of social networks (Breschi and Lissoni, 2004; Singh, 2005). Eventually, scholars realized that other forms of proximity (Boschma, 2005; Torre and Rallet, 2005), beyond physical distance and social networks, could enhance or hinder knowledge diffusion, calling for extending these methods to include measures of cognitive and organizational proximity. This call was answered by the introduction of measures of relatedness (Hidalgo et al., 2007) which formalized the concept of cognitive distance between locations and activities, providing a strong complement to the measures of geographic, cultural, and social proximity that dominated the literature until then.

But geographic, social, and cultural distance are still key factors shaping the diffusion of knowledge and the spatial concentration of complex (Balland et al., 2020) and innovative activities (Audretsch and Feldman, 1996). This means that policy efforts must consider physical geography and cultural factors when thinking about the policy implications of economic complexity.

This brings us to *where* efforts. These are efforts leveraging the opportunities implied by geographical proximity. The idea of learning from neighbors.

A historical example of the role of physical distance in the diffusion of technology is the invention of printing (Eisenstein, 1980; Innis, 2008; Jara-Figueroa et al., 2019; Pettegree, 2010). Removable type printing is an early example of a lucrative and complex technology that diffused from a single location (Mainz, Germany). The diffusion of printing was fast, characterized by intense competition. In fact, the market for printers saturated quickly, reaching a stable number of printers per capita in only 50 years (Jara-Figueroa et al., 2019). Places that were closer to Mainz, however, had an exogenous advantage that allowed them to adopt printing earlier. That meant that Stuttgart and Paris were more likely to adopt printing earlier than Lisbon and Dublin, simply because they were "lucky" enough to be closer to Mainz. Research using this exogenous variation as an instrumental variable has shown that places that were closer to Mainz begot famous scientists or artist—two cultural categories that rose with printing—sooner than places that were further from Mainz and adopted printing later (Jara-Figueroa et al., 2019). This is a clear example of how geographic distance can affect the diffusion of technologies, and in turn, of the activities related to those technologies.

Today, we can observe similar effects in work showing that countries and regions are more likely to enter the economic activities that are present in their geographic neighbors (Bahar et al., 2014; Boschma et al., 2013; Jun et al., 2019). This is an interesting fact when we consider that trade forces should push neighbors to differentiate. Even though countries do trade more with their geographic neighbors (gravity effects), the effect of knowledge spillovers seems to be strong enough to overwhelm the differentiating forces of trade, especially on technologically advanced sectors (Bahar et al., 2014; Jun et al., 2019). From a policy perspective, this observation invites us to consider geographic "gradients in economic complexity." That is, borders separating high and low complexity regions or countries that provide an opportunity for knowledge diffusion or learning.

To grasp onto this intuition, consider Mexico and Cameroon. As a neighbor of the United States, Mexico has benefited from a strong gradient in complexity, and has grown the sophistication of its economy by becoming increasingly integrated with value chains in the United States. Northern states, such as Nuevo León, have benefited from this integration and today enjoy economies with a strong manufacturing base on sophisticated products (Figure 3). Yet, Nuevo León's exports go primarily to its neighbor to the north (85.2% go to the United States). This integration, has not reached the south of Mexico, where states like Guerrero suffer from low complexity and high poverty (27% of population in extreme poverty compared to 1.5% in Nuevo León ("DataMéxico," 2020)). The result is that Northern Mexican states have been pulling Mexico's economic complexity and development, helping transform the Mexican economy into a manufacturing economy (Figure 3). As a matter of fact, in 2020 Mexico exported nearly as many cars as the United States ($41.6B vs $47.6B), and more cars than South Korea ($36.9.8B), Canada ($31.8B), or France ($18.9B). In that same year, Mexico was also the second global exporter of video displays (after China). This structural transformation did not happen overnight, but over decades, fueled in part, by the gradient of complexity between Mexico and the United States.

