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Innovation and inequality in Europe and Italy

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Survey of theories regarding the effects of innovations on inequality

Abstract

In a phase of large increases in innovations and structural changes with lower economic growth and higher inequality and polarization, it is important to know and study the theories on the effects of innovations on inequality. In this paper we will examine the different theories on the link between these two variables, namely the skill-biased and the routine-biased technological change theories, the evolutionary theory and the geographical theories, with particular focuses on the roles of indirect effects and new technologies and on the empirical evidence.

Introduction

There has been a long debate on the effects of innovations in the labour market for the last two centuries. This topic is particularly relevant in this period, as there has been a huge increase in innovations in the last decades (Brynjolfsson and McAfee 2014), that may be correlated with the structural changes in the labour market (DESA 2017). Another reason that justifies the relevance of the topic is that we are in a phase of lower economic growth than in the past and at the same time we are experiencing an increase in income inequality (Piketty 2014), so knowing the links between innovations on one side and growth and inequality on the other side is important to address the best policies to increase growth and reduce inequality.

The rest of the paper is organized as follows: in the sections in the initial part of this survey we will present the debate on the effects of innovations in the history of economic thought, and we will study the different effects (both direct and especially indirect) of process and product innovations, discussing whether the effects of new innovations are different. In the central sections we will discuss the theories regarding the effects of innovations on inequality, with these two variables defined in different ways. These theories will be compared, and their validity analysed with respect to the empirical findings, following the key principle that the theory must be demonstrated by the reality. In the final sections we will also analyse respectively the effects of robotization and digital platforms in the labour market, the importance of the level of the analysis of the effects of innovations on inequality and the geographical effects of innovations on inequality. The last section concludes.

Innovation in the history of economic thought

Economists, philosophers and politicians have tried to understand the effects of innovations (especially on income growth) for a very long time. In the preclassical era (at the very beginning of capitalism, or a bit earlier) the mercantilists were in large part against innovation because of the negative direct effects that can cause (at that time substitution of workers in agriculture), that may be limited only by protectionism.

In opposition to them, the first classical economist (also considered the father of economics) Adam Smith was in favour of innovations: the specialization of labour, the accumulation of capital and the transition from agriculture and craft to industry were all driven by process and product innovations and caused a huge growth in GDP, profits and wages. However not all the classical economists agreed with Smith: David Ricardo (1817), in particular, was critical about the long-time effects of innovations, as they are mostly labour-saving and as less fertile lands will be cultivated the profit rate should reduce, so it would be convenient to reduce employment and increase unemployment. Probably within the classical economists the most critical with respect to innovations were the marxians, who thought that technological advance through innovations was “a mean of control on the labour force” (Calvino and Virgillito 2017). In the same century of Marx and Ricardo there was also a strong movement against innovations, called luddism (named after Ned Ludd), whose followers (the luddites) fought to destroy all machines.

At the end of the nineteenth century, however, the dominant theory became the marginalist neoclassical one, in which there is always market clearing (Say's law) and there is no involuntary unemployment. According to this strand of thought, innovation is a boost for growth and has no negative effects, as there is always equilibrium, if prices and wages can adjust instantaneously. The 1929 crisis broke this ideal world, emphasizing on the one side the role of public institutions in reducing unemployment (Keynes), and on the other side the role of innovations in the economic cycles (Schumpeter).

Joseph Schumpeter is probably the most important economist in the field of innovation. In his Capitalism, Socialism and Democracy (1942) he theorized the concept of creative destruction: competition among firms is not driven by price but by technology, so firms innovate and try to gain profits from the temporary monopoly generated by this innovation. According to Schumpeter (1942) innovations are not regularly introduced, but there is a cycle, and the levels of economic growth and employment fluctuate during this cycle of innovations, however these levels are stable between cycles, so mass permanent unemployment is not an issue. Each cycle is like a wave, most innovations are introduced at the beginning of the wave and foster growth and in most cases employment, but as innovation is a process of creative destruction unemployment may temporarily arise as a result of displacement of workers and different innovativeness of the sectors. In the central part of the wave there are fewer innovations, in a period of relative stability. When the market is saturated and innovations are obsolete, then there is a crisis that may increase temporary unemployment.

After Schumpeter some economists focused on the effects of technological progress (both exogenous and endogenous) on growth, other economists studied the links between innovations, economic cycles and institutional changes, but until recently few economists studied the effects of innovations on inequality. In the last decades however there has been an increase in importance of this topic because of the new types of innovations and the structural changes in the labour market in the post-fordist era.

Product and process innovations and the role of indirect effects

One of the most used distinctions is between product and process innovations. Product innovations are innovations that create new products or increase their quality, process innovations are innovations that modify the process of production by introducing a new technology or changing the combination of inputs. For a long time, the effects of the two types of innovations were studied separately resulting in process innovations considered negative for workers (in terms of employment and wages) and product innovations considered positive, because the former are usually labour-saving and the latter usually labour-augmenting.

However, even if it is true that the direct effects are usually positive in case of product innovations and negative in case of process innovations there are some indirect effects that make the result of an innovation more complex. We can divide these effects into two categories: interactions and compensation mechanisms.

Regarding the interaction effects, process and product innovations are linked one to each other, because a product innovation in one industry may be a process innovation in another industry and viceversa, so to compute the overall effect of the innovation we have to consider the effects in more than one industry. Some innovations may also change the relationships between industries, resulting in different indirect effects and different linkages over time.

The most important (and studied) indirect effects are however the compensation mechanisms: decrease in prices, decrease in wages, new machines, new investments, increase in incomes, new products (Vivarelli 2014, Calvino and Virgillito 2017, Piva and Vivarelli 2017).

1. Decrease in prices: new technologies reduce the production costs, and the reduction in costs should translate into a reduction in prices. The effectiveness of this compensation mechanism depends on the degree of competitiveness of the market: in case of monopoly or oligopoly this mechanism doesn’t work because the decrease in costs translates into an increase in profits rather

than a decrease in prices. Furthermore, according to Piva and Vivarelli (2017) if the innovation is labour-saving even in a competitive market the reduction in prices may not compensate the reduction in demand caused by technological unemployment.

2. Decrease in wages: technological unemployment directly causes a reduction in wages, this reduction in wages should cause an increase in labour demand and employment. This compensation mechanism is based on the hypotheses of full substitutability between capital and labour, but the data and the cumulative and localized nature of technological change don’t support this assumption and in some cases there is no substitutability at all (Vivarelli 2014). Even if there was full substitutability the supporters of this compensation mechanism don’t consider that unemployment and lower wages cause a double reduction in aggregate demand, so even if there was compensation, this could never be complete.
3. New machines: there is a shift of workers from the sector where the innovation is introduced to the sector that produces the machine. This compensation mechanism is rarely valid because workers in different sectors are usually very different.
4. New investments: the extra-profits caused by innovations are all invested. This assumption is optimistic: in the real world not all profits are invested, but even if they were invested in a productive way, they would be probably invested in labour saving technologies and the compensation wouldn’t be complete.
5. Increase in incomes: unions favour the sharing of the profits between firms and workers, this increases the aggregate demand and compensates the negative effects of labour-saving technologies. This is probably the most realistic compensation mechanism, as it was valid in the fordist mode of production, however since the 1980s this mechanism has become less valid as the collective bargaining of unions has been strongly reduced (probably this is one of the reasons of the secular changes in the functional distribution).

6. New products: the introduction and commercialization of new products increases variety and consumption. Since the 1980s this is probably the most effective compensation mechanism, although it has effects only if new products are not exclusively replacements of older ones.

Is this time different? Empirical evidence on structural economic changes

As stated earlier the effects of innovations on inequality hadn't been studied for a long time, at least until the end of the fordist era. Since the 1980s and especially since the beginning of the 2000s the literature on this topic has grown dramatically. Is there any reason for this fact?

The answer to this (rhetorical) question is obviously yes, there are some reasons, but analysing and stressing on some causes instead of others will lead to the different theories we will present in the next paragraphs.

Now let's start from the new characteristics of capitalism that explain the growing interest on the effects of innovations on inequality:

1. The wave of capitalism started in the 1980s is (or was, depending on if we consider it finished or not) driven by information and communication technology (ICT), that is less material than usual drivers of innovations that dominated the other waves (DESA 2017).
2. This wave started at the end of the oil crisis and at the beginning of the deregulation, and at least until the 2008 crisis there have been the liberalization, the privatization, the globalization and the financialization of the markets.
3. In this period there has been a huge increase in international trade, especially intra-industry, strictly related to the fragmentation of production and the development of global value chains.
4. In this period in most advanced countries there has been a reduction in unionization and an increase in flexibility in the labour market along with the diffusion of supply-side policies.
5. Probably for the first time in the history of capitalism the labour share of income has decreased steadily, at least since 2000 (Freeman 2015, Piketty 2014, Brynjolfsson and McAfee 2014).

6. In most advanced economies there has been a stable increase in income inequality, especially in English-speaking countries (Piketty 2014), but the opposite has happened in some of the least advanced ones (DESA 2017). There has also been the diffusion of winner-takes-all markets that reward superstars (people and firms) penalizing all the others (Brynjolfsson and McAfee 2014, Autor et al. 2019).
7. Since the last decades of the 1900s (the 1970s in the US, the 1980s or 1990s for other developed countries) wages and productivity, that until then had grown in the same proportion, have begun to diverge, with the contemporaneous stagnation of the former and growth of the latter (Guarascio and Pianta 2018, Compagnucci et al. 2018). The same divergence has been verifying between median and average income, while the divergence between productivity and employment in the US appeared later, at the beginning of the 2000s (Brynjolfsson and McAfee 2014).
8. Decrease in income growth in countries with aging (also within workers) population such as Italy, Germany and Japan.

Focusing on one or some of the characteristic may lead to different strands of theories on the links between innovations and inequality: skill-biased technological change, routine (task)-biased technological change, theories on changes in indirect effects, theories on labour-saving effects, institutions-driven and demography-driven technological change theories.

Skill-biased and routine (or task)-biased technological change

The first two theories are strictly related one to each other and they may be considered as stages of the evolution of one theory.

The simplest and the oldest of these theories is the skill-biased technological change (SBTC), according to this theory there has been a shift from low and medium skilled workers to high skilled workers. Process innovations substitute easier low and medium skilled workers while product innovations have a positive impact more widespread among workers or more concentrated among high skilled workers, so there is less demand for low and medium skilled workers and more demand for high skilled workers (ZEW 1997). If general training is slower than innovations unemployment may increase. Even if unemployment doesn’t increase there are still effects on inequality because the gains of innovations are concentrated within high skilled workers and those with less skills may not benefit at all, and may get worse off, increasing inequality within occupations.

The secular increase in wage differentials between more educated and less educated workers, that increases wage inequality at least within occupations, may be explained by an increase in demand for high skilled workers higher than the increase in supply for them, as skills can be approximated using the years of education, that is the demonstration of the skill-biased technological change (Katz and Murphy 1992). These increases in demand for high skilled workers and in wage differentials can be partly explained also by the increase in computerization, at least in the last three decades of the 20th century (Autor, Katz and Krueger 1998).

According to Acemoglu (1998) the increase in supply of skills causes itself a subsequent increase in demand for skills and, thus, the skill-biased technological change, so even if the relative demand curve for skill is downward sloping in the short run, it may be upward sloping in the long run.

Acemoglu (2002) explains the skill-biased technological change that occurred in the 20th century as a result of a higher supply of skilled workers that makes more profitable to use technologies complementary to skills, in contrast to what happened in the 19th century in which technology was substitutes of skills and skilled workers (mostly artisans) lost jobs in favour of unskilled workers. In addition, according to Acemoglu (2002) inequality increased since the 1970s because of the acceleration in skill demand caused by ICT.

Empirical evidence shows that there has been a higher increase in employment and wages for high skilled workers than for other workers, but not only the relationship between skills and employment and wages is not linear, but also it is not always positive. In particular the data show that, at least in the US, starting from the 1960s the negative effects are more concentrated within the medium skilled workers and in the 21st century there has been an increase in employment of low skilled workers similar or even higher than the one of high skilled workers (Autor 2015, Barany and Siegel 2018), with a possible reversal after 2000 when skilled people began to move to lower skilled jobs (Beaudry, Green and Sand 2016).

Noting that the empirical evidence is against the theory of pure skill-biased technological change, some authors changed approach and concentrated on tasks rather than skills. Tasks are divided into manual and cognitive (roughly speaking brain or body) and routine and non-routine (programmed rules or not).

The different tasks are well explained in table I of the Autor, Levy and Murnane (2003) study, the one that introduces the concept of routine (or task) biased technological change. According to this study examples of manual routine tasks are picking, sorting and repetitive assembly, examples of non-manual routine tasks are record-keeping, calculation and repetitive customer services, examples of manual non routine tasks are janitorial services and truck driving, examples of non-manual non routine tasks are forming/testing hypotheses, medical diagnosis, legal writing, persuading, selling and managing.

Empirical evidence shows a shift from routine workers to non-routine cognitive workers since the 1980s (Autor, Levy and Murnane 2003) with a constant decrease in non-routine manual workers over time also before the beginning of this wave of capitalism. Autor, Levy and Murnane (2003) explain this shift as a result of the introduction of new innovations (particularly computers) with a key role of substitutability and complementarity between workers and machines, with routine workers substitutes and non-routine cognitive complementary of machines.

More recent studies (WTR 2017, DESA 2017) support the validity of this hypothesis and add other effects of this massive shift of workers between tasks caused by innovation: unemployment, jobless recovery (increasing GDP, decreasing employment), underemployment, polarization of workers with a lot of working poors, few people in the middle class and some rich skilled workers, increasing inequality.

Regarding the polarization, in a theoretical model Autor and Dorn (2008) consider the huge increase in low skilled jobs, and in particular service occupations, caused by the absence of substitutability of workers between these occupations and the others in which innovations appear, so the only effects of innovations in service occupations are through aggregate demand effects, and as aggregate demand grows the demand of service occupations grows. These results are partially confirmed also by the theoretical model in Acemoglu and Autor (2011), in which there is a distinction between the effects on tasks and the effects on skills, unifying the two approaches. In addition, according to Autor and Dorn (2013) the higher is the initial share of routine workers and the higher is the polarization of wages and employment by skills, as routine workers shift to service occupations. Goos, Manning and Salomons (2014) find that job polarization caused by the RBTC can be split into a within-industry component and a between-industry component, that in most cases reinforce one each other, so there is not only a within-industry polarization but also a between-industry one. The latter, however, tends to be less important than the former, especially in high paid sectors (Breemersch, Damijan and Konings 2019). Harrigan, Reshef and Toubal (2016) find that technology-related occupations cause skill upgrading in nonmanufacturing firms and skill polarization in manufacturing firms, and after splitting this polarization into a within-firm and a between-firm component, they find that the second component is more important.

The theories examined in this paragraph consider only the effects within workers, and not the different types of innovations (product vs process, labour-saving vs labour-augmenting) and changes in institutions, geography, demography and functional distribution that are often more important (Piketty 2014, Bogliacino, Guarascio and Cirillo 2017).

Starting from these two approaches some authors studied the effects of innovations in different macrosectors and countries, noting that they are heterogeneous and, in some cases, ambiguous, but in most cases direct effects are negative and indirect effects larger and positive (Gregory, Salomons and Zierahn 2016), especially in manufacturing (Autor and Salomons 2017), favouring mostly high skilled but only in Europe. Moreover, the higher increase in high skilled jobs at the expenses of medium skilled jobs is mostly due to composition effects caused by the increase in average schooling. At least in the US, in fact, by dividing college and non-college degree workers even if there is still a reduction in medium skilled jobs, this is mostly due to the increase in low skilled jobs, especially among non-college degree in urban areas (Autor 2019).

Evolutionary theory

Unlike the SBTC and RBTC theories, that are part of the broader neoclassical theory in which changes are explained as a movement from the old maximizing equilibrium to the new one, the evolutionary theory follows a mix of schumpeterian theory of innovation and keynesian theory of the economy with a particular focus on functional distribution. The key characteristics of the evolutionary theory are the following:

1. Rules and routines: each firm operates according to decision rules and routines, that are specific to each sector or even to each firm and determine their trajectories (Nelson and Winter 1974 and 1982, Dosi 1988), this specificity of rules and routines is caused by the existence of tacit, non-codified knowledge (Dosi 1988, following M. Polanyi 1966).
2. Dynamicity: even if stable in the short run, rules and routines change over time, influencing the evolution of other firms and markets, these changes in techniques are caused by exogenous or endogenous changes in the environment such as demand, supply, other markets, scientific discoveries, innovations and institutions (Nelson and Winter 1974).
3. Selection: based on the dynamics of routines, innovations and institutional and environmental changes, the firms select themselves, the most profitable ones remain on the market and grow, while the others disappear, replaced by new and more innovative firms, in a schumpeterian process of creative destruction (Nelson and Winter 1982).
4. Learning: to survive non-innovative firms have to imitate innovations via learning by doing and by using and become more innovative increasing R&D (Silverberg, Dosi and Orsenigo 1988).

5. Heterogeneities: in this theoretical framework heterogeneities play a crucial role: there are heterogeneities in routines, innovations, workers, labour share and interactions and different kinds of innovations impact in different ways on workers with different skills and on entrepreneurs (Coveri and Pianta 2019). In particular, heterogeneity of firms is permanent (Silverberg, Dosi and Orsenigo 1988) and heterogeneity of routines goes from full routine to radical innovation, with some routines incorporated in innovations in intermediate cases (Nelson and Winter 1982).
6. Institutions: in contrast to the other theories presented above, in this case institutions are very important: regulation of the labour market, regulation regarding innovations, union density, offshoring, public investments, financialization, regulation on competition, globalization, and their interactions all have an impact on the functional distribution and the bargaining power of workers.
7. Bargain: another characteristic of this theory is the simultaneous determination of the profits and wages equation in which among the other variables the counterpart appears with a negative sign revealing the bargain between the two classes of workers and entrepreneurs (Van Reenen 1996). In addition, according to this theory, labour (even high skilled) is not a substitute for capital and substitutability and complementarity are less important than institutions.

Although the evolutionary theory is probably older than the others discussed in this paper and already divided into different classes of models in the 1990s (Nelson 1995), one of the first empirical models of this theory is the one in Pianta and Tancioni (2008), this article is probably one of the most optimistic as using European data from the 1990s they find that innovations have positive effects both on profits and on wages, with process innovations favouring the former and product innovations the latter.

This optimistic view, at least for product innovations, is supported also by Van Roy, Vertesy and Vivarelli (2018), who find that innovations, measured by citation-weighted patents, increase employment.

