*Introduction*

Widening income disparity is increasingly a growing concern for policy makers, politicians and scholars. Growing evidence shows that higher rates of inequality can fuel economic instability and political tension thus increasing country risk, dampening investment and reducing consumption and growth (Carvahlo and Rezai, 2014; Cingano, 2014; Kumhof et al., 2015). It is thus necessary to understand the drivers of inequality and how specific policies, intended to achieve growth, can increase or reduce income disparities. The literature is vast with attempts to study the relationship between innovation, knowledge accumulation and inequality. One observable issue in that literature is how knowledge is measured, specifically is the focus on indicators on "quantity". The use of such indicators follows the uncertain assumption that all knowledge has the same value and all knowledge is arbitrarily additive.

To account for such limitations, *economic complexity* proxies both the quantity and quality of the knowledge present in an economy by simultaneously leveraging information on the industries the economy specializes in and how ubiquitous (common-place) these industries are around the world. The debate and literature on complexity grew fundamentally based on the works of Hausmann and Rodrik (2005), Hidalgo and Hausmann (2009) and Tachella et al. (2012, 2013). Instead of relying on aggregate levels of data from firm, government, household and national accounts, economic complexity implements network theory and spectral analysis to reduce the dimensionality of the data in methods that conserve more detail than mere aggregates (Balland et al., 2021). Since, economic complexity has empirically proven to be a good determinant of economic growth (Hidalgo & Hausmann, 2009; Tachella et al., 2018), it became influential in policy directions. The Smart Specialization policy, EU's innovation policy, has been linked to theories of economic complexity due to its vision of funding regions to diversify their industrial portfolio into technology classes that maximize the complexity of their knowledge core (Rigby et al., 2019). As notions of complexity make their way into public policy debate, it becomes essential, for the sake of inclusive growth, to understand but what type of growth such policies are linked to.

*Research Question & Relevance*

The literature on economic complexity and inequality began with Hartmann et al. (2017) who found evidence of a negative relationship between the two phenomena on an international scale. The authors argue that complex productive structures display the a "high-resolution expression" (p.85) of the institutional and educational systems in which they flourish, thus lies their relationship with income inequality. Since that paper, multiple authors have contributed to the literature, by adding new empirical methodologies (Sbardella et al., 2017; Lee & Vu, 2020; Lee & Wang, 2020), or focusing on specific sub regions around the world (Sbardella et al., 2017; Zhu et al., 2020; Morais et al., 2021).

This paper contributes to the literature on the relationship between economic complexity and inequality. In addition, it contributes to the policy debate on the Smart Specialization Strategies. The main contributions to and distinctions of this paper from the literature are three-fold. First, the paper measures complexity using patent data. Patents provide a strong estimation to the type of knowledge present in an economy (Griliches, 1990; Jaffe and Trajtenber, 2002). They also capture a different part of the innovation eco-system than trade data. Certainly, patents do not capture the entire ecosystem of produced knowledge, but they provide a useful way to focus on technological knowledge to the extent it is transferred into inventions of utility. In addition, the detailed information found in patents, in terms of which technology classes they pertain to, can be utilized to study the evolution of local knowledge. (Boshcma et al., 2015). Second, due to the policy relevance and the context-specific nature of inequality dynamics, the paper analyses the relationship from an EU perspective. Finally, by implementing a 3SLS Systems of Equations methodology, the paper attempts to model the mutually influential effect between income inequality and economic complexity. The conversation on how income inequality can hamper innovation (Fragkandreas, 2022) is under-represented in the complexity debate. Its analysis provides more meaningful insights to this research.