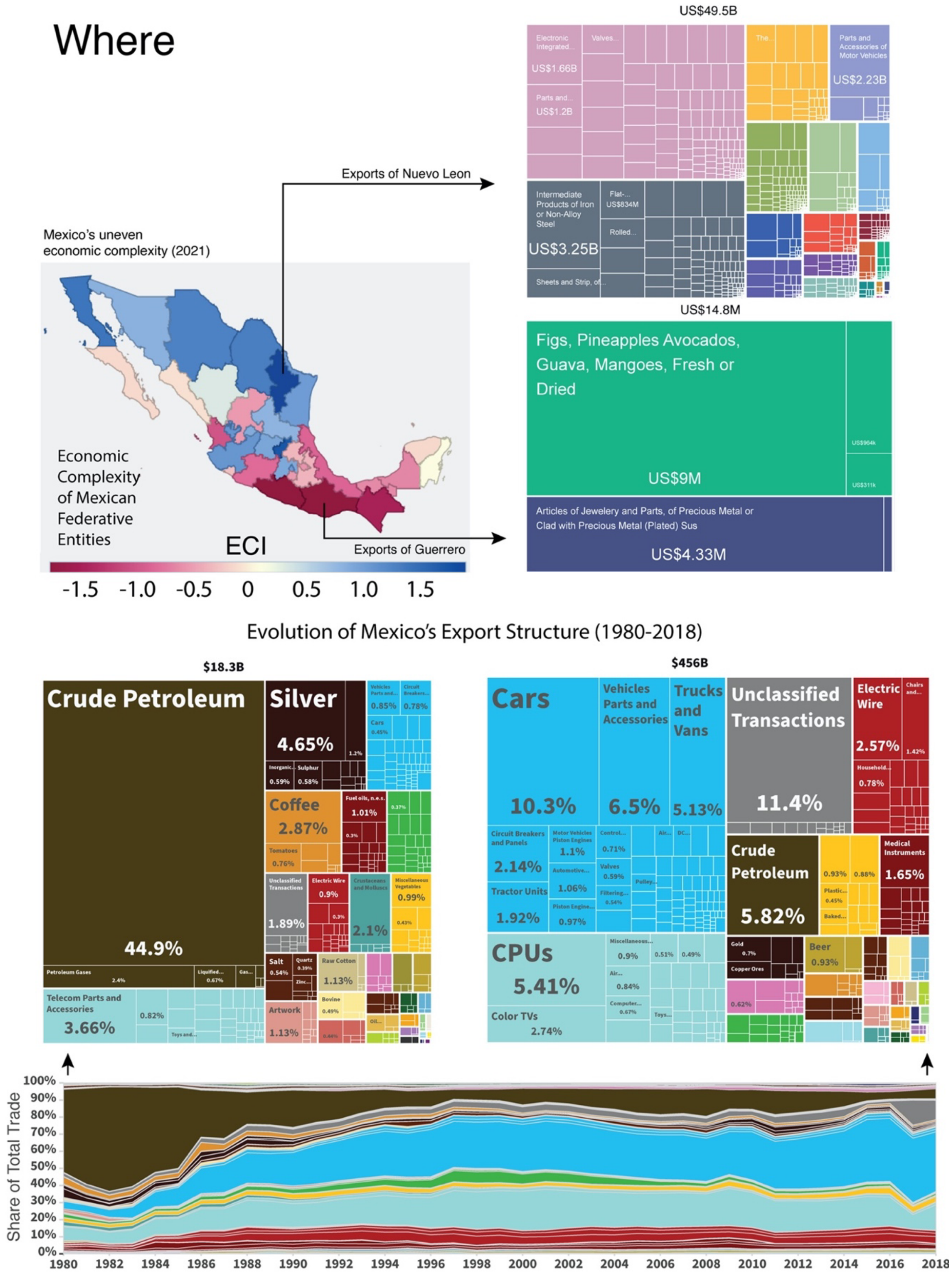

Figure 3. Economic complexity of Mexican states (from datamexico.org). Evolution of Mexico's export structure between 1980 and 2010 (from oec.world).