Bogliacino, Guarascio and Cirillo (2017) introduce another heterogeneity: in contrast to neoclassical views productivity depends on wages, because if a worker is paid more, he/she has more incentives to work better and less incentives to shirk, the heterogeneity in productivity is based on the heterogeneity in effort due to different wages. This study (Bogliacino, Guarascio and Cirillo 2017) shows that there are different effects of innovations on wages between skills levels, with high skilled workers that benefit both from offshoring and R&D, medium skilled that benefit only from R&D and low skilled that instead lose from offshoring.

One of the most comprehensive studies belonging to the evolutionary theory is probably Coveri and Pianta (2019), this study introduces globalization and unionization as elements that may have effects on innovations and labour market inequality. Coveri and Pianta (2019), therefore, study the effect of product and process innovations and also offshoring together with openness and union density and find that product innovations have positive effects both on wages and on profits, process innovations have no effects, offshoring, especially high tech, has positive effects on profits and negative on wages and union density has (surprisingly) no effects.

To sum up, the recent studies agree that product innovations have more positive effects on wages than offshoring and process innovations. Moreover, as entrepreneurs are usually richer than workers (even if in the last decades the share of workers in the top percentiles of income is increasing (Piketty 2014)) and innovations favour high skilled workers over low skilled ones, innovations (except maybe the product ones) increase both total inequality and wage inequality.

The new pervasive innovations: ICT, robotization, artificial intelligence and platforms

As already stated in one of the previous paragraphs this wave of capitalism is different from the others because the main driver of technological change is ICT, that is less material than the previous ones. Nevertheless, in the last decades there has also been a huge increase in robotization, which has caused a lot of effects, both direct and indirect. In particular, as noted by Autor and Salomons (2017), the larger effects, both the negative direct and the positive direct ones, are in manufacturing, that is the macrosector in which more innovations and more robots have been introduced. In this paragraph we are going to present the different positions regarding the effects of the introduction of ICT, new robots and artificial intelligence (that may be considered itself an evolution of robots) and platforms.

Regarding ICT, Michaels et al. (2014) find that it increases polarization in the labour market, in particular it increases the wage bill share (hours worked multiplied hourly wages, with effects on both variables) of high skilled workers, decreases the one of medium skilled workers and has no effects on the wage bill share of low skilled workers.

According to Gallipoli and Makridis (2018) the reduction in the skill premium found by Beaudry, Green and Sand (2016), when accounting for the different task content of jobs, is limited to non-ICT high skilled jobs. Moreover, Gallipoli and Makridis (2018) confirmed that ICT has reduced employment in manufacturing, contributing to polarization.

Starting from 2018 several studies have analysed the impact of robotization on productivity and employment. The first and most cited one is Graetz and Michaels (2018), according to this study robotization increases productivity and growth, decreases prices and has a skill-biased effect on wages, as it increases wages of high skilled workers and decreases wages of low skilled ones.

Dauth et al. (2017 and 2021) confirm these findings, showing that robotization shifts workers from the manufacturing to the service sector and this reallocation is mainly due to young workers finding jobs in the service sector. In addition, it decreases wages of low and medium skilled people (but not of high skilled people) and the labour share of income, with no effects on total employment.

A more pessimistic view is expressed by Acemoglu and Restrepo (2020), who find that the exposure to robots reduces employment and wages, especially in the bottom half of the distribution.

This reduction in employment, especially of middle skilled and young workers, is confirmed also by Carbonero, Ernst and Weber (2018), but only for emerging countries, and by Chiacchio, Petropoulos and Pichler (2018) in Europe, even if in their study they find ICT increases employment, thus, different technologies may have different effects.

Differently from the other studies examined above, Bekhtiar (2021) criticizes the results of Graetz and Michaels (2018) as manufacturing and non-manufacturing industries are different and rejects the hypothesis of skill-biased technological change, as he finds that robots reduce wages and increase polarization.

A more optimistic view is expressed by Camina (2020) that, among the other effects, finds that robots and other technologies, including ICT reduce employment in the short term, but increase it in the long term in Spain, and by Green Leigh, Kraft and Lee (2019), who finds that robots increase even manufacturing employment in the US

Some concern regarding the possible decrease in the labour share of income caused by robotization has been expressed by other authors in other studies, such as Freeman (2015) or West (2015). The former correlates the growth in inequality to it, stating that to reduce the decrease in the labour share of income and inequality, workers should own part of the robots. The latter, instead, notes the rapid increase in the number and complexity of robots, computerized algorithms, artificial intelligence, augmented reality and other innovations, that are substitutes for labour and increase the unemployment, the polarization of workers and the mismatch between demand and supply of jobs. West (2015) also makes some proposals of policies, among them he advises to give benefits outside the jobs, a basic income and/or an income tax credit and encourage profit sharing.

These policies are more or less the same advised by Brynjolfsson and McAfee (2014), but these two authors are more optimistic: they think we are in the “second machine age” (the first being the industrial revolution begun with the invention of the steam engine), and that technology is what has changed humanity the most. According to them not all tasks can be easily automated by robots or artificial intelligence, but technology advancements in these decades have been enormous, computers are able to drive a car and beat champions in difficult games like chess or Jeopardy.

Brynjolfsson and McAfee (2014) note that one of the main differences between ICT and other technologies is that their efficiency doubles in a very short period of time (between 18 months and 2 years) without slowing and this exponential growth, combined with the digitization, leads to a higher rate of innovations in this sector. Another difference between them is that ICT provide free services not counted in the GDP, so their contribution to well-being is more difficult to calculate (it may grow even with a declining GDP).

Brynjolfsson and McAfee (2014), however, recognize that even if technology has been the main source of growth, automation may have some important side effects, such as unemployment in some sectors and increase in inequality in winner-takes-all markets, that may be larger than the positive effects for most people. Another side effect is the increase in employment share of high skilled people and the decrease in employment share of medium skilled people caused by the fall in the price of ICT (Jerbashian 2019)

Other authors are even more optimistic than Brynjolfsson and McAfee, among them we can consider most of members of the SBTC and RBTC theories discussed above and the authors of the World Trade Report 2017. This study (WTR 2017) underlines the historical growth in employment associated to the growth in innovations as indirect positive effects are usually higher than direct negative effects even when the innovation is labour-saving. This study cites other studies that confirm the positive effects of product innovations and the ambiguous (but not always negative) effects of process innovations and reassure stating that the pessimistic forecasts like the one of Frey and Osborne 2013 (loss of 47% of jobs in 20 years) are completely unfounded and the introduction of artificial intelligence and robots will be slower than expected by most studies, allowing to a more efficient reallocation of workers, also towards new jobs that will be created.

Even the Department of Economic and Social Affairs of the United Nations has published a study on this topic (DESA 2017). This study underlines that innovations have had positive effects on wages and employment throughout history and there is no reason to worry that this industrial revolution will be different, even if it is based on ICT and AI. Technological revolutions driven by radical innovations, however, caused structural changes in the past, such as the movement of agricultural workers in the countryside to industrial and urban centres in the first industrial revolution. According to DESA (2017) politics should have a greater role to boost innovations rather than block it, to govern and counteract the possible negative effects, for example providing social protection to unemployed, giving more power to unions and increasing education and life-long learning.

DESA (2017) is probably one of the first study to analyse the lag between the introduction of radical innovations and their effects, that makes the impact and the timing of technological revolution difficult to identify. Other complications are the different starting points and dynamics of technologies and inequality in the different parts of the world, and the globalization, that may be a source of simultaneous causality (more innovative firms export more, but exporting firms have more incentive to be more innovative). The appearance of global value chains, favoured by technological innovations and reduction in transportation costs, has determined processes of offshoring and reshoring that may increase both income and wage inequality between countries.

Most of the innovations discussed above have more impact in the industrial sector, but there are innovations that have a greater impact on services, among them the newest, more important and more pervasive are online platforms. There are two types of online platforms: in capital platforms (such as Airbnb and Ebay) participants sell goods or rent assets, in labour platforms (such as Foodora and JustEat) participants perform discrete tasks (Farrell and Greig 2016), and both types are growing even more than ICT and are changing the economy.

Labour platforms are creating the economy of minijobs: they employ usually young people with high volatility of income and substitute income from other kinds of jobs, rather than increasing total income of workers (Farrell and Greig 2016). Workers in these platforms are less protected than workers in traditional jobs, and are usually poorer, so as labour platforms are substitutes for other jobs and income from them is usually low, workers may potentially be locked in a poverty trap, with a reduction in training and skills (Guarascio and Sacchi 2017, Franzini and Guarascio 2018).

According to these two studies, to reduce the negative effects of labour platforms passive and active labour policies, training programs and policies, macroeconomic and industrial policies, reforms of antitrust and property rights laws, increase in importance of unions and public investments are needed.

Even if when talking about platforms we usually mean labour platforms, there are even more participants in capital platforms. These platforms seem to have less impact than the others because income from capital platforms mostly increases total income, however in some cases the effects are evident, for example Airbnb has increased spatial concentration of earnings in the already concentrated rental market in Rome (Celata 2017).

From firms to sectors to the whole economy: the roles of aggregation and elasticities

In the previous paragraphs we analysed the different theories and studies on the effects of innovations on wage inequality, wages, employment and growth, but there are different levels at which these variables can be measured, and authors disagree on which level is the best for doing analysis.

The first level is the firm level: we can study the effects of innovations within and between firms for all firms, to do this we need precise microdata without errors and outliers, that may be misleading, in this case the indirect effects are considered between each firm and the others.

The second level is the sectoral level: we can study the same things at a higher level, for example regrouping firms using some classifications (for example the Pavitt or the NACE) and then study the effects sector by sector, in this case we can consider the different firms in the same sector as identical or different depending on the specificity of the model.

The third level is the country level: in this case we consider the effects at a macroeconomic level, indirect and composition effects (except the international ones) are internalized so we can consider the overall effect of innovations on inequality.

Between the second and the third level we can consider another level that can be either geographic (different regions of the same country) or organizational (different macrosectors).

There are pros and cons for each level of study. At the firm level when studying the different effects of different innovations on different firms the results may be too different and specific to each firm to be estimated and we need lots of data, however in a big dataset the higher level of detail allows to distinguish the effects of different innovations (at least process and product) on firms with different characteristics and the impact of different compensation mechanisms (Calvino and Virgillito 2017).

When firms in the same sector are similar and innovations are sector-specific the sectoral level has the advantage to reduce the number of observations without losing information, or increasing it by allowing the study of market expansion effects and business stealing (Calvino and Virgillito 2017) and is easier to compute, but if firms in the same sector are very different in some important characteristics related to innovativeness and/or inequality (e. g. size, market power, leader and follower patterns) some information may be lost.

When differences and complementarities are low within macrosectors or within the same region and high between macrosectors and/or regions maybe the best level is the 2.5, especially when indirect effects are different only at this level, data are simpler to find and models are simpler to build, but the classification may be controversial.

The country level is probably the highest level, in this case we can study the overall net effects of innovations on the whole economy, calculation is easy, data are usually more reliable, and the big picture is there, but if it is a sum of smaller different pictures and interactions between them, at this level we cannot capture this complexity.

Peters et al. (2014), in particular, analyse the heterogeneity of the effects of innovations both in the levels of aggregation and during the business cycle. They find that the business cycle affects more the sales of old products than the sales of new products and this may explain the better results in terms of employment growth in innovators than non-innovators, with the difference that even if always positive is higher during recession periods. They also find that small firms grow more than bigger firms and that product innovations have a positive effect on employment growth and reduce the fluctuations over the cycle, in particular reducing employment losses in recessions, process and organizational innovations seem, instead, to not have any particular impact.

Disaggregating by sector employment grows more in all services than in manufacturing (but there is a discrete heterogeneity) and process and organizational innovations continue to have in most cases no effects (except for the negative effects of organizational in upturns). Therefore, most of the heterogeneity between sectors is due to product innovations, with innovators that sell the new products and a lower quantity of the old products and non-innovators that sell a higher quantity of the old products. These effects are particularly large in the sector of telecommunications, that is the most innovative within services, but excluding this sector the heterogeneity between sectors and between different phases of the business cycle is similar within manufacturing (where however employment in the high-tech sectors fluctuates more) and within services.

Regarding the business cycle sensitivity according to this study (Peters et al. 2014) innovations matter more in sectors where the value added is more volatile than the overall GDP, but only in manufacturing. Different size of firms is another source of heterogeneity, with bigger firms that gain more from innovations but not increase employment because of general productivity gains (not explained by innovations), showing in some cases a jobless growth. The effects are different also between country groups, but the differences are caused only by sales of old products of non-innovators, that are more volatile during the business cycle in eastern European countries, less volatile in north-western ones, with southern ones in the middle.

Summing up the different results of different studies (most of them are briefly summarized in Calvino and Virgillito 2017), the majority confirms the positive overall effects of product innovations on employment and productivity growth, whereas the effects of process innovations, especially on employment, are more ambiguous at all levels and varies significantly more between the different studies, being in some studies on Germany (Lachenmaier and Rottmann 2011 and Zimmermann 2009) higher than the effects of product innovations. The results are usually specific to each sector, country or group of countries (for example in Holzl 2009, Harrison et al. 2014) but sometimes firms within sectors or regions are different and in other cases (for example in Autor and Salomons 2017) regrouping macrosectors doesn't seem to change the effects and the differences are higher between countries or regions, so the evidence on which is the best level for the analyses on the effects of different types of innovations on different outcomes are inconclusive. Even if inconclusive, however, it is important to understand that different interactions at different levels may change the results or the interpretation of them.

In most cases the different results are caused by a key variable that has been omitted in this survey until now: elasticity. Innovations, in fact, have different effects on different variables depending on the different elasticities.

One of the few studies that have considered elasticities (in this case elasticity of employment to productivity) is Autor and Salomons (2017). In this study the authors find different results at micro (negative) and macro (positive) levels regarding the effects of innovations on employment and employment rate, this finding may be a proof of the existence and the importance of the indirect effects. Autor and Salomons (2017) also confirm the heterogeneities of the effects of innovations between macrosectors, with the increase in employment in all macrosectors except mining, utilities and construction, between countries and also between decades (positive relationship not found in the 2000s).

In another study Blien and Ludewig (2017) analyse the importance of elasticities (in this case the more "scholastic" elasticities of demand to price and of demand to income) in explaining different levels of unemployment within Germany. They find that the higher are the two elasticities (in absolute value) in the different sectors the higher is the increase in employment, this result is particularly valid for the price elasticity, while the effects of the income elasticity are of the opposite sign in some specifications (they use different statistical methods).

Autor et al. (2019) study other elasticities to analyse the reduction in the labour share of income: the elasticity of labour to the mark-up and output elasticity with respect to labour, with the former negative and the latter positive. They find that only the first elasticity has changed in the last decades, so the reduction in the labour share of income and the growth in inequality is mostly due to increasing mark-ups.

Piketty (2014) explains the same reduction in the labour share of income considering the elasticity of substitution between capital and labour and the capital to income ratio: when the elasticity is higher than one, as according to Piketty (2014) it seems to have been in more developed countries, then the increase in the capital to income ratio leads to higher capital (and lower labour) share of income (however other studies find an elasticity below one (Guschanski and Onaran 2018)).

Some studies have decomposed the relative impact of the different channels on inequality, in particular Firpo, Fortin and Lemieux (2018) find that in the US education has been skill-biased, as it has increased both the 90-50 and the 50-10 wage ratios, occupation shifts and deunionization, instead have increased the 90-50 wage ratio have reduced the 50-10 wage ratio, increasing the polarization of wages. Kristal and Cohen (2016) find that in the US labour market institutions explain half of the variations in wage inequality in the US and computerization explains another quarter (the last quarter is either explained by other factors or not explained). Following the methodology of Firpo, Fortin and Lemieux (2018), Kaltenberg and Foster-McGregor (2020) find that automation has increased inequality in Europe between 2002 and 2014 especially in the upper tail of the distribution (90-50 wage ratio), while other characteristics have had only marginal effects.

Innovations, inequality and geography

The studies analysed in the previous paragraphs show a high heterogeneity in the effects of innovations on inequality and growth, especially between countries, sectors and sectors in different countries, but there are heterogeneities also between different areas within the same countries. In this paragraph we will discuss the studies that consider the geographical heterogeneities, both within and between countries.

Innovations are linked to spatial inequality because they are more spatially concentrated than people and firms (Feldman and Kogler 2010) and change the distribution of them, so to understand the effects of innovations on income and wage inequality we need to answer to the following questions: why are innovations more concentrated than people and firms? How does the former change the spatial distribution of the latter? Do innovations increase or decrease spatial inequality?

Neither every person nor every firm is innovative, only the most creative people and firms are able to innovate. Creativity is needed to innovate but it’s not sufficient to innovate a lot: sharing creative ideas increases creativity and the skills necessary to be more innovative, so the higher is the number of contacts with innovative people and firms, the higher is the innovativeness of a person or a firm.

The places where it is easier to have contacts with a lot of people and firms are the places where they are more concentrated: the cities, this is a classical externality of urbanisation (Jacobs 1969). However, if people and firms share similar ideas the increase in innovativeness is limited, thus, to become very innovative cities have to be more diverse.

Innovations are for these reasons spatially concentrated in the largest and most diverse cities, but this doesn’t mean that innovations per se change the distribution of people and firms, we need other explanations for this phenomenon.

According to Florida (2002 and 2005) to boost growth the cities should attract the creative class (which is composed by innovative people, workers in knowledge-based sectors and other creative people) even more, because more innovative and high skilled people increase growth.

The creative class was already attracted by cities because of the externalities of urbanisation cited above, in fact not only people become more innovative if they share more ideas with more people, but the creative people like to share ideas more than other people do, so they are more willing to live and/or work in the cities, especially in the centre of them. When a city has a high proportion of creative people it is more innovative and attracts other creative people, increasing the concentration of innovations, innovative people and innovative firms.

In the last decades technology has done big steps forward and now codified knowledge is easy to acquire, so it may seem that close contact is not as important as in the past, but what makes the creative class so innovative is not codified knowledge but the tacit one, and to share and increase tacit knowledge face-to-face contacts are essential (Storper and Venables 2004, Rodriguez-Pose and Crescenzi 2008), so tacit knowledge is becoming more important than the codified one.

To share and increase tacit knowledge, however, it is not necessary that the place is diverse, in fact this kind of knowledge is easier to share in more specialized places, in which there are not only externalities of urbanization, but also externalities of specialization (Marshall 1890), this explains why the San Francisco area is more innovative than the Los Angeles or New York areas that have a larger population and have at least the same diversity. The existence and the interaction of these externalities is confirmed by Echeverri-Carroll and Ayala (2009) who find that working in both high-tech industries and high-tech cities increase wages and the interaction term between the two is strongly positive and by Kogler, Rigby and Tucker (2013) who also show that the specialization of cities is positively correlated with patenting per capita. Externalities of urbanization and specialization lead to different kinds of innovations in different places: conventional innovations in the same field are realized in more specialized suburban areas whereas unconventional innovations linking very different fields are realized in more diversified and densely populated urban areas, and thus, as conventional innovations are more than unconventional ones, suburban areas appear to be more innovative than urban ones (Berkes and Gaetani 2019). People become more innovative when they move close to other innovative people, and for this reason there would be a large reduction in patenting (and thus innovativeness) in the US if innovative people were not clustered (Moretti 2019).