*Methodology*

Following the literature, we expect that education, government spending and globalization make a contribution to the relationship between economic complexity and inequality. Those measures are contextualized in equation (1).

$$(1)\quad Inequality_{i,t} = \beta_0 + \beta_1 Complexity_{i,t} + \beta_2 R\&D\_Spending_{i,t-1} + \beta_2 Migration_{i,t-1} + \beta_3 Foreign\_Employment_{i,t-1} + \beta_4 Social\_Expenditure_{i,t-1} + \alpha_i + u_t + \varepsilon_{i,t}$$

Inequality is measured by using the GINI Index, the 80$^{th}$ vs. 50$^{th}$ percentile income ratio, the 80$^{th}$ vs. 20$^{th}$ percentile income ratio and the 50$^{th}$ vs. 20$^{th}$ percentile income ratio. While equation (1) provides the baseline for the relationship between the two components, the methodology further attempts to capture the two-way dynamic between complexity and income inequality. In order to do that, first a Granger test for Panel Data is implemented to test for the presence of reverse Granger causality between these two variables (Dumitrescu and Hurlin (2012). Once this is established, a systems of simultaneous equations methodology is implemented in order to account for the presence of mutual effects. In the second equation, variables which are arguably components of economic complexity are used as explanatory variables. Those include educational attainment measured through the tertiary attainment of the population, life-long learning proxies to control for continuous training and learning even amongst the labour force, institutional quality of the business market and how conducive it is to innovation captured through the number of days required to open a business, percentage of foreign employment to account for knowledge coming from abroad and the employment rate of the labour market.

$$(2)\quad Complexity_{i,t} = \gamma_0 + \gamma_1 Inequality_{i,t} + \gamma_2 Educational\_Attainment_{i,t-1} + \gamma_3 Adult\_Training_{i,t-1} + \gamma_4 Days\_to\_Open\_Business_{i,t-1} + \gamma_5 Foreign\_Employment_{i,t-1} + \gamma_5 Employment\_Rate_{i,t-1} + \alpha_i + u_t + \varepsilon_{i,t}$$

*Preliminary Results*

Equation (1), implemented through a basic OLS model with lagged measures, finds a negative and significant relationship between complexity and income inequality. The negative and significant relationship is true when calculating complexity using both a four-year and a five-year moving average. The results remain robust when we control for the specific years of 2008, 2009 and 2010 to ensure that the noise created due to the economic crisis at the time does not influence our findings too heavily. The results are also robust when we include a dummy variable to control for the EU-15 countries, countries which have a GDP higher than 50% of the EU average and countries whose manufacturing industry contributes to more than 50% of gross value added compared to the EU average. To quantify the results and on average across the models we apply, a one-standard deviation increase in complexity decreases our GINI coefficient by 1.78 units. The negative relationship is in-line with the findings presented by Hartmann et al. (2017), Sbardella et al. (2017) and the OLS analysis of Lee & Vu (2020). This confirms that the negative relationship between these two phenomena holds true even when using patent data to measure complexity and also when focusing purely on the European context.

Despite using lagged-variables in our analysis to control for reverse causality issues, the methodology does not capture causality. Indeed, for countries to become more complex in the first place, the regional innovation ecosystem needs to be conducive to such types of innovation and knowledge to flourish. It is widely acknowledged in this literature that the institutional ecosystem needs to co-evolve with the knowledge structure (Hartmann et al., 2017; Sbardella et al., 2017). This could imply that more equal societies are themselves correlated with higher levels of economic complexity. Vast literature on the consequences of inequality can motivate this theory by explaining how inequality can hamper economic growth, social trust and mobility and skill development (Nel, 2006; Stiglitz, 2012; Corak, 2013). Through this mechanism, inequality hampers innovation and thus reduces economic complexity.

Empirically, this reverse causality is evident when we implement a Granger Causality test, adapted for Panel Data (Dumitrescu and Hurlin, 2012), on our GINI variable and Complexity Variable. The results confirm that complexity Granger cause inequality, and also inequality Granger cause complexity. This motivates our implementation of a 3SLS model which will be implemented and discussed in future drafts of this paper.

*Discussion*

The paper contributes to the specific literature on the relationship between economic complexity and inequality and the general literature on knowledge accumulation, diversity, specialization and income inequality. From a policy perspective, this paper provides evidence on what type of growth do innovation policies that motivate regions to become more "economically complex" can lead to. Nonetheless, the role of human capital, skill formation and accumulation and training should not be underestimated here. Otherwise, the capacity of a nation to achieve higher levels of economic complexity is limited and so is its capacity to translate higher levels of economic complexity into lower levels of income inequality.