Now consider the case of Cameroon, a country in a very different geographic situation. Unlike Mexico, Cameroon lacks geographic neighbors with a significantly more sophisticated economic structure (they are in a region with limited gradients in economic complexity, and thus, limited regional learning opportunities). This means that for a country like Cameroon, absorbing knowledge by integrating with the value chains of its neighbors is a more limited development strategy.[‡]

Location matters. Countries like Mexico or Czechia are at an advantage when it comes to learning form their neighbors. By following *where* approaches, these countries could integrate with their neighbors and reap the benefits of their complexity. This is in fact a classic development idea that can be found in the *flying geese model* (Kojima, 2000) of development touted for decades by east Asian economies. The basic idea is to copy the economic successes of your geographic neighbors by leveraging their knowledge, physical proximity, and historical and cultural similarities. But where approaches can also go beyond the geography of production, and into the geography of trade destinations. In fact, extensions of the idea of relatedness to bilateral data (Jun et al., 2019) have shown that the effects of geography extend not only to what you export, but to where you export too.

But how can countries and regions integrate with their neighbors? Here is where we can find a few key policy levers, such as changes in transportation and improvements in language skills and communication technologies.

Recent literature in economic geography has shown that improvements in transportation can accelerate geographic spillovers. For instance, work leveraging the expansion of high-speed rail in China has shown the impact of rail to be larger for industries that are shared by the provinces connected by rail (Gao et al., 2021), suggesting that faster rail connections promote knowledge diffusion and learning. Similarly, historical data from Sweden has been used to show that the introduction of trains in the eighteenth century

[‡] When considering diversification through value-chains, is important to keep in mind that evidence points to backward/upstream linkages as the key direction of diversification (Bahar et al., 2019; Bontadini and Savona, 2017; López González et al., 2019).

accelerated the growth of cities located on the shortest paths between large urban centers (and for which the introduction of rail can be considered exogenous)(Berger and Enflo, 2017). This agrees with research using the introduction of discount flights and changes in travel rates to document increases in scientific co-authorships and patenting rates among the connected cities (Catalini et al., 2020; Hovhannisyan and Keller, 2015). Overall, these studies suggest that reductions in travel time promote geographic spillovers (by effectively reducing physical distance).

There is also evidence showing that the introduction of communication technologies can also "reshape geography." Research using data on the gradual arrival of internet to Africa has documented a positive effect on employment, especially in high skilled occupations (Hjort and Poulsen, 2019). Similarly, using data on internet penetration in China, researchers have shown that internet rollouts boosted firm manufacturing exports (Fernandes et al., 2019). When it comes to economic complexity, a study using the number of secure servers and a civil liberty index to instrument for internet adoption showed a positive effect of internet usage in economic complexity (Lapatinas, 2019). But communication technologies can be about more than digital connectivity. For example, research studying the effects of machine translation in an international trade platform estimated that machine translation resulted in a 10% increase in the exports mediated through that platform (Brynjolfsson et al., 2019).

Whether physical or digital, geography matters. *Where* approaches are about understanding the geographic constraints, and opportunities, implied by the spatial position of an economy. This involves leveraging within and between country learning opportunities, through cooperation, transportation, and communication technologies. While these technologies have the ability to "reshape" space, their strength may still not be quite enough to "fold it," inviting us to think strategically about how to use them in combination with other approaches.

4. Who

Who approaches focus on the agents of structural change (Elekes et al., 2019; Neffke et al., 2018), that is, the people that lead or catalyze efforts of structural upgrading, by either bringing knowledge to a region or setting up the ecosystem required for such upgrading to take place (Uyarra and Flanagan, 2021).