The creative class people are more skilled and innovative than the other people, they are also more mobile and richer, and they value more the amenities of the city, so they are more prone to move to the city centre even if its costs (especially housing) are higher, increasing inequality even more (Diamond 2016). This phenomenon is accelerated by the increase in working hours of skilled people, who have less leisure time and to reduce wasted commuting time they are disposed to pay more to live near their workplaces, that are usually in the city centre (Edlund, Machado and Sviatschi 2015)

As people with low and middle income are usually less mobile, they move in the suburbs or in other parts of the cities and this increases polarization within the cities and income segregation. The latter in particular is driven by inequality both directly (poor people cannot pay the same of rich people) and indirectly (best neighbourhoods increase their value more than the worst) (Watson 2006). As high skilled high income who move to the city centres are in most cases white there is not only income segregation, but also racial segregation (even if in some cases it would be a reversal to the mean as the percentage of white was higher in the suburbs) (Baum-Snow and Hartley 2016).

Innovations (as seen in the other paragraphs) are substitutes for medium skilled people that perform routine tasks and complement for high skilled people that perform non-routine non-manual tasks and have a not clear link with low skilled people that perform non-routine manual task. High income high skilled people belonging to the creative class have a higher demand of home services (Mazzolari and Ragusa 2007) and personal services (Kaplanis 2010), that are produced and consumed locally (they are non-tradable) and performed as non-routine manual tasks. This increase in demand, and the relocation of workers who have lost their job and found a new one in this sector (Autor and Dorn 2008), explain why in the same city not only high skilled (and income) people, but also low skilled (and income) ones increase their share of employment and their wages and incomes. As there is a reduction in medium skilled (and income) people share of employment within cities with lower or at most stable wages and incomes, cities are and become more polarized and unequal as the share of creative class increases.

Even when accounting for the creative class, however, other factors such as deunionization, low minimum wages and high shares of immigrants increase inequality, in some cases even more than the share of creative class people (Donegan and Lowe 2008).

The increasing skill bias of agglomeration economies and the higher complementarity between high skilled workers and capital not only have increased inequality more in the largest cities (Baum-Snow, Freedman and Pavan 2014), but have also reduced the convergence of high skilled people wages between U.S. cities from 1980 (Giannone 2017).

According to Kemeny and Storper (2020) the shift from convergence to divergence in different measures (income, percentage of college graduates, return to college graduation, housing costs, income inequality) may be due to the beginning of the third industrial revolution in the 1980s and is not an isolated phenomenon, as it occurred also at the beginning of the second industrial revolution, while the opposite occurred during the 1940-1980 period, in which the technologies were more mature.

Berkes and Gaetani (2018) confirm most of the effects of innovations on income segregation: innovations in high-tech sectors increase income segregation both because of the effects on inequality (innovations increase inequality, that in turn increases income segregation) and because of sorting (innovative people choose to cluster to reduce commuting costs and enjoy new endogenous residential amenities). According to Florida and Mellander (2017) however even if innovations are among the factors that are positively correlated with income, education and occupational segregation and may increase them, the effects on the changes in segregation are insignificant and, in most cases, negative.

To sum up, innovations are more unevenly distributed than people and also innovative people are more concentrated both in the most diverse and in the most specialized cities and as they demand more home services, workers that perform them and that are usually low-income people tend also to concentrate in these cities, that are, thus, more segregated, polarized and unequal, also because other people are expelled by the increasing housing costs.

Innovations increase also other types of spatial inequalities, for example inequality between different regions or different states, this is directly linked with the spatial concentration of innovative firms and people and the income growth generated by innovations: the more innovative regions are usually richer and have a higher per capita income growth (Hale and Galbraith 2004).

Florida and Mellander (2014) find that innovations and creative class are more correlated with wage inequality than with income inequality (that is more linked to race and poverty), this is probably because income inequality is measured on the entire distribution while wage inequality cuts the lower part, and innovations and creative class compose only the upper tail of the distribution (they are few rich people).

As suggested by the evolutionary theory some studies find that there is a strong path-dependency, for example Glaeser, Resseger and Tobio (2009) find that inequality in 2000 was strongly positive correlated with the college graduation rate in 1940 and to some extent also to college enrolment in 1850 and that the increase in inequality in 2006 was strongly correlated with the college graduation rate in 1980, and college graduation rates themselves are strongly correlated and divergent between different areas in the US.

This evidence is based mainly on studies regarding the USA, but other studies find similar results also in Europe, although with some differences, for example Wessel (2005) finds that even in Norway Oslo is more unequal than the rest of the country because of increasing top income inequality. The first studies that measured the impact of innovations on wage inequality outside the US, however, were Lee (2011) for Europe, Lee and Rodriguez-Pose (2013) for a confrontation between Europe and the USA, Bolton, Breau and Kogler (2014) for Canada. All of these studies find that innovations, and in particular ICT patents, increase wage inequality, but there are some differences between the effects of other institutions, in particular unionization reduces inequality only in Europe and there is less inequality in more densely populated cities in Europe (in the US and in Canada the opposite is true). Permana, Lantu and Suharto (2018) find that in the EU innovations and technological specialization increase both income and top income inequalities with higher effects 3 years after the priority year of the patents.

In contrast to these studies, Antonelli and Gehringer (2017) in a study on 39 countries find that innovations reduce income inequality because of creative destruction: entrants are more innovative than incumbents and for this reason innovations reduce the barriers to entry in the market and, thus, also the rents of the incumbents. These findings are confirmed also by several other studies. Benos and Tsiachtsiras in their study on 29 countries, both European and non-European, find that innovations (measured in different ways) decrease inequality (measured in different ways) and that the effects of government size (negative) and unemployment (positive) are higher than the effects of finance. Biurrun (2020) in his study on 20 European countries finds that innovations (measured as R&D expenditure) and social protection reduce income inequality both between and within countries. The effects may be very different depending on the measure of innovation used, for example Wlodarczyk (2017) finds a positive effect of R&D on inequality, but a negative effect of patents and of their creativity index (even if in all cases mostly insignificant). In addition, Aghion et al. (2018), while confirming the importance of the rents of the incumbents in their study on 50 United States plus DC, find that innovations are positively correlated with the top 1% income inequality (but not other measures of inequality).

Outside the US few studies have analysed the effects of innovations on inequality in regions within a single country. Liu and Lawell (2015) find that innovations decrease inequality in China but only up to a turning point (that however is high), this is probably because innovativeness is positively correlated with the proportion of highly educated workers only when the former is not high. Capparucci and Veraschagina (2017) in a structural model find that innovations and inequality reduce one each other in Italy. In contrast, Andreassen (2018) finds that innovations increase inequality especially between regions.

As shown by these different findings and confirmed by De Palo, Karagiannis and Raab (2018) the effects of innovations on inequality depend on the different measures of inequality, on the different models and on the different geographical units examined.

Conclusions

In this paper we have examined the different studies that link innovations to inequality, especially in the labour market, and other socioeconomic characteristics. Most studies on the effects of innovations are very recent, and even if they had been linked to socioeconomic changes, only in the last decades the link between innovations and inequality has become a main topic because of the astonishing growth in both.

After introducing the differences between product and process innovations, we have explained the various theories that justify the effects of innovations in different ways, from the more linear skill-biased e routine-biased technological change theories in which skills and tasks are more important to the more dynamic evolutionary theory in which heterogeneities have a key role. We have also explained why the new innovations may be different from the older ones (and therefore worth to be studied), and that when studying the effects of innovations on different variables, especially inequality, the role of elasticities and levels of study may be crucial. In the last section we have focused on the effects of innovations on inequality from a geographic point of view, as beside the effects on personal and functional inequality innovations may have a big impact on spatial inequality.

The studies mostly confirm that innovations have effects on inequality, however the sign of the effects is very different depending on the different study and the different measures of innovation and inequality, so the question on whether innovations increase or decrease inequality has not been answered definitively.

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Innovations and income inequality in the European regions

Abstract

Innovations and income inequality have been increasing over time. Is there a link between the increasing trend of these variables? In this paper we will focus on these trends investigating whether patterns of innovations affect income inequality. To this aim we use two new databases (TechEvo and ARDECO) for data on, respectively, patents and other socioeconomic variables, from several European countries for the period 2003-2015 and carry out estimates on the associations of innovativeness with income inequality (quintile ratios). We find that innovations and population density, differently from other studies, are not correlated with income inequality in the European regions.

Keywords: innovation, inequality, European regions, heterogeneity, urbanization

JEL classification: D63, J24, O30, O33, O34, R12

Introduction

There has been a huge and exponential increase in innovations in the last decades (Brynjolfsson and McAfee 2014). At the same time various structural changes have happened in the labour market, such as the polarization of workers (Usanov and Chivot 2013) and the substitution of routine tasks by machines (DESA 2017). We are also in a phase of lower economic growth than in the past and at the same time we are experiencing an increase in wage and income inequality, especially in anglo-saxon countries (Piketty 2014). Lastly, the spatial distribution of innovations, growth and inequality is not even, instead, they are concentrated in only a few cities and regions (Feldman and Kogler 2010).

These structural changes may be linked one to each other: some kinds of innovations may lead to high income inequality if, as theorized by the skill-biased technological change theory (SBTC), skills are positively correlated with income and innovations favour more high skilled workers. In this case they also favour high income people more than low and medium income (Acemoglu 2002, Aghion et al. 2018). According to the routine-biased technological change theory (RBTC), innovations may also increase income inequality by increasing polarization, as routine jobs that are easier to be substituted by machines are usually performed by medium skilled medium income workers (Autor, Levy and Murnane 2003). As most innovations are believed to favour cities more than rural areas, and as cities are usually richer, inequality between regions may increase just for this reason (Hale and Galbraith 2004). As innovations take place in cities, then the effects of innovations on income inequality should be greater within cities than within rural areas, so if innovations increase income inequality as theorized, the former should be more unequal than the latter, as found by Baum-Snow, Freedman and Pavan (2014).

Innovations are also linked to growth, as technological progress boosts it, however innovations are a cause of creative destruction (Schumpeter 1942, Nelson and Winter 1982), in which someone wins and someone loses, and according to the evolutionary theory the effects may be very different depending on incomes, skills, sectors and regions. The relationship between innovations and inequality is even more complex to study, as there are indirect effects that may act in the opposite direction of the direct ones and be so large to counterbalance them (Calvino and Virgillito 2017).

In this paper we will discuss the associations of innovations (measured as patents per capita and their logarithm) with income inequality (measured as quintile ratios) on a panel of 88 European regions from 18 countries (in some cases only one region of a country or only the country itself) from 2003 to 2015. We control for endogeneity by lagging all independent variables for one year, except for innovativeness, that as should have effects for more than one year is lagged for 1 to 3 years and by adding several socioeconomic and education variables. Because of the high persistence and possible endogeneities of most variables, we use the Arellano-Bover/Blundell-Bond GMM system estimator.

The international comparison is important because in different countries or even regions, depending on institutions, there are different dynamics of innovativeness, inequality and other socioeconomic characteristics. These different dynamics may also lead to opposite results, supporting different theories.

Studies, like ours, focused on regions in different parts of a continent (or even better, if possible, in different parts of the world) are useful because they analyse the relationship between innovations and inequality using the correct area in which innovations have more effects (the region), and at the same time the results found are not specific of particular regions or countries.

A lot of research has been carried out on the relationship between innovation and inequality in the US, but there are only few studies on Europe and most of them have focused on European countries, rather than regions. The regional level on analysis is, indeed, one novelty of this paper, and to study this relationship we will use, in addition to EUROSTAT data, two new databases that (to our knowledge) have never been used to study specifically this relationship: the TechEvo one for innovation variables and the ARDECO one for socioeconomic variables (the two databases have been jointly used only for papers on regional economic resilience like Toth et al. (2020)).

The TechEvo database is a slightly modified version of the PATSTAT database on innovation and it is divided into various datasets which contain data on patents, inventors and companies from 1980 to 2016 from all the world.

The ARDECO database (formerly known as ERD database) contains socioeconomic variables and is divided into two big groups of datasets depending on the lowest level contained (NUTS2 or NUTS3). The first group contains data on active population, compensation of employees, gross fixed capital formation and hours worked, the second group, instead, contains data on employment, GDP, GVA and population. All data from this database are from 1980 to 2015 and cover the 27 EU Countries, UK and Norway.

The advantages of these two databases are the long time period covered and the geographical detail, as all data are at the NUTS2 level (regional) or even the NUTS3 level (provincial). These advantages are partly reduced by the shorter time period and the different levels for which other variables are available, but we are still able to study the associations between innovations and income inequality for more than 10 years for almost 100 regions belonging to 20 different countries.

Our paper contributes to the debate on the effects of innovations on inequality in several ways. Firstly, as innovations has mainly local effects, we study regions rather than countries, secondly, even if the resulted panel is unbalanced, we cover a longer period than most other studies, thirdly, we study the associations of innovations in different sectors with income inequality. For all these reasons, this study may help to clarify the relationship between innovations and income inequality.

In line with the evolutionary theory, we expect that the associations of innovations with inequality vary depending on the country, with more similar associations in closer and more similar countries, but with a high heterogeneity not only between countries but also between different regions within countries. This heterogeneity is due to different rules and routines adopted by firms and institutions that are different in each country and even in each region and may change innovativeness and its effects on inequality.

Following other geographical theories, we also expect population density to be a key factor in explaining income inequality, with higher inequality in more densely populated areas. As population density should be positively correlated with innovativeness, if we do not consider it, we could find a spurious positive correlation between innovativeness and income inequality even when the true association between these two variables is negative.

We reject most of these expectations by showing that innovations, population density and education are not correlated with income inequality, but we cannot exclude heterogeneities between countries and/or regions.

The rest of the paper is organized as follows: in the second section we will illustrate the theories on innovations and inequality with a particular focus on the geographical studies on Europe, in the third section we will describe the data and descriptive statistics, in the fourth section we will explain the model, in the fifth section we will present the results, with also the robustness checks, the sixth and last section concludes and presents some policy implications.

Related literature

There are different theories that link innovations and inequality. For the skill-biased technological change one (henceforth SBTC) the increase in inequality is a consequence of technological change that is complementary to skill: as the quantity of innovation increases wages and employment increase, but only for the high skilled innovative workers, with no or limited gains for medium and some loss for low skilled workers (Acemoglu 2002). In addition, even if there has been an increase in supply of skills, the observed increase in inequality has been caused by shifts in demand within occupations (Katz and Murphy 1992), at least partly explained by the increase in computerization (Autor, Katz and Krueger 1998). According to Acemoglu (1998) the SBTC is a direct consequence of the increase in this supply of skills, so even if the short-term relative demand for skills is downward sloping the long-term one may be upward sloping if the technological change is a skill-biased one.

Looking at the data the SBTC theory seems valid for the last decades of the 20^{th} century but not for the first decades of the 21^{st}, in which something different has happened: wages have increased more for low than for medium skilled workers and even low skilled employment have increased more than the high skilled one (Autor 2015 and 2019). For this reason, starting with the Autor, Levy and Murnane (2003) article, the SBTC theory has evolved into the routine-biased technological change theory (RBTC): tasks are divided into 4 different groups: routine manual, routine non-manual, non-routine manual and non-routine non-manual (the last sometimes divided into cognitive and interactive), depending on whether they have programmed rules (routine) or not (non-routine) and whether they are manual or not. Based on this categorization medium skilled workers lose more than low skilled ones because routine tasks in which they are mostly employed are easier to be substituted by machines than the non-routine manual tasks performed mostly by low skilled workers. Moreover, the increase in employment in low skilled jobs at the expense of medium skilled ones not only has increased inequality, but also polarization, and a higher initial share of routine workers is associated to a higher polarization of wages and employment by skills, as unemployed routine workers find job in low service occupations (Autor and Dorn 2013 for the US but similar results are found by Goos, Manning and Salomons 2014 for Europe, Goos and Manning 2007 for the UK and Spitz-Oener 2006 for Germany). With the introduction of the differences between the various kinds of tasks, the RBTC theory may explain the u-shape distribution of the increases in wages and employment and the polarization of wages and jobs, but this is not the only theory that may explain these structural changes.

An alternative theory that may explain the effects of innovations on various socioeconomic variables is the evolutionary theory (Nelson and Winter 1974 and 1982, Dosi 1988). According to this theory, innovation is a process of creative destruction in which the most innovative firms win, and the others lose, while workers fight for gaining a higher share of the profits derived from innovation. Innovations are based on rules and routines, specific to each sector and each firm, that change over time and influence the evolution of the other firms and sectors. Other important factors that have effects on innovativeness and drive the evolution of rules and routines are the institutional environment, the selection of firms in the process of innovation, imitation and learning by doing, and the bargaining process between entrepreneurs and workers. All these things are heterogeneous between firms and impact in different ways also on inequality and growth, both within and between firms and sectors. In addition to these characteristics, the nature of innovations (product vs process) and the indirect effects (interactions between innovations and compensation mechanisms) have an important role on determining the effects of innovations on wages, employment and inequality (not only wage or income inequality but also functional inequality).

To sum up, for the evolutionary theory heterogeneities, institutions, interactions and compensation mechanisms have key roles in explaining the effects of the different kinds of innovations on different outcome variables.

Most studies (Pianta and Tancioni 2008, Bogliacino, Guarascio and Cirillo 2017, Coveri and Pianta 2019) that follow this theory have analysed the effects of innovations on profits and wages, rather than inequality, finding that product innovations increase both wages and profits and that there is a distributional conflict between them. These studies find that workers are heterogeneous and that the effects of innovations and the distributional conflict tend to favour high skilled workers more than low skilled ones. Moreover, process innovations have less effects than product innovations not only on profits and wages, but also on employment (Peters et al. 2014, Harrison et al. 2014).

More recent studies have begun to study the relationship between innovations and income inequality, finding that innovations reduce income inequality, both within and between countries, especially when income inequality is high, but at the same time there are also other variables that reduce income inequality, such as government spending and social protection expenditures (Antonelli and Gehringer 2017, Biurrun 2020).

These three theories (SBTC, RBTC, evolutionary) may explain complementary parts of inequality: Firpo, Fortin and Lemieux (2018) separating the different sources of wage inequality find that education, occupation shifts and deunionization have all increased the 90-10 and the 90-50 wage ratios but only education has increased the 50-10 wage ratio, on the contrary, occupation shifts and deunionization have reduced the 50-10 wage ratio, increasing the polarization of wages. Kristal and Cohen (2016) confirm the importance of both labour market institutions and computerization, as the formers (and among them especially unionization) explain half of the variations in wage inequality in the US and the latter explains another quarter (the last quarter is either explained by other factors or not explained). Kaltenberg and Foster-McGregor (2020) find that most of the increase in inequality in Europe between 2002 and 2014 can be explained by automation especially in the upper tail of the distribution (90-50 wage ratio), while other characteristics have had only marginal effects.

The relationship between innovation and inequality is even more complex as, in addition to direct effects that are usually more negative for workers, there are also indirect effects that are usually more positive and may counterbalance the direct ones (Gregory et al. 2016, Autor and Salomons 2017). These indirect effects can be divided in interactions and compensation mechanisms: there are interactions when an innovation is a process innovation in one sector or firm and a product innovation in another sector or firm, and just for this reason the same innovation may have different effects in different firms or sectors. The most important indirect effects are the compensation mechanisms: decrease in prices (new technologies decrease production costs and this decreases prices), decrease in wages (technological unemployment decreases wages and increases labour demand and employment), new machines (workers change jobs from the sectors that introduce innovations to the sectors that produce them), new investments (extra profits caused by innovations are invested), increase in incomes (profits are shared between firms and workers increasing aggregate demand) and new products (if they are not a replacement there is an increase in variety and consumption) (Vivarelli 2014, Piva and Vivarelli 2017, Calvino and Virgillito 2017). Even if none of these compensation mechanisms is sufficient by itself to change the sign of the relationship between innovations and inequality, their combination may do it, although not instantaneously, as indirect effects, and especially compensation mechanisms, take some time before showing all their impact.

Innovation may affect also spatial inequality because it changes the spatial distribution of workers and people. Innovative people tend to be concentrated in the more diverse and densely populated cities and in the more specialized areas (Berkes and Gaetani 2018), in particular they (as also other creative, educated and rich people belonging to the so-called creative class) prefer to live in the city centres because there are more amenities (Diamond 2016) and more possible contacts and as the share of creative people increases and as the importance of tacit knowledge is higher than the one of codified knowledge (Storper and Venables 2004) other creative and innovative people move to the city centres from outside, increasing the concentration of innovative people and innovations. This process of concentration is increasing over time and as more innovative and skilled people increase growth, this growth tends to be always more concentrated in only a few places, with all the others lagging. In addition, innovative people consume more home (Mazzolari and Ragusa 2007) and personal services (Kaplanis 2010) provided by low skilled low income people, so not only high income high skilled people but also low income low skilled people work and live in the city centres and innovation increases polarization within the cities, potentially increasing income inequality and income segregation.

For all these reasons, and in particular because of the geographical concentration of innovations and their effects, it is important to study the relationship between innovations and income inequality in Europe at the regional level.

Most research has been conducted on the US but, in addition to the papers cited above, only a few papers have studied the effects of innovations on inequality in Europe, and the effects are very different depending on which measures of innovation and inequality are used and the time periods and the geographical levels considered.

According to the first two studies in chronological order (Lee 2011, Lee and Rodriguez-Pose 2013), innovations (patents per capita) increased wage inequality (GINI of wages and for the second also Theil index) especially in ICT between 1995 and 2001 at the regional level. Wlodarczyk (2017) find mixed effects with R&D increasing income inequality (GINI, top 3% and top 1%) and patents and the creativity economic index having little decreasing effects between 2005 and 2014 at the country level. De Palo et al. (2018) find that the effects of innovations (patents per capita and patents per active population) on income inequality (GINI, top 1%, top 10%, 90/10 and 90/50 ratios) between 2002 and 2014 at the regional level were either not statistically significant (in the fixed effects model) or statistically significant but with contrasting results strongly dependent on the regressions (in the GMM model). Permana et al. (2018) find that innovations (patents per capita) increased income inequality (GINI and top 10%) between 2003 and 2014 at the country level. Benos and Tsiachtsiras (2019), in the end, find that innovations (patents, also weighted by citations, claims, generality and family) decreased inequality (top 1% in most specifications, but also top 10% and GINI) between 1978 and 2005 at the country level.

As most of these studies have used the country level of analysis, as most innovations are introduced locally and have only a local impact, and as the associations between innovations and inequality may be different using different geographical levels, we contribute to the literature on innovations and inequality by studying the relationship between innovations and inequality at the regional level and for a longer period than most of the previous studies, and by distinguishing between the different sectors in which innovations are made.

We find that innovations, population density and education have no significant associations with income inequality, that is associated only to some other social variables.

Data and descriptive statistics

For the analysis on innovation, we use 3 datasets from the TechEvo database, the number of observations is over 3 million applications of patents from all the world, with both priority and filing year between 1980 and 2016 and with mean granted (by the European Patent Office) 0.55 and mean triadic (granted by other authorities in other countries) 0.32. The share of an inventor in a patent is 0.42, so more than 2 people contribute to each application, the share of a company in a patent instead is 0.95, it means that almost all patents have been requested by inventors in the same company.

We use patents per capita (lagged from 1 to 3 years) as the measure of innovation, in contrast to R&D and citations of patents (the two alternative variables used in literature for innovativeness) for two reasons, one practical and the other theoretical: the practical reason is that the TechEvo database is built on patent applications and does not contain data on citations of patents and on R&D expenditures, the theoretical reason is that as patents are an output of innovation efforts and not an input like R&D, they are the outcome of successful innovations, in addition citations are usually used only to specify the limits of intellectual property and depend more on the age of the patent than on its quality, so they don’t add useful information.

Even if patents are widely considered and used as a good measure of innovativeness, they have their own limits: the most important ones are that not all patented innovations are commercialized, not all patents have the same importance and patents measure almost exclusively product innovations. We partially solve this problem by using the gross fixed capital formation from the ARDECO database, as this variable, already used as a control by Biurrun (2020), measures the increase in fixed assets and may be considered a measure of the embodied technological change. Some studies (among them Bogliacino, Guarascio and Cirillo 2017 and Coveri and Pianta 2019) have used the expenditure in machinery and equipment from the Community Innovation Survey to measure process innovations, but in both cases the geographical level of analysis is the country one, and not the regional one like in our paper (the regional level captures better the local effects of innovations), and as the Community Innovation Survey is actually composed by several surveys (one wave every two years) with questions and observations changing in each survey, data from different surveys may not be comparable.

For the socioeconomic variables we use all the 8 datasets from the ARDECO database, 4 are at a NUTS2 level (active population, compensation of employees, gross fixed capital formation and hours worked) and 4 at a NUTS3 level (employment, GDP, GVA and population), from 1980 to 2015 for 29 European countries (all datasets at NUTS3 level also have data at NUTS2 level). The NUTS3 (NUTS2) dataset is composed by 60984 (13392) observations with mean GDP/population 21000, mean GVA/employed 42000 and an employment rate of 43%.

After merging by NUTS2 and year the innovation and the socioeconomic datasets the observations are still more than 3 million, mostly from Germany. To transform the dataset into a panel we have taken the means by region and either priority or filing year (with priority year meaning the first year in which the patent has been filed at any institution and filing year meaning the year in which the patent has been filed at the European Patent Office).

As the income inequality variable (quintile ratios of disposable income from EUROSTAT) has regional data only for a few countries at the NUTS2 level, the analysis can be conducted only for this level and for these countries (see table 2 in the appendix for a detailed summary)

For a robustness check we will use some data on education and employment (education level of 25-64 and 30-34 years old, percentage of early leavers, percentage of neet, employment of young people by level of education, employment rate by age, education, type of contract, hours worked by age, employment by tenure) from 2000 to 2019 provided by EUROSTAT for the 27 EU countries, UK, the 4 EFTA countries, Macedonia, Montenegro Serbia and Turkey, but we can use only the data from 2000 to 2015 (as it is the last year of the ARDECO database) and only for the countries covered by the other datasets. We will also use the percentage of people employed in high tech sector and/or high skilled and the percentage of scientists and engineers to measure employment of (potentially) innovative people.

The final dataset, obtained from the merge of all datasets, is composed by only 3745 (3757) observations when the year considered is the priority (filing) one and contains data from the countries for which inequality data are available.

The summary of all variables with the original time periods and sources is shown in table 1 (in the appendix), for our analysis we use only the 2003-2015 period that is common to all time-varying variables (2000-2015 for innovativeness using the lags). All descriptive statistics for the period 2000-2015 can be found in table 3.

Table 3: descriptive statistics				
Variables	Mean	S. deviation	Maximum	Minimum
80/20 ratio EUROSTAT	4.606	1.314	11.6	2.7
Innovativeness	0.102	0.127	1.034	0.000
Innovativeness company	0.089	0.117	1.015	0
Innovativeness government	0.002	0.005	0.074	0
Innovativeness hospital	0.000	0.000	0.009	0
Innovativeness university	0.003	0.006	0.104	0
Innovativeness other (unknown)	0.008	0.009	0.114	0
Gross fixed capital formation	8.987	10.577	124.611	0.131
Mean granted	0.428	0.204	1	0
Mean triadic	0.173	0.158	1	0
Mean gratri	0.111	0.118	1	0
Mean filing-priority years	0.750	0.203	1.071	0
GDP/population	25.023	15.243	191.074	1.667
Employment/population	0.457	0.072	0.761	0.282
Yearly wages	24.600	13.825	170.680	1.450
Population density	0.447	1.128	10.621	0.003
Education 25-64 low female	29.707	14.980	86	2.8
Education 25-64 low male	26.315	16.673	89.7	1.8
Education 25-64 medium female	45.494	14.984	78.4	7.6
Education 25-64 medium male	49.514	16.146	83	7.7
Education 25-64 high female	24.856	10.492	70.7	5.7
Education 25-64 high male	24.216	9.505	71.8	4.2
Education 30-34 low female	21.370	12.019	81.1	1.3
Education 30-34 low male	23.532	14.406	88.2	1.9
Education 30-34 medium female	48.192	14.942	88.5	10.7
Education 30-34 medium male	51.590	15.586	89.1	8.3
Education 30-34 high female	32.803	13.530	82.2	4.7
Education 30-34 high male	27.470	11.192	86.9	5.1
Early leavers female	13.244	6.649	51	1.4
Early leavers male	16.924	9.426	66.3	1.4
Neet female 15-24	12.936	6.153	47.2	2.2
Neet male 15-24	11.267	5.735	38.2	1.1
Employment low skilled F 15-34	47.492	14.188	88	9.5
Employment low skilled M 15-34	68.073	14.459	97.7	8.5

Employment medium skilled F 15-34	70.973	11.864	95.9	22.3
Employment medium skilled M 15-34	85.097	8.627	100	41.2
Employment high skilled F 15-34	81.867	9.945	100	34.5
Employment high skilled M 15-34	90.410	8.199	100	45.7
Scientists and engineers	3.389	1.638	10.6	0.8
High skilled	19.930	8.027	61.7	4.1
High tech	17.748	5.856	38.4	4.7
Both high tech and skilled	10.417	4.249	32.9	2.7
Employment rate female 15-24	36.265	15.810	76.2	4.7
Employment rate female 25-34	69.293	10.315	90.6	21.1
Employment rate female 35-44	73.686	9.881	91.2	25.2
Employment rate female 45-54	70.273	12.283	92.5	23.3
Employment rate female 55-64	38.479	14.818	77.4	4.9
Employment rate male 15-24	40.908	14.028	78.6	9.6
Employment rate male 25-34	83.696	7.628	97.6	44.1
Employment rate male 35-44	88.319	5.645	98.6	63.4
Employment rate male 45-54	84.256	6.747	98.5	53.3
Employment rate male 55-64	56.072	11.911	82	22.3
Weekly hours worked female 15-24	32.247	6.120	47.3	13.3
Weekly hours worked male 15-24	36.276	4.975	49	17.7
Weekly hours worked female 25-64	33.987	4.205	44.5	22.6
Weekly hours worked male 25-64	41.652	1.938	50	36.6
Employment rate full time female	0.130	0.035	0.258	0.033
Employment rate full time male	0.222	0.024	0.305	0.146
Employment rate part time female	0.067	0.043	0.189	0.002
Employment rate part time male	0.022	0.015	0.089	0.001

Empirical framework

According to the aforementioned literature innovation should increase income inequality, not only because of a skill bias (as more educated and skilled are usually richer) or because of a routine bias (as technology favours high skilled and income people who work in non-routine non-manual jobs over medium skilled and income people who work in routine jobs), but also because of the increase in urbanization and polarization within the most innovative cities. However, innovations may have different impacts depending on institutions, and there should be other indirect effects that may compensate the inequality growth.

We can distinguish which of the different theories are more plausible by looking at the results and confronting them with the theoretical expectations. According to SBTC innovativeness should be positively and monotonically correlated with inequality as the most innovative people are also the most skilled. According to RBTC innovativeness should tend to be positively correlated with inequality, but with results depending on the measure of inequality adopted. According to the evolutionary theory there should be a lot of heterogeneity between countries, with institutions and redistribution having a high potential impact on the relationship between innovativeness and inequality. According to the geographical theories, innovativeness is positively correlated with inequality because of externalities of urbanization, as innovations and innovative people tend to be concentrated in the largest cities.

As according to us the regional level is very important, and maybe more important than the country level, all estimates on the associations of innovativeness with income inequality are carried out using NUTS2 regions.

We expect that innovativeness is more significant using the second and the third lag of it, as innovations need time to spread and have an impact on other socioeconomic variables like inequality. Even if most studies have used at most 1 year of lag, at least one study (Permana et al. 2018) found that the effects are higher 3 years after the filing of the application. As we expect different associations in each of the different years after the innovations take place, we use all the lags from 1 to 3 years with the first lag that should capture mostly direct effects, that according to theory should be positively correlated with inequality, and the third one mostly indirect effects, that instead should be negatively correlated with it. The choice of the number of lags may be considered a compromise between the precision and definition of the kind of effects (direct or indirect) that increase when higher lags are added, and the number of observations that instead decrease. In addition, we expect population density positively correlated with inequality and the education variables that have different results, with especially neet and early leavers positively correlated with inequality.

In our empirical analysis (modeled in the formulas below) we first study the relationship between innovativeness and income inequality using the absolute values of all variables, then we study the same relationship using the logarithms for the independent variables GDP per capita and innovativeness. All regressions are carried out using the Arellano-Bover/Blundell-Bond GMM system estimator.

1a) $ineq_{tr} = \beta_0 + \alpha_1 ineq_{t-1r} + \alpha_2 inn_{t-1sr} + \alpha_3 inn_{t-2sr} + \alpha_4 inn_{t-3sr} + \alpha_5 \frac{pop}{area}_{t-1r} + \alpha_6 W_{t-1r} + \varepsilon$

1b) $ineq_{tr} = \beta_0 + \alpha_1 ineq_{t-1r} + \alpha_2 \log(1 + inn_{t-1sr}) + \alpha_3 \log(1 + inn_{t-2sr}) + \alpha_4 \log(1 + inn_{t-3sr}) + \alpha_5 \frac{pop}{area}_{t-1r} + \alpha_6 W_{t-1r} + \varepsilon$

In these formulas β_0 is the intercept, ineq is inequality measured by quintile ratios, inn is innovativeness measured as the number of patents per capita for the previous 3 years, W is a heterogeneous group of control variables: gdp per capita, employment rate, yearly wages, gross fixed capital formation, mean of patents granted by EPO, by other institutions and their product, mean of time between the priority and the filing year, with these last four variables included because the percentage of granted patents may be correlated with both innovativeness and inequality and to analyse which year is more important between the priority and filing one, ε is the error term, the subscript $t-1r$ means that all variables are calculated for each previous year (time t) and region (r), and the addition of the subscript s means that innovativeness is measured also for the sector in which innovations are introduced. As the time periods are different for each variable we consider only the 2003-2015 period, but as we use also three lags for innovativeness and as we have data for a longer time for it, we use data for innovativeness from 2000 to 2015.

As education may have a role in explaining part of inequality, some robustness checks are performed using some education variables (education of people 25-64 years old, education of people 30-34 years old, early leavers, neets and employment by level of education of people 15-34 years old). Other robustness checks are also performed using some employment variables: employment of 15-34 by level of education, the percentage of high tech and/or skilled and of scientists and engineers, employment rate by age and sex, weekly hours worked by age and sex and full time or part time employment rate.

Results

The results of the models are presented in tables 4a, 4b, 5a and 5b (in all these tables presented the years used are the priority ones, but results are similar when using filing years, see table 6a, 6b, 7a and 7b in the appendix). In tables 4a, 4b, 6a and 6b the innovativeness variables and GDP per capita are in absolute values, in tables 5a, 5b, 7a and 7b they are in logarithms.

All regressions show that, when divided by sector, innovations are in almost all cases not correlated with income inequality. The only exception in which innovativeness is constantly correlated to the quintile ratios is the first year of lag of innovativeness made by hospitals, and even in this case there are some caveats: the first one is that this kind of innovation includes only a very small amount of innovations made, the second one is that the relationship depends on the year considered (it is positive and statistically significant when priority years are used, but negative when filing years are used), the third one is that, in almost all regressions, the relationship after 2 or 3 years is of the opposite sign of the relationship in the first year.

Even if innovativeness is not correlated with income inequality, based on the results of our regressions, other variables are: gross fixed capital formation, that can be considered a measure of process innovations, is positively correlated with the quintile ratios, whereas yearly wages are negatively correlated with them. Both these results indirectly show that the functional distribution of income has an impact on income inequality: where gross fixed capital formation, and thus process innovations, is high, firms invest more to increase profits, and, without an increase in wages, the capital share of income; where yearly wages are high, workers have more bargaining power, and the labour share of income is higher. Since gross fixed capital formation is positively correlated with inequality and yearly wages are negatively correlated with it, we can conclude that an increase in the labour share of income tends to decrease inequality.

All other variables, including even population density, seem to be not correlated with income inequality, except for the employment rate, that is positively correlated in the regressions in which the employment of young people by level of education variables are used. Among the other control variables not shown in the tables, the most significant are the employment of young middle skilled people and low skilled male (negatively correlated), early leavers (with opposite results depending on sex), neets (positively correlated), the percentage of scientists and engineers (the narrowest group of high techs, positively correlated) and the percentage of full-time female employed (negatively correlated). Based on these results, we can state that more polarization of workers (represented by less middle skilled workers and more scientists and engineers), more vulnerability of young people (represented by more early leavers and more neets) and less gender equality in the workplaces (represented by less full-time female workers) tend to increase income inequality.

The low significance of most variables may be due to the high number of clusters relative to the number of observations for which all variables are defined, but in almost all specifications the signs and magnitudes of all variables are confirmed, so we can consider these results reliable, at least for this subset of European regions and for the period considered in this study. Other reasons for the low significance of most variables may be that institutions are very different depending on the country and have a large impact on the correlations between variables within different regions.