An important branch of this literature focuses on the role of foreign or non-local actors (e.g. migrants and foreign firms). This literature has shown that non-local actors help locations enter unrelated activities. In fact, several papers support this claim. Using matched employer-employee data, (Neffke et al., 2018) showed that "incumbents mainly reinforce a region's current specialization [and that] unrelated diversification […] originates [mostly] via new establishments […] with nonlocal roots." Similarly, (Elekes et al., 2019) used Hungarian manufacturing data to show that foreign owned firms deviate more from a region's current pattern of specialization. Lo Turco and Maggioni (Lo Turco and Maggioni, 2019) used data on Turkish manufacturing firms to show that entries into new actives are more related to the product mix of foreign firms than to that of domestic firms or local imports. Crescenzi et al (Crescenzi et al., 2020) use patent data to show that foreign multinationals have a positive effect on innovation rates, but that this effect is smaller for technology leaders, since these tend to engage in fewer alliances with local firms. These findings are related to work showing that migrant inventors bring new knowledge to the regions they migrate into (Bahar et al., 2020; Caviggioli et al., 2020; Miguelez and Moreno, 2018; Miguelez and Noumedem Temgoua, 2020; Parsons and Vézina, 2017), to work showing that business travel tend to promote the development of the industries in the home countries of travelers (Coscia et al., 2020), and to literature emphasizing the role of foreign direct investment and technology transfer in structural upgrading and development (Lee and Lim, 2001; Mu and Lee, 2005). Overall, this research shows that foreign actors represent a force that is complementary to *what* approaches, by providing paths away from relatedness.

A related strand of research focuses on the social networks of innovators and the relationship between the structure of these networks and the types of innovation produced by the innovators. Using patent data, (Tóth and Lengyel, 2021) find that firms are more likely to develop high-impact innovations when they hire inventors with a diverse network. Similarly, (van der Wouden and Rigby, 2019) find that "inventors in specialized cities value spatial proximity less and cognitive proximity more than inventors in diversified cities [since the latter can] partner with non-local inventors."

Finally, there are also case studies describing efforts by local actors to catalyze an environment for innovation. For instance, (Uyarra and Flanagan, 2021) interviewed 21 regional actors in Galicia, Spain, in work looking to understand a local effort to develop the unmanned aerial vehicle (UAV) industry. The case documents a coordination effort where local actors try to combine local assets, such as a disused military airfield, while attempting to attraction market leaders into the region.

Overall this case suggests that local actors behave in ways that are compatible with the findings of the quantitative literature, by working to attract non-local knowledge in efforts to promote diversification into unrelated activities.

5. The 4Ws

Today, economic complexity tools are popular in economic geography, international development, and innovation studies. Yet, their policy implications can remain unclear. One reason behind this is that many recent research efforts tend to focus on either the *what*, *when*, *where*, and *who* of structural change. Without putting these four ideas together, the implications of economic complexity ideas can remain unclear.

This lack of cohesion can lead to misunderstandings. On the one hand, there has been work equating the policy implications of complexity to solely *what* efforts (the identification of related activities efforts) (Balland et al., 2018; Deegan et al., 2021; Hausmann et al., 2014), often ignoring dimensions of timing (*when*), geographic proximity (*where*), or the role played by different agents in the process of structural change (*who*). On the other hand, there is qualitative literature that has been more critical of the quantitative work (Hassink and Gong, 2019; MacKinnon et al., 2019; Uyarra and Flanagan, 2021), but has nevertheless struggled to propose concrete alternatives while building on a relatively narrow understanding of the quantitative literature. In some ways, these misunderstandings may be an embarrassment of riches, since there are many research papers focused on single-*Ws* that it is hard to see the forest because of the tress.

But in other ways, these misunderstandings may represent another embodiment of the tension between positive and normative approaches. After all, relatedness and complexity tools provide positive descriptions of reality. They help quantify the "inertial forces" limiting structural change. But that does not mean that the recommendation is to follow the inertia. So, when these approaches are misconstrued as normative, they lead to recommendations that are not what the methods intend to provide.

A more constructive way to resolve this tension is to build on the duality that exists between scientific and professional fields, such as physics and engineering, or biology and medicine. Scientific fields tend to be positive. They are concerned about the way the world is (e.g. understand the principles of physics and biology). Professional fields tend to be more normative, aiming to shape the world according to human needs and desires (build flying machine and cure diseases).