Table 4a: AB/BB regressions, dependent variable 80/20 ratio EUROSTAT, using priority years					
Variables/models	1	2	3	4	5

First lag of quintile ratios	0.440*** (0.048)	0.407*** (0.048)	0.463*** (0.050)	0.438*** (0.051)	0.415*** (0.050)
First lag of innovativeness of companies (in absolute values)	0.874 (1.045)	0.361 (1.057)	0.506 (1.102)	0.362 (1.061)	0.992 (1.079)
Second lag of innovativeness of companies (in absolute values)	-0.270 (1.630)	-0.338 (1.649)	-1.630 (1.722)	-1.091 (1.632)	-0.503 (1.648)
Third lag of innovativeness of companies (in absolute values)	0.760 (1.604)	-0.146 (1.611)	-0.279 (1.679)	-1.324 (1.588)	-0.158 (1.615)
First lag of innovativeness of government or no-profits (in absolute values)	-7.353 (23.003)	-7.660 (22.980)	-8.203 (25.187)	-0.763 (24.277)	-3.431 (24.856)
Second lag of innovativeness of government or no-profits (in absolute values)	-9.959 (25.645)	-14.528 (25.776)	-3.946 (28.734)	1.467 (27.517)	17.462 (28.414)
Third lag of innovativeness of government or no-profits (in absolute values)	-2.295 (26.667)	0.664 (26.800)	-14.475 (30.733)	5.924 (29.466)	10.712 (29.300)
First lag of innovativeness of universities (in absolute values)	-4.990 (13.358)	9.792 (13.752)	1.855 (14.017)	-0.163 (13.622)	8.378 (13.872)
Second lag of innovativeness of universities (in absolute values)	22.500 (14.096)	33.999** (14.309)	16.599 (15.506)	20.187 (14.316)	35.588** (14.648)
Third lag of innovativeness of universities (in absolute values)	-14.623 (17.274)	-7.924 (17.332)	16.936 (18.390)	18.574 (17.806)	6.698 (18.255)
First lag of innovativeness of hospitals (in absolute values)	320.494** (125.093)	315.785** (127.904)	311.085** (128.468)	558.852*** (140.867)	460.711*** (134.538)
Second lag of innovativeness of hospitals (in absolute values)	-147.277 (112.101)	-83.425 (115.424)	-121.960 (123.259)	-107.739 (121.853)	-143.597 (113.499)
Third lag of innovativeness of hospitals (in absolute values)	-50.246 (101.801)	-28.113 (103.385)	-124.238 (106.793)	-195.724* (112.783)	-90.263 (102.650)
First lag of innovativeness of other (in absolute values)	11.603 (7.152)	8.369 (7.387)	10.267 (8.115)	13.508* (7.968)	-0.587 (8.159)
Second lag of innovativeness of other (in absolute values)	-1.236 (7.234)	-3.425 (7.369)	-2.038 (7.946)	2.769 (7.763)	2.020 (8.093)
Third lag of innovativeness of other (in absolute values)	16.597** (7.741)	12.331 (7.938)	7.135 (8.709)	17.034** (8.125)	15.200* (8.938)
Population density	0.948* (0.548)	0.450 (0.600)	0.035 (0.524)	0.920* (0.515)	0.038 (0.545)
Gross fixed capital formation	0.043** (0.018)	0.018 (0.021)	-0.033 (0.020)	0.044** (0.017)	0.062*** (0.017)

GDP/population (in absolute values)	-0.018 (0.020)	-0.027 (0.022)	-0.025 (0.022)	-0.045** (0.020)	-0.022 (0.020)
Employment/population	-0.967 (1.725)	1.567 (1.909)	3.314* (1.934)	2.749 (1.756)	2.118 (1.984)
Yearly wages	-0.043** (0.018)	-0.029 (0.018)	-0.029 (0.019)	-0.034* (0.018)	-0.037** (0.018)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Priority year	0.047*** (0.012)	0.073*** (0.019)	0.062*** (0.018)	0.050*** (0.013)	0.022 (0.015)
Constant	-90.329*** (23.406)	-101.678 (78.301)	-108.751 (79.582)	-97.565*** (26.485)	-41.776 (29.408)
Number of observations	695	693	632	626	658
Wald chi2	339.54	360.12	353.36	421.95	373.17
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table 4b: AB/BB regressions, dependent variable 80/20 ratio EUROSTAT, using priority years					
Variables/models	1	2	3	4	5
First lag of quintile ratios	0.419*** (0.051)	0.409*** (0.048)	0.414*** (0.051)	0.421*** (0.048)	0.454*** (0.050)
First lag of innovativeness of companies (in absolute values)	0.536 (1.086)	-0.087 (1.100)	0.398 (1.083)	0.165 (1.071)	0.550 (1.082)
Second lag of innovativeness of companies (in absolute values)	-1.522 (1.629)	-0.332 (1.669)	-0.227 (1.652)	-0.043 (1.675)	-0.217 (1.680)
Third lag of innovativeness of companies (in absolute values)	0.711 (1.595)	0.387 (1.640)	0.445 (1.624)	-0.077 (1.641)	0.176 (1.674)
First lag of innovativeness of government or no-profits (in absolute values)	-14.261 (25.299)	5.558 (25.068)	4.417 (25.119)	3.267 (24.917)	-0.873 (24.743)
Second lag of innovativeness of government or no-profits (in absolute values)	-6.353 (28.340)	2.982 (28.579)	9.992 (28.086)	9.265 (27.838)	-4.263 (26.984)
Third lag of innovativeness of government or no-profits (in absolute values)	-8.707 (29.681)	9.059 (29.630)	11.059 (29.802)	7.164 (29.290)	7.815 (27.740)
First lag of innovativeness of universities (in absolute values)	9.158 (13.184)	0.095 (13.582)	8.391 (14.190)	2.918 (13.604)	8.887 (13.968)

Second lag of innovativeness of universities (in absolute values)	26.231* (14.534)	20.896 (14.345)	35.564** (14.967)	27.169* (14.385)	35.245** (14.742)
Third lag of innovativeness of universities (in absolute values)	-0.017 (17.418)	2.148 (17.662)	-0.277 (17.848)	-4.154 (17.690)	-6.323 (17.578)
First lag of innovativeness of hospitals (in absolute values)	292.849** (127.152)	350.414*** (125.837)	347.447*** (128.794)	315.149** (124.907)	325.813** (128.620)
Second lag of innovativeness of hospitals (in absolute values)	-80.883 (118.884)	-81.949 (112.894)	-111.899 (117.209)	-72.194 (112.977)	-94.253 (114.280)
Third lag of innovativeness of hospitals (in absolute values)	-49.772 (99.840)	-8.850 (102.226)	-50.670 (103.938)	-4.983 (101.654)	-61.923 (102.863)
First lag of innovativeness of other (in absolute values)	11.211 (7.825)	14.132* (7.895)	14.066* (7.871)	11.125 (7.842)	9.132 (7.710)
Second lag of innovativeness of other (in absolute values)	1.359 (7.929)	8.606 (8.071)	5.311 (7.959)	-0.532 (7.837)	-1.504 (7.663)
Third lag of innovativeness of other (in absolute values)	12.549 (8.345)	14.477* (8.544)	15.062* (8.309)	11.482 (8.234)	10.070 (8.177)
Population density	-0.700 (0.528)	0.926 (0.579)	-0.304 (0.712)	0.641 (0.547)	-0.034 (0.594)
Gross fixed capital formation	0.075*** (0.019)	0.029 (0.019)	0.019 (0.021)	0.024 (0.019)	0.030 (0.020)
GDP/population (in absolute values)	-0.034* (0.020)	-0.001 (0.021)	-0.020 (0.022)	-0.040* (0.021)	-0.045** (0.023)
Employment/population	10.353*** (2.404)	0.871 (1.934)	4.635 (2.876)	1.650 (1.967)	9.617*** (3.236)
Yearly wages	-0.037** (0.018)	-0.046** (0.019)	-0.048** (0.018)	-0.040** (0.018)	-0.039** (0.018)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Priority year	0.003 (0.017)	0.058*** (0.018)	0.067*** (0.021)	0.058*** (0.016)	0.046*** (0.014)
Constant	-2.415 (33.459)	-112.532*** (36.574)	-130.974*** (42.682)	-116.498*** (34.382)	-90.014*** (28.524)
Number of observations	620	680	681	681	678
Wald chi2	441.01	364.42	367.08	370.24	359.79
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table 5a: AB/BB regressions, dependent variable 80/20 ratio EUROSTAT, using priority years					
Variables/models	1	2	3	4	5
First lag of quintile ratios	0.451*** (0.047)	0.412*** (0.048)	0.475*** (0.049)	0.466*** (0.050)	0.425*** (0.048)
First lag of innovativeness of companies (in logarithms)	1.043 (1.272)	0.491 (1.281)	0.735 (1.358)	0.703 (1.315)	1.282 (1.319)
Second lag of innovativeness of companies (in logarithms)	-0.906 (1.954)	-0.708 (1.978)	-2.570 (2.086)	-1.924 (1.632)	-0.940 (1.996)
Third lag of innovativeness of companies (in logarithms)	0.645 (1.961)	0.211 (1.952)	-0.444 (2.056)	-1.592 (1.966)	0.056 (1.988)
First lag of innovativeness of government or no-profits (logaritms)	-8.044 (23.328)	-6.914 (23.921)	-7.922 (25.582)	-0.780 (24.819)	-2.505 (25.174)
Second lag of innovativeness of government or no-profits (in logarithms)	-9.978 (26.019)	-14.237 (26.046)	-3.180 (29.225)	1.892 (28.203)	18.886 (28.841)
Third lag of innovativeness of government or no-profits (in logarithms)	-0.673 (26.931)	2.471 (26.908)	-11.485 (31.085)	7.561 (30.143)	12.911 (29.596)
First lag of innovativeness of universities (in logarithms)	-4.472 (13.596)	11.491 (13.954)	1.538 (14.284)	-0.124 (13.973)	8.401 (14.096)
Second lag of innovativeness of universities (in logarithms)	22.540 (14.331)	36.987** (14.607)	15.203 (15.805)	20.057 (14.675)	36.492** (14.865)
Third lag of innovativeness of universities (in logarithms)	-15.214 (17.603)	-5.158 (17.642)	16.752 (18.714)	18.761 (18.330)	7.616 (18.652)
First lag of innovativeness of hospitals (in logarithms)	323.217** (126.070)	321.793** (128.524)	310.369** (129.650)	553.930*** (142.737)	459.192*** (135.540)
Second lag of innovativeness of hospitals (in logarithms)	-157.925 (112.223)	-86.360 (115.521)	-141.722 (123.133)	-149.897 (122.664)	-161.852 (113.354)
Third lag of innovativeness of hospitals (in logarithms)	-64.064 (101.641)	-36.030 (102.627)	-144.432 (106.301)	-241.216** (112.570)	-109.105 (101.954)
First lag of innovativeness of other (in logarithms)	11.606 (7.388)	9.254 (7.574)	10.526 (8.439)	14.588* (8.360)	0.456 (8.426)
Second lag of innovativeness of other (in logarithms)	-2.275 (7.424)	-2.552 (7.509)	-3.292 (8.214)	1.784 (8.034)	2.621 (8.299)
Third lag of innovativeness of other (in logarithms)	15.450** (7.817)	11.747 (7.910)	5.328 (8.773)	15.710* (8.313)	14.785* (8.495)
Population density	0.817 (0.561)	0.502 (0.607)	-0.089 (0.553)	0.788 (0.530)	0.105 (0.564)

Gross fixed capital formation	0.045** (0.018)	0.019 (0.021)	0.035* (0.021)	0.054*** (0.017)	0.067*** (0.017)
GDP/population (in logarithms)	-0.038 (0.341)	-0.645* (0.391)	-0.064 (0.351)	-0.445 (0.330)	-0.416 (0.336)
Employment/population	-1.439 (1.581)	1.070 (1.798)	2.741 (1.852)	1.200 (1.602)	1.678 (1.860)
Yearly wages	-0.052*** (0.018)	-0.022 (0.019)	-0.041** (0.019)	-0.045** (0.018)	-0.035** (0.018)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Priority year	0.050*** (0.011)	0.077*** (0.018)	0.070*** (0.017)	0.056*** (0.013)	0.022 (0.015)
Constant	-96.312*** (23.114)	-109.307 (77.409)	-131.451 (77.636)	-108.576*** (26.412)	-42.489 (29.625)
Number of observations	695	693	632	626	658
Wald chi2	333.78	358.81	346.90	406.91	369.25
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table 5b: AB/BB regressions, dependent variable 80/20 ratio EUROSTAT, using priority years

Variables/models	1	2	3	4	5
First lag of quintile ratios	0.444*** (0.050)	0.410*** (0.048)	0.418*** (0.050)	0.433*** (0.047)	0.465*** (0.049)
First lag of innovativeness of companies (in logarithms)	0.819 (1.348)	-0.127 (1.338)	0.500 (1.317)	0.250 (1.303)	0.660 (1.316)
Second lag of innovativeness of companies (in logarithms)	-2.509 (1.997)	-0.775 (2.007)	-0.635 (1.984)	-0.352 (2.021)	-0.602 (2.020)
Third lag of innovativeness of companies (in logarithms)	-1.305 (1.963)	0.195 (1.982)	0.748 (1.981)	0.228 (1.984)	0.575 (2.027)
First lag of innovativeness of government or no-profits (in logarithms)	-13.916 (25.885)	5.193 (25.310)	5.119 (25.362)	5.547 (25.217)	1.069 (25.065)
Second lag of innovativeness of government or no-profits (in logarithms)	-6.539 (29.078)	2.089 (28.977)	10.607 (28.414)	10.574 (28.217)	-2.969 (27.325)
Third lag of innovativeness of government or no-profits (in logarithms)	-7.050 (30.343)	8.923 (29.871)	12.053 (30.009)	9.675 (29.564)	11.882 (27.935)
First lag of innovativeness of universities (in logarithms)	9.240 (13.952)	0.564 (13.738)	9.308 (14.319)	4.618 (13.834)	10.243 (14.195)

Second lag of innovativeness of universities (in logarithms)	26.168* (14.920)	20.880 (14.522)	37.452** (15.125)	30.257** (14.651)	38.379** (15.033)
Third lag of innovativeness of universities (in logarithms)	-2.529 (14.878)	1.805 (17.892)	1.532 (18.183)	-0.537 (18.040)	-3.327 (17.898)
First lag of innovativeness of hospitals (in logarithms)	302.875** (129.508)	355.229*** (126.285)	347.952*** (129.243)	311.782** (125.696)	325.586** (129.475)
Second lag of innovativeness of hospitals (in logarithms)	-105.157 (119.378)	-78.232 (113.140)	-118.473 (117.587)	-90.052 (113.318)	-114.899 (114.574)
Third lag of innovativeness of hospitals (in logarithms)	-80.682 (100.041)	-10.388 (101.831)	-60.766 (103.333)	-25.152 (101.510)	-83.465 (102.649)
First lag of innovativeness of other (in logarithms)	10.928 (8.197)	13.832* (8.122)	15.245 (8.114)	12.528 (8.029)	10.925 (7.921)
Second lag of innovativeness of other (in logarithms)	-1.000 (8.253)	8.104 (8.218)	5.850 (8.092)	-0.612 (7.974)	-1.073 (7.826)
Third lag of innovativeness of other (in logarithms)	10.143 (8.517)	14.143* (8.524)	14.979* (8.319)	9.974 (8.324)	8.787 (8.306)
Population density	-0.946* (0.536)	0.803 (0.600)	-0.326 (0.698)	0.706 (0.555)	0.083 (0.611)
Gross fixed capital formation	0.079*** (0.019)	0.028 (0.019)	0.021 (0.021)	0.032* (0.019)	0.036* (0.020)
GDP/population (in logarithms)	-0.004 (0.342)	0.177 (0.357)	-0.408 (0.390)	-0.910** (0.406)	-0.949** (0.418)
Employment/population	9.261*** (2.327)	1.133 (1.932)	4.153 (2.904)	0.818 (1.749)	7.909** (3.122)
Yearly wages	-0.057*** (0.018)	-0.051*** (0.018)	-0.045** (0.019)	-0.034* (0.018)	-0.034* (0.019)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Priority year	0.011 (0.016)	0.059*** (0.017)	0.069*** (0.021)	0.061*** (0.015)	0.054*** (0.014)
Constant	-18.008 (33.513)	-116.013*** (34.683)	-135.070*** (42.463)	-121.572*** (33.318)	-103.716*** (27.741)
Number of observations	620	680	681	681	678
Wald chi2	405.51	362.90	365.35	368.10	357.04
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Conclusions

In this paper we have analysed the effects of innovations and, as a second variable of interest, population density on income inequality in the European regions. As innovativeness, urbanization and income inequality have all increased in the last decades, we contribute to the debate on whether the former two are associated to an increase or a decrease in the third one by studying these associations in the European regions between 2003 and 2015. Most theories predict a direct relationship between innovations and income inequality, either because innovations may favour high skilled people (SBTC), because innovations may substitute routine middle income workers (RBTC), or because innovations concentrate in cities and externalities of urbanization may increase inequality (geographical theory). The only theory that does not predict this direct relationship, and allows the possibility of an inverse relationship, is the evolutionary theory. According to this theory, indeed, better institutions may increase innovativeness and at the same time decrease inequality.

Our study is related to other recent studies that from different points of view have analysed the link between innovations and inequality, in particular to Antonelli and Gehringer (2017) for the evolutionary perspective, Permana et al. 2018 for the lags of innovativeness and De Palo et al. (2018) for the regional level and the Arellano-Bover/Blundell-Bond estimator used. We have combined these things and found that the results of the analysis that we have carried out in this paper are very different from what found and expected in literature for three reasons: firstly, in no sector innovations are correlated with income inequality. Secondly, even if cities and most densely populated areas are usually considered more innovative and unequal, we have found that also population density is not correlated with inequality. Thirdly, the most significant variables are social variables not related to innovation or urbanization.

Even if this study has employed good data on innovation and socioeconomic variables, regional data on income inequality are very few, for this reason the results are valid only in a subset of European countries and regions, and some of them suffer from collinearities. There is a need of more and better data on regional income inequality, if possible, at the same NUTS2 level, as for now only few countries publish yearly data on income inequality at the regional level, and these countries measure it in different ways, making the comparison and the analysis at the European level very hard. Unfortunately, EUROSTAT publishes only the quintile ratio at the regional level and not other indexes like the GINI, so we cannot rule out that the results we have found are specific to this index.

As in our study the only variables correlated with income inequality are social variables, based on what we have found, we advise to introduce policies that favour female and young employment and increase wages, especially at the bottom and the middle of the distribution. As innovations increase growth without increasing inequality, also policies that favour them may be advised. All these policies are particularly important for peripherical and less developed regions and countries, that are in most cases less innovative and more unequal. The differences in institutions between countries may mask the effects of other variables, but as stated in the previous paragraph, data on regional inequality are very limited, so we cannot advise other policies and we cannot analyse the heterogeneity of the results by country, with the exception of Italy (this heterogeneity is analysed in Tummolo 2022).

A future investigation is needed to study whether there are heterogeneities in the effects of innovations on inequality depending on the countries in which they are introduced, and also to study whether the country or regional specialization has an impact on the effects of innovations on income inequality.

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Appendix

Table 1: summary of variables, time periods and sources

Variables	Time periods	Sources
Innovation variables	1980-2016	TechEvo database
Socioeconomic variables	1980-2015	ARDECO database
Education variables	2000-2019	EUROSTAT
Employment variables	2000-2019	EUROSTAT
Area (land and total)	2013 and 2016	EUROSTAT
Quintile ratios	2003-2020	EUROSTAT

As each variable covers different time periods, we consider only the 2003-2015 period, except for innovativeness (2000-2015 using the lags)

Table 2: detailed summary by country of time periods of quintile ratios of disposable income

Country	Regions	Time periods
Austria	All	2014-2015

Bulgaria	All	2008-2015
Cyprus	Whole country NUTS2	2005-2015
Denmark	All	2007-2015
Estonia	Whole country NUTS2	2004-2015
Finland	All (regions changed in 2008)	2008-2015 (FI19 2004-2015)
Greece	Only Attiki	2003-2015
Croatia	All	2013-2015
Hungary	All	2005-2015
Italy	All	2004-2015
Luxembourg	Whole country NUTS2	2005-2015
Latvia	Whole country NUTS2	2005-2015
Malta	Whole country NUTS2	2005-2015
Norway	All	2003-2015 except 2004
Romania	All	2007-2015
Sweden	All	2008-2015
Slovenia	All	2008-2015
Slovakia	All	2005-2015

Table 6a: AB/BB regressions, dependent variable 80/20 ratio EUROSTAT, using filing years

Variables/models	1	2	3	4	5
First lag of quintile ratios	0.476*** (0.047)	0.443*** (0.049)	0.492*** (0.051)	0.490*** (0.051)	0.429*** (0.049)
First lag of innovativeness of companies (in absolute values)	1.583 (1.467)	1.577 (1.487)	0.471 (1.527)	1.104 (1.483)	1.635 (1.478)
Second lag of innovativeness of companies (in absolute values)	0.307 (1.694)	-0.101 (1.698)	-0.885 (1.837)	-1.876 (1.783)	-1.336 (1.778)
Third lag of innovativeness of companies (in absolute values)	-0.480 (1.625)	-0.862 (1.626)	-1.096 (1.769)	-0.699 (1.755)	0.545 (1.701)
First lag of innovativeness of government or no-profits (in absolute values)	-14.241 (26.257)	-15.861 (26.370)	-21.703 (29.647)	-9.968 (28.776)	-15.603 (28.931)
Second lag of innovativeness of government or no-profits (in absolute values)	28.179 (25.686)	29.167 (25.834)	0.259 (29.437)	13.950 (28.815)	25.450 (27.990)
Third lag of innovativeness of government or no-profits (in absolute values)	-6.321 (30.106)	-4.499 (30.222)	-3.328 (30.981)	-3.455 (30.422)	-14.598 (30.220)
First lag of innovativeness of universities (in absolute values)	-5.441 (14.707)	3.737 (14.986)	7.487 (16.373)	2.789 (15.196)	11.164 (15.338)

Second lag of innovativeness of universities (in absolute values)	8.064 (14.147)	12.380 (14.178)	19.372 (15.168)	26.055* (14.682)	16.871 (14.821)
Third lag of innovativeness of universities (in absolute values)	-37.861** (18.025)	-33.691* (18.084)	-4.019 (20.402)	-29.712 (18.845)	-30.449 (19.183)
First lag of innovativeness of hospitals (in absolute values)	-246.361** (113.804)	-211.919* (118.334)	-221.579* (128.022)	-293.763** (124.470)	-255.356** (113.915)
Second lag of innovativeness of hospitals (in absolute values)	118.097 (91.664)	144.410 (93.077)	22.072 (97.743)	3.810 (99.174)	70.565 (91.387)
Third lag of innovativeness of hospitals (in absolute values)	57.950 (96.949)	95.846 (97.979)	176.506* (103.042)	157.425 (109.956)	33.902 (95.309)
First lag of innovativeness of other (in absolute values)	1.113 (7.843)	-1.686 (7.954)	-3.858 (8.572)	-3.723 (8.435)	-0.914 (8.756)
Second lag of innovativeness of other (in absolute values)	11.055 (7.524)	7.405 (7.744)	6.251 (8.926)	14.029* (8.370)	11.996 (8.580)
Third lag of innovativeness of other (in absolute values)	-2.703 (8.070)	-3.608 (8.215)	-1.927 (9.210)	-4.061 (8.990)	-5.141 (8.514)
Population density	0.720 (0.549)	0.461 (0.593)	0.154 (0.536)	0.713 (0.535)	-0.170 (0.539)
Gross fixed capital formation	0.032* (0.017)	0.011 (0.020)	0.016 (0.020)	0.032* (0.017)	0.051*** (0.016)
GDP/population (in absolute values)	-0.002 (0.021)	-0.017 (0.023)	-0.024 (0.024)	-0.024 (0.021)	-0.008 (0.021)
Employment/population	-1.471 (1.773)	0.801 (1.944)	3.395* (1.999)	1.922 (1.858)	2.487 (2.023)
Yearly wages	-0.037** (0.018)	-0.023 (0.018)	-0.015 (0.020)	-0.022 (0.018)	-0.026 (0.018)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Filing year	0.063*** (0.011)	0.070*** (0.019)	0.076*** (0.019)	0.062*** (0.013)	0.039*** (0.013)
Constant	-123.570*** (22.224)	-89.709 (79.711)	-129.333 (81.984)	-122.768*** (25.929)	-77.616 (26.734)
Number of observations	694	692	629	623	657
Wald chi2	328.18	346.53	344.71	370.57	368.66
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table 6b: AB/BB regressions, dependent variable 80/20 ratio EUROSTAT, using filing years					
Variables/models	1	2	3	4	5
First lag of quintile ratios	0.479*** (0.051)	0.443*** (0.048)	0.418*** (0.050)	0.444*** (0.047)	0.469*** (0.050)
First lag of innovativeness of companies (in absolute values)	1.015 (1.514)	0.957 (1.494)	1.841 (1.474)	1.578 (1.488)	1.606 (1.513)
Second lag of innovativeness of companies (in absolute values)	-0.707 (1.773)	0.001 (1.754)	0.274 (1.732)	-0.004 (1.726)	-0.104 (1.740)
Third lag of innovativeness of companies (in absolute values)	-1.096 (1.727)	0.021 (1.654)	0.646 (1.672)	-0.966 (1.665)	-0.793 (1.682)
First lag of innovativeness of government or no-profits (in absolute values)	-15.583 (29.589)	-17.260 (29.005)	-9.801 (28.682)	-11.224 (28.416)	-18.123 (26.592)
Second lag of innovativeness of government or no-profits (in absolute values)	17.970 (29.650)	28.011 (28.553)	35.968 (28.434)	27.229 (27.979)	26.995 (26.197)
Third lag of innovativeness of government or no-profits (in absolute values)	2.234 (30.820)	-0.541 (30.352)	4.332 (30.061)	-8.855 (29.970)	-4.286 (30.388)
First lag of innovativeness of universities (in absolute values)	1.486 (15.485)	2.929 (15.060)	9.547 (15.234)	6.282 (15.013)	10.321 (15.172)
Second lag of innovativeness of universities (in absolute values)	17.229 (15.062)	6.135 (14.558)	12.624 (14.735)	11.242 (14.403)	9.128 (14.415)
Third lag of innovativeness of universities (in absolute values)	-27.643 (19.878)	-20.606 (18.682)	-28.860 (18.568)	-27.896 (18.482)	-31.765* (18.308)
First lag of innovativeness of hospitals (in absolute values)	-223.002* (122.797)	-180.343 (115.296)	-262.263** (119.410)	-151.077 (115.772)	-186.530 (116.225)
Second lag of innovativeness of hospitals (in absolute values)	79.173 (92.250)	146.935 (92.316)	86.249 (93.021)	137.858 (91.775)	106.356 (92.711)
Third lag of innovativeness of hospitals (in absolute values)	51.978 (97.309)	86.908 (97.837)	48.371 (97.045)	78.439 (97.017)	49.112 (98.019)
First lag of innovativeness of other (in absolute values)	5.641 (8.806)	4.765 (8.685)	2.870 (8.345)	-3.191 (8.445)	-3.889 (8.160)
Second lag of innovativeness of other (in absolute values)	8.415 (8.760)	12.208 (8.582)	12.760 (8.317)	6.686 (8.308)	7.004 (7.991)
Third lag of innovativeness of other (in absolute values)	-3.097 (9.125)	-0.388 (8.896)	-1.579 (8.557)	-6.057 (8.567)	-5.565 (8.641)
Population density	-1.003* (0.545)	0.650 (0.571)	-0.145 (0.694)	0.477 (0.547)	0.255 (0.591)

Gross fixed capital formation	0.065*** (0.019)	0.022 (0.018)	0.011 (0.020)	0.013 (0.019)	0.023 (0.019)
GDP/population (in absolute values)	-0.013 (0.021)	0.013 (0.022)	-0.011 (0.022)	-0.029 (0.022)	-0.037 (0.023)
Employment/population	10.851*** (2.554)	0.488 (1.962)	4.187 (2.864)	1.814 (2.056)	8.222** (3.266)
Yearly wages	-0.034* (0.018)	-0.037** (0.019)	-0.040** (0.018)	-0.034* (0.018)	-0.032* (0.018)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Filing year	0.017 (0.016)	0.072*** (0.017)	0.063*** (0.021)	0.074*** (0.015)	0.067*** (0.013)
Constant	-30.644 (32.168)	-140.653*** (35.109)	-124.688*** (42.683)	-148.124*** (32.911)	-131.254*** (26.994)
Number of observations	618	678	679	679	677
Wald chi2	405.87	344.33	358.15	358.16	347.94
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table 7a: AB/BB regressions, dependent variable 80/20 ratio EUROSTAT, using filing years

Variables/models	1	2	3	4	5
First lag of quintile ratios	0.481*** (0.046)	0.439*** (0.048)	0.507*** (0.050)	0.508*** (0.049)	0.432*** (0.047)
First lag of innovativeness of companies (in logarithms)	1.670 (1.798)	1.933 (1.815)	0.308 (1.903)	1.267 (1.859)	1.992 (1.824)
Second lag of innovativeness of companies (in logarithms)	-0.007 (2.038)	-0.211 (2.031)	-1.513 (2.241)	-2.763 (2.205)	-1.897 (2.164)
Third lag of innovativeness of companies (in logarithms)	-0.736 (1.957)	-0.658 (1.950)	-1.401 (2.152)	-1.099 (2.157)	0.889 (2.070)
First lag of innovativeness of government or no-profits (logaritms)	-13.727 (26.522)	-15.892 (26.506)	-20.730 (30.153)	-8.745 (29.342)	-15.178 (29.124)
Second lag of innovativeness of government or no-profits (in logarithms)	30.001 (25.813)	31.102 (25.764)	5.142 (29.807)	16.623 (29.392)	26.212 (28.060)
Third lag of innovativeness of government or no-profits (in logarithms)	-5.094 (30.400)	-2.128 (30.300)	1.074 (31.340)	-0.718 (31.029)	-12.967 (30.331)
First lag of innovativeness of universities (in logarithms)	-5.835 (14.899)	5.921 (15.206)	5.320 (16.700)	1.452 (15.507)	11.699 (15.474)

Second lag of innovativeness of universities (in logarithms)	7.659 (14.342)	14.048 (14.340)	18.187 (15.448)	25.307* (15.008)	17.672 (14.952)
Third lag of innovativeness of universities (in logarithms)	-38.764** (18.267)	-32.166* (18.263)	-1.401 (20.672)	-30.533 (19.248)	-30.203 (19.391)
First lag of innovativeness of hospitals (in logarithms)	-247.222** (113.719)	-209.428 (117.518)	-243.784* (127.630)	-314.975** (124.621)	-262.648** (113.211)
Second lag of innovativeness of hospitals (in logarithms)	118.201 (91.652)	145.850 (92.350)	5.268 (97.357)	-14.093 (99.247)	65.953 (90.778)
Third lag of innovativeness of hospitals (in logarithms)	54.665 (97.236)	103.599 (97.833)	165.444 (103.737)	153.007 (111.203)	33.204 (94.790)
First lag of innovativeness of other (in logarithms)	0.180 (8.061)	-0.186 (8.120)	-5.831 (8.915)	-5.238 (8.736)	-0.096 (8.942)
Second lag of innovativeness of other (in logarithms)	10.493 (7.622)	7.400 (7.738)	4.175 (9.052)	13.206 (8.578)	12.570 (8.678)
Third lag of innovativeness of other (in logarithms)	-3.416 (8.202)	-2.950 (8.304)	-3.614 (9.477)	-4.915 (9.252)	-4.697 (8.661)
Population density	0.604 (0.564)	0.590 (0.606)	-0.047 (0.571)	0.506 (0.550)	-0.091 (0.558)
Gross fixed capital formation	0.031* (0.018)	0.011 (0.020)	0.018 (0.020)	0.036** (0.017)	0.053*** (0.016)
GDP/population (in logarithms)	0.164 (0.351)	-0.592 (0.418)	0.082 (0.359)	-0.012 (0.337)	-0.225 (0.337)
Employment/population	-1.323 (1.603)	0.511 (1.802)	2.838 (1.892)	1.118 (1.666)	2.470 (1.855)
Yearly wages	-0.043** (0.017)	-0.013 (0.019)	-0.031 (0.018)	-0.034* (0.018)	-0.022 (0.018)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Filing year	0.065*** (0.011)	0.072*** (0.018)	0.084*** (0.018)	0.067*** (0.013)	0.039 (0.013)
Constant	-127.133*** (21.780)	-90.300 (78.213)	-152.651 (80.562)	-131.824*** (25.705)	-76.678 (26.856)
Number of observations	694	692	629	623	657
Wald chi2	325.02	347.60	337.29	360.65	368.17

Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses

Table 7b: AB/BB regressions, dependent variable 80/20 ratio EUROSTAT, using filing years					
Variables/models	1	2	3	4	5
First lag of quintile ratios	0.497*** (0.050)	0.443*** (0.047)	0.418*** (0.049)	0.446*** (0.046)	0.474*** (0.049)
First lag of innovativeness of companies (in logarithms)	1.051 (1.896)	1.001 (1.829)	2.199 (1.811)	1.934 (1.825)	2.005 (1.860)
Second lag of innovativeness of companies (in logarithms)	-1.356 (2.169)	-0.371 (2.114)	0.181 (2.095)	0.019 (2.077)	-0.130 (2.103)
Third lag of innovativeness of companies (in logarithms)	-1.963 (2.113)	-0.119 (1.994)	-0.670 (2.019)	-0.894 (2.003)	-0.714 (2.027)
First lag of innovativeness of government or no-profits (in logarithms)	-13.993 (30.151)	-18.194 (29.272)	-9.395 (28.906)	-10.381 (28.581)	17.136 (26.827)
Second lag of innovativeness of government or no-profits (in logarithms)	20.714 (30.150)	27.112 (28.716)	37.494 (28.492)	30.085 (28.060)	31.015 (26.268)
Third lag of innovativeness of government or no-profits (in logarithms)	4.869 (31.363)	-1.109 (30.505)	5.970 (30.273)	-5.872 (30.121)	0.534 (30.674)
First lag of innovativeness of universities (in logarithms)	-0.236 (15.830)	2.636 (15.241)	10.163 (15.416)	8.255 (15.198)	12.355 (15.435)
Second lag of innovativeness of universities (in logarithms)	15.993 (15.374)	5.361 (14.744)	13.470 (14.932)	13.712 (14.592)	10.409 (14.614)
Third lag of innovativeness of universities (in logarithms)	-29.536 (20.285)	-21.205 (18.863)	-28.576 (18.771)	-25.953 (18.641)	-30.839* (18.506)
First lag of innovativeness of hospitals (in logarithms)	-233.723* (123.088)	-167.010 (115.543)	-265.216** (119.526)	-162.597 (115.493)	-203.832* (116.168)
Second lag of innovativeness of hospitals (in logarithms)	71.746 (92.391)	155.837* (92.215)	84.188 (92.748)	127.941 (91.531)	94.060 (92.698)
Third lag of innovativeness of hospitals (in logarithms)	43.540 (97.815)	89.136 (97.787)	51.541 (97.131)	82.122 (96.948)	51.797 (98.325)
First lag of innovativeness of other (in logarithms)	-8.272 (9.138)	3.883 (8.873)	3.411 (8.532)	-2.412 (8.555)	-3.182 (8.317)
Second lag of innovativeness of other (in logarithms)	6.728 (8.924)	12.209 (8.606)	12.872 (8.361)	5.603 (8.384)	6.328 (8.092)
Third lag of innovativeness of other (in logarithms)	-4.801 (9.359)	-0.634 (9.002)	-1.495 (8.672)	-6.631 (8.667)	-5.883 (8.776)
Population density	-1.239** (0.554)	0.489 (0.597)	-0.122 (0.688)	0.649 (0.561)	0.444 (0.619)

Gross fixed capital formation	0.065*** (0.019)	0.018 (0.018)	0.012 (0.020)	0.020 (0.019)	0.029 (0.019)
GDP/population (in logarithms)	0.335 (0.366)	0.395 (0.362)	-0.272 (0.400)	-0.868** (0.431)	-0.880** (0.443)
Employment/population	10.242*** (2.426)	1.253 (1.931)	3.937 (2.859)	1.366 (1.782)	6.872** (3.131)
Yearly wages	-0.052*** (0.018)	-0.041** (0.018)	-0.037** (0.018)	-0.025 (0.018)	-0.026 (0.019)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Filing year	0.024 (0.016)	0.070*** (0.016)	0.064*** (0.021)	0.075*** (0.015)	0.072*** (0.013)
Constant	-45.280 (32.144)	-137.843*** (33.004)	-125.686*** (42.371)	-147.754*** (31.903)	-140.487*** (26.369)
Number of observations	618	678	679	679	677
Wald chi2	396.71	343.77	357.26	360.58	346.96
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Innovations and inequalities in the Italian regions and provinces

Abstract

Italy is less innovative and more unequal than the rest of Europe. At the same time, it has probably the worst performance in terms of growth and employment. In this paper we will study the link between innovations and inequality in Italy. We use four different panel models, two with the Arellano-Bover/Blundell-Bond GMM system estimator and two Dynamic Durbin Spatial Models and several different variables to measure different kinds of inequality (total income inequality from 2003 to 2015 at the regional level, inequality of taxpayers from 2000 to 2011 at the provincial level), finding that the relationship between innovations and inequality depends on the measure of inequality employed and on the geographical level analysed and that other factors, such as population density, are more important.