Relatedness and complexity represent positive descriptions of reality. An economy may be related to an activity but that does not necessarily imply that the economy should attempt entering it. This is just like when physics tells us how gravity works, not to imply that flight is impossible, but to teach us that building an airplane requires taking the pull of gravity into consideration. Thus, the policy implications of economic complexity are not to double down on what are natural tendencies for economies (enter related activities), but to try to shape economies while taking these natural constraints and path dependencies into account. This implies a duality between an applied field, focused on policy, and a basic field, focused on the principles of economic complexity.

In this framework, what approaches describe the lay of the land. Relatedness and complexity tell us if an economy has any quick wins available, whether structural change is difficult for that economy, or whether there are some paths that may be easier to climb. Complexity gives us an idea about an economy's potential output, and help us understand which paths can be considered an upgrade for an economy. But to move the needle one needs to invoke the other *W*s. One needs to "defy gravity," albeit pragmatically.

When approaches tell us that there are windows of opportunities that we need to be vigilant about, how to identify them, and about the importance of seizing the opportunity when it arrives. Where approaches invite us to look for opportunities among our geographic and cultural neighbors, but also, to be strategic about the development of infrastructure and about the location of knowledge intense activities. Who approaches help us bend the principle of relatedness even further, by telling us about the key role played by the unrelated knowledge of migrants and their ability to bring economies to places that go beyond where locals can take them. The first *W* is about what is inertial. The last three are about how to think about changing an economy's state of motion.

But how do we bring these ideas into practice? What are the policy levers of economic complexity? As a machine learning toolbox, economic complexity methods do not provide new tools, but can help us improve how we evaluate and target tools that all countries and regions already have in operation.

Most countries, for instance, have national initiatives to fund science, technology, and innovation. By combining what, when, where, and who approaches, these initiatives can be organized into portfolios of related and unrelated activities, with a portfolio balancing strategy informed by a country's current level of economic complexity or development. The tools of economic complexity can also help organize these portfolios, by classifying projects as related or unrelated for each location and calibrating expectations for the success of related and unrelated diversification attempts. National innovation plans can also get a better lay of the land, of where the country or region is, and what are the sectors they expect to enter in the next 5, 10, or 20 years.

The tools of economic complexity also tell us about the importance of non-local knowledge, but also, about the importance of bringing non-local knowledge to an active ecosystem. On the one hand, they support the idea of visas and resident permits for high-skill migrants. Attracting talent is key in today's world. On the other hand, they emphasize the need to bring non-local actors into the best possible local ecosystems, avoiding the temptation to create white elephant projects, such as the Yachay city of technology in Ecuador, a "knowledge hub" built hours away from any of the country's few urban centers (Vega-Villa, 2017).

Economic complexity tools also invite us to think about transportation links in terms of learning. Train lines, aircraft routes, internet connections, and automated translation software are all able to bend space, even if a little bit. The collective learning benefits of these technologies, however, are rarely used to motivate public investment, but should be a key argument to consider in their long-term strategic development.

But putting complexity ideas into practice may still be difficult, in part, because as a machine learning approach, economic complexity is a data hungry methodology that requires reliable fine-grained information. Without such data, even the most basic diagnoses may go beyond the analytical capacities of many local development offices. These analytical capacities, however, can be promoted through economic data observatories, such as the one used today by Mexico's secretary of the economy as part of their smart diversification strategy. DataMexico (https://datamexico.org) has not only helped provide a unified showcase for dozens of government datasets, but has become a tool that the secretary of the economy is using to train embassies and local governments in support of their efforts to attract foreign investment. Tools alone, however, are never enough, they are only a starting point for local experts that can use them to dialogue with national statistics. The fine-grained knowledge available only to local actors are another key to the puzzle.

Still, there is much to learn when it comes to the policy implications of economic complexity. My hope is that by organizing some recent contributions into the 4Ws framework we push forth a literature that can dig deeper into these approaches, their interactions, and extensions.

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