Introduction

Since the beginning of the third millennium the world, and in particular Europe, has experienced various events that have been leading to a structural change in our society: in addition to at least three big economic crisis (the housing bubble one in 2008, the sovereign debt one in 2011 and the pandemic one in 2020) that have reduced growth, there has been an increase in income and wage inequalities (Piketty 2014), an even larger increase in innovativeness (Brynjolfsson and McAfee 2014) and the polarization of the labour market (Usanov and Chivot 2013, Autor 2019)

Italy is a special case to study in Europe for different reasons: it has the lowest economic growth since 2000, it is the only OECD country where wages decreased from 1990 to 2020 (OECD 2021), it has one of the highest income inequalities and one of the lowest rates of innovativeness (Capparucci and Veraschagina 2017, Biurrun 2020) and, finally, Italy is probably the most heterogeneous country, with a historical and even increasing divide between the north and the south (Acciari and Mocetti 2013, Franzini et al. 2017). The differences between these two areas of Italy are of particular interest, as the north is persistently more equal, more innovative and richer than the south (see maps at the end of the appendix), and these three characteristics may be linked one to each other.

According to some theories like the skilled-biased and the routine-biased technological change theories (respectively SBTC and RBTC, more details in the section "related literature") innovations may increase inequality because they favour high skilled high income people over low and medium skilled and income people (Acemoglu 2002, Acemoglu and Autor 2011). For RBTC it may also increase polarization as, differently from what affirmed by the SBTC, low income low skilled workers are less substitutable by machines than medium income medium skilled workers employed in routine jobs (Autor, Levy and Murnane 2003). For other theories (especially the evolutionary theory) innovations may also decrease inequality by reducing the monopoly rents of incumbents (Antonelli and Gehringer 2017). As most innovations take place in cities (Feldman and Kogler 2010, Crescenzi et al. 2020) and as innovations tend to increase incomes, they may favour cities over rural areas, increasing spatial inequality even without increasing total income inequality. Innovations may also have different effects depending on the different kinds of innovations, on different sectors (or even firms) in which they are introduced, or on different institutions, so the effects may be very heterogeneous and different in each case (Nelson and Winter 1982). Indirect effects may also act in the opposite way from the direct ones, and they may be even larger than them (Calvino and Virgillito 2017).

To sum up, there is no consensus on the sign and magnitude of the effects of innovations on inequality, and probably they may depend on the specific context in which innovations are implemented. This specificity is probably not only the main reason why there is still a debate between different theories, even if they predict opposite outcomes. It is also the main reason why studies that, like ours, are focused on regions and provinces belonging to a single country are useful: they can highlight effects or associations that may not be present when studying the relationship between innovations and inequality in broader areas such as a continent.

In this paper we will study the associations of innovations with total income inequality in the Italian regions between 2003 (2004 when the inequality variable is the quintile ratio) and 2015 and with inequality of taxpayers in the Italian provinces between 2000 and 2011. To control for endogeneity, we lag all independent variables for one year, and as innovations should have effects for more than one year, we lag it for 1 to 3 years. In addition, but only in the regional regressions, we add several socioeconomic, education and employment variables (data for these variables are available only at the regional level). Because of the high persistence and possible endogeneities of most variables, we use the Arellano-Bover/Blundell-Bond GMM system estimator. As Italian regions, or even provinces, are very different, innovations may have different correlations with the different kinds of inequality in the various areas. It's for this reason that we study the relationship between innovations and inequality using different data at the regional and the provincial levels. The effects of innovativeness and other variables on income inequality may depend also on what happens in neighbour regions or provinces. To study these spatial indirect effects, we also use a Dynamic Spatial Durbin Model (DSDM), even if only the dependent variables can be lagged.

The different time periods are due to data constraints: ISTAT data on GINIs are available only from 2003, EUROSTAT data on quintile ratios are available only from 2004 and data on taxpayers are available only from 2000 to 2011 (more details in table 1 in the appendix).

To study these associations we will use several different databases: for variables on innovations, and in particular for innovativeness, measured as patents per capita and their logarithm, we will use the TechEvo database, for socioeconomic variables we will use the ARDECO (formerly ERD) database, for total income inequality we will use ISTAT data for GINI with and without imputed rents and EUROSTAT data for quintile ratios at the regional level and for inequality of taxpayers we will use freely downloaded data by Sauro Mocetti on GINI and share of income of top 10% at the provincial level.

The advantages of the TechEvo and the ARDECO databases are the long time period covered and the geographical detail, as all data are at the NUTS2 level (regional) or even the NUTS3 level (provincial). Even if these advantages are partly reduced by the shorter time period and the different levels for which other variables are available, nevertheless we are able to study the associations between innovations and inequality (of total income and of taxpayers) for more than 10 years at both the regional and the provincial level.

One novelty of the paper is the confrontation between the associations of innovations with income inequality and the ones with inequality of taxpayers. Indeed, only few papers, among them Florida and Mellander (2014), have studied the different effects on wage and income inequality finding that innovations seem to be more linked to the former than to the latter, but these papers were focused only on the US and no paper has carried out this confrontation studying the Italian regions.

Another novelty of the paper is the use of the Dynamic Spatial Durbin Model to study the effects of innovations on inequality. Indeed, to our knowledge, it is the first time that a spatial model is used to study this relationship.

In addition to be our first novelty, the analysis of the associations of various kinds of innovations with various kinds of inequality at different levels can be considered the main contribution of our study, especially as it is focused on a deeply divided country like Italy. Another contribution is provided by the analysis of spillovers between regions and provinces in the models that use the

Dynamic Spatial Durbin Model, that gives a more detailed picture of the spatial relationship between innovations and inequality.

We expect innovations to be negatively correlated with inequality, but only after some years and because of indirect effects. According to us, indeed, the indirect effects should be more important than the direct ones. Because of the characteristics of Italy listed above, we expect wages (only in regional data), GDP per capita and/or the employment rate to be negatively correlated with inequality, especially when all the distribution is considered using the GINI indexes. As urbanization should increase diversity, we also expect population density positively correlated with inequality. We also expect that variables in neighbouring regions and provinces are correlated with the different measures of inequality.

We find that innovativeness and population density have different associations with income inequality and inequality of taxpayers in the different models, neither confirming nor rejecting these expectations.

The rest of the paper is organized as follows: in the second section we will illustrate the theories on innovations and inequality with a particular focus on the regional studies on Italy and Europe, in the third section we will describe the data and descriptive statistics, in the fourth section we will explain the models, in the fifth section we will present the results, with some different specifications (but some tables will be presented in the appendix), the sixth and last section concludes and presents some policy implications.

Related literature

Different theories have linked innovations and inequality. The first mainstream theory is the skill-biased technological change one (SBTC). According to this theory technology is complementary to skills and, thus, innovations increase wages of high skilled people more than wages of low skilled people and for this reason increase inequality (Acemoglu 2002). The shift in demand for skills from low skilled to high skilled even within occupations (Katz and Murphy 1992) has increased inequality even if also the supply of skills has increased, creating an upward sloping relative demand curve for skills (Acemoglu 1998). This increase in inequality and this change of skills within occupations may be partly explained by computerization (Autor, Katz and Krueger 1998).

As the data showed that medium skilled people have gained less (or lost more) than low skilled ones, starting from the 2000s the simple and linear SBTC theory has been replaced by a modified version called routine-biased technological change theory (RBTC). According to this theory there are 4 different groups of tasks: routine manual, routine non-manual, non-routine manual and non-routine non-manual (the last originally divided in non-routine interactive and non-routine cognitive). The two routine groups (tasks that have programmed rules) comprise tasks easier to be substituted by machines and mostly performed by medium skilled and medium income people, whereas the non-routine non-manual tasks are neither substitutes nor complements of machines and are usually performed by low skilled low income people and routine cognitive tasks are complements of machines and performed by high skilled high income people (Autor, Levy and Murnane 2003). As medium skilled people lose jobs because of labour-saving innovations, they find job in low paid service occupations increasing polarization of wages and employment by skills (Autor and Dorn 2013 for the US, Goos, Manning and Salomons 2014 for Europe, Goos and Manning 2007 for UK and Spitz-Oener 2006 for Germany). The increase in medium skilled people employed in traditionally low skilled low wage jobs has reduced their income not only relative to other people, but also at the absolute level, at least in the US (Autor 2019). Standardization that follows innovations may reduce inequality, but according to Acemoglu and Restrepo (2017) its effect is lower than the inequality increasing effect of innovations, especially when there are forces that lead to an excess of automation.

The mainstream SBTC and RBTC theory are just two of several theories on innovations and inequality. Among the other theories, the most structured is probably the evolutionary theory (Nelson and Winter 1982). According to this theory firms follow different trajectories determined by their own rules and routines specific to each firm (firms are heterogeneous, in opposition to the neoclassical homogeneous firms) or each sector and not perfect, as there is no maximization. There is a schumpeterian process of creative destruction (Schumpeter 1942) in which the firms which innovate the most or with a better timing win, and the others lose, but not necessarily finding a stable equilibrium, as firms are heterogeneous and some of them may imitate innovations via learning by doing or by using and other ones may increase R&D spending to innovate more (Silverberg et al. 1988). As large firms tend to be more innovative and imitation is difficult due to the importance of tacit knowledge, firms tend to be more concentrated in oligopolies over time (Dosi 1988). This theory is called evolutionary because like in biological evolution the natural selection of firms, caused also by innovations and institutions, is very important and shapes the market, determining which firms and routines survive and which not (Nelson and Winter 1982).

According to the evolutionary theory there is also a bargain between entrepreneurs and workers that determines the profit and wage shares. For this reason, most papers (among them Pianta and

Tancioni 2008, Bogliacino, Guarascio and Cirillo 2017, Coveri and Pianta 2019) have focused on the effects of innovations on profits and wages, highlighting the differences between process and product innovations, with product innovations that increase wages at least of medium and high skilled, while process innovations tend to decrease or have no effects on them (by contrast, profits tend to increase with both kinds of innovations). Product innovations tend to have more effects, and in most cases positive, on employment than the process ones (Peters et al. 2014, Harrison et al. 2014).

Few studies following the evolutionary theory have analysed the effects of innovations on personal inequality, among them Antonelli and Gehringer (2017) in a study on 39 countries find that due to the creative destruction they cause, innovations reduce income inequality especially in countries where inequality is higher, but the most important variable is government spending. This negative relationship is also confirmed by Biurrun (2020), who in a study on 20 European countries finds that innovations (measured as R&D expenditure) and social protection reduce income inequality both between and within countries.

As the different theories have shown, the total effects of innovations on inequality are not clear and depend on the variables studied. In addition to the different measures of innovativeness and inequality and the different kinds of innovations (process or product), the existence of indirect effects makes the total effects of innovativeness even more complex to study. These indirect effects may be divided into interactions between innovations and compensation mechanisms. There are interactions for example when a product innovation in one sector (or firm) is used as a process innovation in another sector (or firm), in this case the innovation has different impacts in the different sectors (or firms). There are compensation mechanisms when the introduction of the innovation changes something in the market and this change reduces the negative impacts of the direct effects. These compensation mechanisms are decrease in prices (new technologies decrease production costs and this decreases prices), decrease in wages (technological unemployment decreases wages and increases labour demand and employment), new machines (workers change jobs from the sectors that introduce innovations to the sectors that produce them), new investments (extra profits caused by innovations are invested), increase in incomes (profits are shared between firms and workers increasing aggregate demand) and new products (if they are not a replacement there is an increase in variety and consumption) (Vivarelli 2014 Piva and Vivarelli 2017, Calvino and Virgillito 2017). Different studies have found that positive indirect effects on employment and wages at different levels more than counterbalance the negative direct effects (Gregory et al. 2016, Autor and Salomons 2017).

Innovations may also have effects on geographical inequality both within and between countries and regions. According to Florida (2005) the creative class, composed by innovative people and other creative people, such as artists, favours growth in cities. Innovations are, indeed, concentrated in cities and more specialized areas (Berkes and Gaetani 2018), because of externalities of urbanization (Jacobs 1969) and specialization (Marshall 1890), that are very important for innovators as tacit knowledge and face to face contact are more important than codified knowledge (Storper and Venables 2004).

This strand of literature (that we call geographic) is less theoretical and more empirical, and each study has found different results. Most studies find that innovations seem positively correlated with inequality in the US (Donegan and Lowe 2008, Florida and Mellander 2014, even if only with wage inequality) and in Canada (Bolton, Breau and Kogler 2014, but not when more covariates are added), but not in China (Liu and Lawell 2015, but in this case inequality is defined as the ratio between urban and rural income).

The relationship between innovations and inequality is less clear in Europe. Indeed, even if according to Lee (2011) and Lee and Rodriguez-Pose (2013) innovations increase wage inequality at the regional level and according to Permana et al. (2018) innovations increase income inequality at the country level, according to Benos and Tsiachtsiras (2019) innovations reduce income inequality at the country level and in Wlodarczyk (2017) and De Palo et al. (2018) the effects on income inequality depend on the specification used (and the former is at the country level while the latter at the regional level). Finally, according to Tummolo (2022) innovations in different sectors are not correlated with income inequality. As almost all these papers have used fixed effects, the results depend more on the different datasets, countries, levels and variables considered than on the methodology adopted.

To study the effects (or at least the associations) of innovations on inequality the geographical level is very important, as most innovations have local effects, innovations are concentrated in few areas and this concentration may lead to an increase in inequality. Few studies have analysed the effects of innovations on inequality in regions within a single country: Capparucci and Veraschagina (2017) using in a structural model EUROSTAT data on patents per million inhabitants for innovations and data from Acciari and Mocetti (2013) for regional inequality (the same we use in this paper, but with a forced aggregation as they were at the provincial level) find that in Italy both innovations reduce inequality and viceversa. Andreassen (2018), using in an OLS and in a fixed effects models Norwegian data on patents per million inhabitants and patents per economic regions for innovations and GINI, Bonferroni coefficient and C3 index for wage inequality, finds that in Norway innovations increase inequality especially between regions.

The limited number of studies and the specific characteristics of Italy and the Italian regions and provinces has led us to try to “fill this hole”. For this reason, this paper contributes to the literature by showing that the associations of innovations with total income inequality at the regional level and inequality of taxpayers at the provincial level are very different, and therefore innovations may have different effects at each level.

Data and descriptive statistics

We use various sources from different institutions for each variable or group of variables. For innovativeness we use the TechEvo database, keeping only the innovations made by inventors residing in Italy (a little more than 200 thousands of the 3 million total observations) between 1980 and 2016, with mean granted by EPO 0.56, mean granted by other authorities in other countries 0.23, mean share of an inventor in a patent 0.51 and mean share of a company in a patent 0.95 (on average 2 people from the same company contribute to each application). As the number of patents in the original dataset was repeated for each inventor, to compute the real number of patents we have multiplied it for the mean of the shares of the inventors in each region or province. Innovativeness is thus measured as this real number of patents per thousand residents in each geographical unity.

We use patents instead of R&D because patents are a measure of output, rather than input, so they explain successful innovations that may have an impact on the market. An alternative measure would have been citations of patents, but citations are more correlated with the age of the patents than with their quality and most citations are used to specify the limits of the patents rather than their importance. Patents, however, have their own limits: they measure product innovations, but rarely process innovations and not all innovations patented are commercialized. As a proxy of process innovations, we use gross fixed capital formation (GFCF) from the ARDECO database, but as data on GFCF are only at a regional level we use it only in the regional model.

For the socioeconomic variables we use data from the ARDECO database: employment, GDP, GVA and populations both at NUTS2 (regional) and NUTS3 (provincial) level, active population, compensation of employees, GFCF and hours worked only at NUTS2 level. In the model (and thus in the regressions) we don’t use active population and GVA, the first one because we use mean income for all the population and not only the active, the second one because it is collinear to GDP. We also combine some of these variables, but in the study of inequality of taxpayers as there are less variables available, the analysis is limited and we cannot consider, for example, the effects of wages.

After merging the two datasets by NUTS2 (or NUTS3) for each variable we have taken the mean by region (province) and by priority (the year in which patents are filed at the first institution) or filing (the year in which patents are filed at EPO) year to transform the dataset into a panel.

For the inequality variables we use two groups of data from three sources. For total inequality at the regional level, we use the quintile ratios from EUROSTAT and two GINIs of disposable income from ISTAT (with and without imputed rents), with mean quintile ratios 5.11, mean GINI with imputed rents 0.28 and mean GINI without imputed rents (the measure internationally used) 0.31.

For inequality of taxpayers at the provincial level, we use GINI and top 10% share of income (gross for self-employed and net for employees) with mean GINI 0.39 and mean top 10% 27.93 (data for top 10% are already in percentage).

For the education variables, we use EUROSTAT data on education of 25-64 years old, education of 30-34 years old, percentage of early leavers and the percentage of neets. For the employment variables, we use employment of 15-34 by level of education, the percentage of high tech and/or skilled and of scientists and engineers, employment rate by age and sex, weekly hours worked by age and sex and full time or part time employment rate. All these variables are at the regional level, so we can use them only for the analysis on total income inequality.

The final dataset for the regional data is composed by 336 observations, corresponding to 21 regions multiplied 16 years (2000-2015), for the regressions we consider the 2003-2015 (2004-2015 when using quintile ratios) period except for the three years of the lags of innovativeness. For the regressions that study the spatial effects we use two reduced regional datasets of 273 (when the inequality variable is GINI) and 252 observations (when the inequality variable are the quintile ratios), with only the few selected variables for which all data are available for the 2003-2015 period (2004-2015 for quintile ratios).

The final dataset for the provincial data is composed by 1650 observations, corresponding to 110 provinces multiplied 15 years (1997-2011). For the spatial analysis we use also in this case the reduced and balanced dataset of 1320 observations.

The summary of all variables, time periods and sources can be found for the regional dataset in table 1 and for the provincial dataset in table 2 (both in the appendix). The descriptive statistics can be found in table 3 and in table 4 for respectively the regional dataset and the provincial dataset, these statistics are from the datasets using priority years.

Table 3: descriptive statistics for the regional dataset				
Variables	Mean	S. deviation	Maximum	Minimum
GINI with imputed rents	0.276	0.025	0.356	0.225
GINI without imputed rents	0.309	0.025	0.396	0.256
80/20 ratio EUROSTAT	4.996	1.030	10.2	3.4
Innovativeness	0.060	0.053	0.254	0
Gross fixed capital formation	13.694	13.143	65.828	0.880
Mean granted	0.486	0.179	1	0
Mean triadic	0.132	0.120	0.75	0
Mean gratri	0.095	0.091	0.5	0
Mean filing-priority years	0.707	0.175	1	0
GDP/population	24.449	6.290	35.802	14.094
Employment/population	0.416	0.063	0.536	0.298
Yearly wages	22.377	2.414	27.227	17.380
Population density	0.174	0.107	0.429	0.036
Education 25-64 low female	46.507	8.596	64.8	27.6
Education 25-64 low male	47.949	7.601	65.3	31.2
Education 25-64 medium female	38.882	5.299	52.1	26.6
Education 25-64 medium male	39.958	5.564	52.8	27.7
Education 25-64 high female	14.615	4.104	25.7	6.3
Education 25-64 high male	12.092	2.559	20.8	6.3
Education 30-34 low female	30.403	10.191	55.7	11.5
Education 30-34 low male	37.937	9.313	60.8	17.8
Education 30-34 medium female	47.473	5.679	65	31.8
Education 30-34 medium male	47.305	6.649	64.2	30.4
Education 30-34 high female	22.376	7.393	44.1	8.2
Education 30-34 high male	15.001	3.951	26.5	7.1
Early leavers female	15.312	5.408	30.5	4.5
Early leavers male	21.664	6.872	42	8.1

Neet female 15-24	17.666	6.981	37.9	6.5
Neet male 15-24	16.492	7.661	35.7	4.6
Employment low skilled F 15-34	42.384	16.074	75.5	11.7
Employment low skilled M 15-34	72.747	15.432	97.7	29.7
Employment medium skilled F 15-34	61.937	17.185	89.5	25.2
Employment medium skilled M 15-34	78.851	13.458	100	43.7
Employment high skilled F 15-34	68.616	13.363	100	34.5
Employment high skilled M 15-34	77.287	12.132	100	45.7
Scientists and engineers	1.770	0.484	3.2	0.8
High skilled	10.832	2.806	19.5	4.7
High tech	14.739	3.069	20.5	8.4
Both high tech and skilled	6.131	1.454	10.3	2.8
Employment rate female 15-24	18.697	8.864	53.1	4.7
Employment rate female 25-34	56.487	16.635	77.7	21.1
Employment rate female 35-44	61.523	15.129	84.2	32.3
Employment rate female 45-54	56.265	13.558	82.8	30.1
Employment rate female 55-64	26.149	8.727	50.8	10.7
Employment rate male 15-24	27.650	9.796	60.1	10.6
Employment rate male 25-34	76.872	12.217	96.3	44.1
Employment rate male 35-44	88.671	7.579	98.6	63.4
Employment rate male 45-54	86.242	5.945	95	65.6
Employment rate male 55-64	47.118	7.328	66.8	29.1
Weekly hours worked female 15-24	34.068	2.803	41.8	28
Weekly hours worked male 15-24	38.734	1.713	43.8	33.7
Weekly hours worked female 25-64	33.541	1.263	36.7	30.4
Weekly hours worked male 25-64	41.111	0.910	43.4	38.2
Employment rate full time female	0.111	0.025	0.165	0.061
Employment rate full time male	0.216	0.026	0.276	0.146
Employment rate part time female	0.041	0.017	0.094	0.008
Employment rate part time male	0.012	0.004	0.024	0.004

Table 4: descriptive statistics for the provincial dataset				
Variables	Mean	S. deviation	Maximum	Minimum
GINI of taxpayers	0.392	0.026	0.461	0.336
Top 10% share of taxpayers	27.944	1.129	32.359	25.320
Innovativeness	0.062	0.063	0.491	0
Mean granted	0.539	0.206	1	0
Mean triadic	0.176	0.173	1	0
Mean gratri	0.128	0.140	1	0
Mean filing-priority years	0.704	0.230	1	0
GDP/population	23.033	6.124	46.957	11.540
Employment/population	0.400	0.065	0.601	0.253
Population density	0.252	0.359	2.622	0.031

Empirical framework

As shown in the section "related literature" innovations may have different relationships with inequality, positive for SBTC and RBTC theories, mostly negative for studies following the evolutionary theory, not defined for geographical studies. As studies from the different theories have so different results, as there are indirect effects to complicate the analysis and as Italy is a particular case for its historical characteristics as a country divided into the north and the south (Acciari and Mocetti 2013, Franzini et al. 2017, Capparucci and Veraschagina 2017), we don't start with a clear hypothesis on the sign of the effects of innovations on inequality.

The descriptive statistics by region, however, lead us to think about a negative relationship between these two variables, as inequality tends to be higher in the south, where innovativeness tends to be lower. The south has also a lower GDP per capita, a lower employment rate and lower wages than the north, and all these variables may be linked one to each other and have effects on inequality, or at least correlations with it.

As innovations should take time to spread and have effects (Antonelli and Gehringer 2017, Permana et al.2018), we use three lags (from one to three years) and expect the lags to be significant and have different correlations one to each other. In particular, as indirect effects should decrease inequality, higher lags should be more negatively correlated in the regressions than the first one. The choice of the number of lags may be considered a compromise between the precision and definition of the kind of effects (direct or indirect) that increase when higher lags are added, and the number of observations that instead decrease. Moreover, according to Permana et al. (2018) the effects are higher 2-3 years after the priority year, so we cannot limit our study and consider only the first lag, and at the same time increasing the number of lags to more than 3 years may be useless.

In this paper we use four models to study the effects of innovativeness on inequality, the first two use the Arellano-Bover/Blundell-Bond GMM system estimator, in particular the first one is the model with regional data that studies the effects on total income inequality, the second one is the model with provincial data that studies the effects on inequality of taxpayers. The third and fourth model, instead, study the spatial effects of innovations and other control variables on inequality in regions (model 3) and provinces (model 4) using the Dynamic Spatial Durbin Model with the spatial weight matrix computed using the inverse distance between centroids of regions and provinces. Even if to our knowledge we are the first to study this relationship using spatial models, there are some caveats in using these models, as only the dependent variables and their spatial lags can be time lagged, so all independent variables are contemporaneous.

Each model has its own pros and cons: the first model is more complete, as it uses more variables that cover various relationships, but regions are only 21 and there is a high heterogeneity within them. The second model is more disaggregated, and as innovations have local effects may capture better the relationship, but has also less variables, so innovativeness may seem to have effects only because other variables are correlated (and because of different levels they cannot be used as instrumental variables). The third and fourth model are even less complete as there are less variables and there are not lags of the independent variables, but they study the indirect effects of other regions or provinces.

In all models we first study the relationship between innovativeness and income inequality (total and of taxpayers) using the absolute values of all variables, then we study the same relationship using the logarithms for the independent variables GDP per capita and innovativeness. The regressions of the first two models are carried out using the Arellano-Bover/Blundell-Bond GMM system estimator. In regressions using the Dynamic Spatial Durbin Model (those of the third and fourth models), fixed effects that control for time-invariant regional or provincial characteristics and robust standard errors that control for heteroskedasticity are applied.

Model 1 is described in the formulas below:

1a) $ineq_{tr} = \beta_0 + \alpha_1 ineq_{t-1r} + \alpha_2 inn_{t-1r} + \alpha_3 inn_{t-2r} + \alpha_4 inn_{t-3r} + \alpha_5 \frac{pop}{area}_{t-1r} + \alpha_6 W_{t-1r} + \varepsilon$

1b) $ineq_{tr} = \beta_0 + \alpha_1 ineq_{t-1r} + \alpha_2 \log(1 + inn_{t-1r}) + \alpha_3 \log(1 + inn_{t-2r}) + \alpha_4 \log(1 + inn_{t-3r}) + \alpha_5 \frac{pop}{area}_{t-1r} + \alpha_6 W_{t-1r} + \varepsilon$

In these formulas β_0 is the intercept, ineq is inequality measured by either the GINI index (with or without imputed rents) or the quintile ratios, inn is innovativeness measured as the number of patents per capita for the previous 3 years, pop/area is the population density, W is a heterogeneous group of control variables: gdp per capita, employment rate, yearly wages, gross fixed capital formation, education variables (education of people 25-64 years old, education of people 30-34 years old, early leavers, neets), employment variables (employment by level of education of people 15-34 years old, employment of high tech and high skilled people, employment by age, hours worked and full time or part time), mean of patents granted by EPO, by other institutions and their product, mean of time between the priority and the filing year. Among the last four variables, the first three are included because the percentage of granted patents may be correlated with both innovativeness and inequality, while the fourth is included to analyse which year is more important between the priority and filing one) ε is the error term and the subscript $t-1r$ means that all variables are calculated for each previous year (time t) and region (r) As the time periods are different for each variable, we consider only the 2003-2015 period (2004-2015 for quintile ratios), but as we use also three lags for innovativeness and we have data for a longer time for it we use data for innovativeness from 2000 to 2015.

Model 2 is described in the formulas below:

2a) $ineq_{tp} = \beta_0 + \alpha_1 ineq_{t-1p} + \alpha_2 inn_{t-1p} + \alpha_3 inn_{t-2p} + \alpha_4 inn_{t-3p} + \alpha_5 \frac{pop}{area}_{t-1p} + \alpha_6 W_{t-1p} + \varepsilon$

2b) $ineq_{tp} = \beta_0 + \alpha_1 ineq_{t-1p} + \alpha_2 \log(1 + inn_{t-1p}) + \alpha_3 \log(1 + inn_{t-2p}) + \alpha_4 \log(1 + inn_{t-3p}) + \alpha_5 \frac{pop}{area}_{t-1p} + \alpha_6 W_{t-1p} + \varepsilon$

This model is similar to the regional one. Most independent variables, indeed, are the same of the regional model, but they are all at the NUTS3 (provincial level, hence the subscript p instead of r) and as for some variables there are no data at the provincial level some of them are not included. The dependent variables on inequality (ineq), instead, are different: GINI and top 10% share of taxpayers, the first one captures all the distribution, the second one only the upper tail. Another difference between the two models is the time period, that in this case is 2000-2011 for all variables instead of 2003-2015 or 2004-2015.

Model 3 is described in the formulas below:

3a) $ineq_{tr} = \beta_0 + \alpha_1 ineq_{t-1ri} + \alpha_2 inn_{tri} + \alpha_3 \frac{pop}{area}_{tri} + \alpha_4 W_{tri} + \gamma_1 ineq_{t-1rj} + \gamma_2 inn_{trj} + \gamma_3 \frac{pop}{area}_{trj} + \gamma_4 W_{trj} + \varepsilon$

3b) $ineq_{tr} = \beta_0 + \alpha_1 ineq_{t-1ri} + \alpha_2 \log(1 + inn_{tri}) + \alpha_3 \frac{pop}{area}_{tri} + \alpha_4 W_{tri} + \gamma_1 ineq_{t-1rj} + \gamma_2 inn_{trj} + \gamma_3 \frac{pop}{area}_{trj} + \gamma_4 W_{trj} + \varepsilon$

In this model the only lagged variables are the inequality ones, while the others are contemporaneous. In addition to the usual variables related to the region i for which inequality is regressed (their coefficients are denoted with α and their subscripts are tri), we regress also the variables related to other regions j that have effects on the region i (their coefficients are denoted with γ and their subscripts are trj). As to perform spatial regressions we need a balanced panel, and as the education variables, the employment variables and some other control variables have some missing values, the variables included in W are only gross fixed capital formation, gdp per capita, employment rate and yearly wages.

Model 4 is described in the formulas below:

4a) $ineq_{tp} = \beta_0 + \alpha_1 ineq_{t-1pi} + \alpha_2 inn_{tpi} + \alpha_3 \frac{pop}{area}_{tpi} + \alpha_4 W_{tpi} + \gamma_1 ineq_{t-1pj} + \gamma_2 inn_{tpj} + \gamma_3 \frac{pop}{area}_{tpj} + \gamma_4 W_{tpj} + \varepsilon$

4b) $ineq_{tp} = \beta_0 + \alpha_1 ineq_{t-1pi} + \alpha_2 \log(1 + inn)_{tpi} + \alpha_3 \frac{pop}{area}_{tpi} + \alpha_4 W_{tpi} + \gamma_1 ineq_{t-1pj} + \gamma_2 inn_{tpj} + \gamma_3 \frac{pop}{area}_{tpj} + \gamma_4 W_{tpj} + \varepsilon$

This model is the provincial version of model 3, but in this case the only variables in W are GDP per capita and employment rate (the other control variables are available only at the regional level).

Results

In this section we present the results of model 1 using priority years (years in which innovations are first filed at any institution) for innovativeness and using levels for innovativeness and GDP per capita: in tables from a1 to a6 we present the results of the model on total income inequality at the regional level, using as dependent variables respectively GINI without imputed rents (the measure most used at the international level), GINI with imputed rents and quintile ratios. Results using the logarithms for innovativeness and GDP per capita and results using filing years (years in which innovations are filed at EPO) for innovativeness are presented in the appendix in tables from a7 to a24.

In each group of 6 tables the dependent variables are respectively GINI without imputed rents in the first two, GINI with imputed in the third and fourth and quintile ratios in the last two. In odd tables control variables are the education ones, in even tables control variables are the employment ones.

In this section we also present in tables b1 (using priority years) and b2 (using filing years) all the results of the model on inequality of taxpayers at the provincial level (model 2), using as dependent variables GINI (in the first and third columns) and top 10 % share of taxpayers (in the second and fourth columns) and both absolute values (in the first two columns) and logarithms (in the third and fourth columns) for innovativeness and GDP per capita. We also present the results of the spatial models (3 and 4) in tables c1, c2, d1 and d2.

In the regional model 1 the use of different variables for inequality leads to somewhat different results: innovativeness is in almost all regressions negatively correlated with inequality but not statistically significant (and when significant the magnitude of the impact is quite small). As expected, population density is positively correlated with inequality, although not always statistically significant.

Other results are that GDP per capita is negatively correlated with inequality and the employment rate is negatively correlated, at least when the inequality variable used is the GINI (both with and without imputed rents), this is something surprising, as we should expect more employment leading to lower inequality. Almost other variables are not correlated with inequality, except for early leavers female and hours worked of young female and old male (positively) and yearly wages and the percentage of patents granted by institutions other than EPO (negatively and yearly wages not always significant). All variables lose significance when the inequality variable is the quintile ratio, this may be due either to a really not significant relationship between quintile ratios and all other variables or to a poor quality of the data (even if the original database is the official EUROSTAT one). All results are confirmed when we use logarithms of innovations and GDP and when we use the filing years instead of the priority ones.

Table a1: Regressions with dependent variable GINI without imputed rents using priority years					
Variables/models	1	2	3	4	5
First lag of GINI without imputed rents	0.216*** (0.066)	0.192*** (0.068)	0.245*** (0.072)	0.244*** (0.068)	0.251*** (0.067)
First lag of innovativeness (in absolute values)	-0.080 (0.063)	-0.081 (0.063)	-0.012 (0.068)	-0.125* (0.067)	-0.026 (0.066)
Second lag of innovativeness (in absolute values)	-0.080 (0.084)	-0.095 (0.086)	-0.104 (0.103)	-0.017 (0.102)	-0.156 (0.100)
Third lag of innovativeness (in absolute values)	-0.029 (0.083)	-0.049 (0.085)	-0.001 (0.095)	-0.097 (0.091)	0.023 (0.096)
Population density	0.122** (0.059)	0.121* (0.068)	0.058 (0.057)	0.080* (0.045)	0.082 (0.051)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
GDP/population (in absolute values)	-0.002 (0.002)	-0.002 (0.002)	-0.004** (0.002)	-0.002 (0.002)	-0.004** (0.002)
Employment/population	0.256 (0.163)	0.312* (0.168)	0.371** (0.169)	0.240 (0.174)	0.401** (0.170)
Yearly wages	-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.002 (0.002)	-0.003 (0.002)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Priority year	-0.000 (0.000)	0.001 (0.001)	-0.001* (0.001)	0.001* (0.001)	-0.000 (0.001)
Constant	0.647 (0.915)	-1.300 (3.457)	4.646 (3.192)	-1.749 (1.126)	0.943 (1.303)
Number of observations	251	247	233	218	229
Wald chi2	63.36	74.62	69.84	86.37	70.53
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a2: Regressions with dependent variable GINI without imputed rents using priority years					
Variables/models	1	2	3	4	5
First lag of GINI without imputed rents	0.281*** (0.070)	0.267*** (0.068)	0.280*** (0.071)	0.233*** (0.068)	0.241*** (0.069)
First lag of innovativeness (in absolute values)	-0.046 (0.069)	-0.031 (0.067)	-0.023 (0.075)	-0.001 (0.066)	-0.045 (0.068)
Second lag of innovativeness (in absolute values)	-0.155 (0.103)	-0.152 (0.101)	-0.059 (0.103)	-0.101 (0.096)	-0.087 (0.093)
Third lag of innovativeness (in absolute values)	0.067 (0.097)	0.104 (0.097)	0.042 (0.097)	-0.002 (0.093)	0.008 (0.090)
Population density	0.082 (0.056)	0.077 (0.060)	0.107* (0.058)	0.093* (0.054)	0.103* (0.053)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)	0.000 (0.000)
GDP/population (in absolute values)	-0.004** (0.002)	-0.003* (0.002)	-0.005** (0.002)	-0.004** (0.002)	-0.004** (0.002)
Employment/population	0.407* (0.211)	0.458*** (0.167)	0.536** (0.240)	0.343** (0.167)	0.469* (0.249)
Yearly wages	-0.003 (0.003)	-0.003 (0.002)	-0.001 (0.003)	-0.004* (0.002)	-0.003 (0.002)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Priority year	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Constant	1.438 (1.732)	1.750 (1.919)	-1.210 (2.666)	-2.560 (1.759)	-1.168 (2.040)
Number of observations	224	229	233	233	236
Wald chi2	78.02	74.46	65.34	74.06	72.75
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a3: Regressions with dependent variable GINI with imputed rents using priority years					
Variables/models	1	2	3	4	5

First lag of GINI with imputed rents	0.239*** (0.066)	0.190*** (0.067)	0.270*** (0.070)	0.291*** (0.070)	0.260*** (0.066)
First lag of innovativeness (in absolute values)	-0.123** (0.055)	-0.126** (0.055)	-0.042 (0.060)	-0.136** (0.059)	-0.040 (0.059)
Second lag of innovativeness (in absolute values)	-0.013 (0.075)	-0.023 (0.077)	-0.062 (0.092)	-0.007 (0.091)	-0.098 (0.091)
Third lag of innovativeness (in absolute values)	0.022 (0.074)	0.006 (0.075)	0.020 (0.084)	-0.050 (0.081)	0.053 (0.087)
Population density	0.147** (0.059)	0.159** (0.063)	0.077 (0.056)	0.075* (0.040)	0.083* (0.050)
Gross fixed capital formation	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
GDP/population (in absolute values)	-0.003* (0.001)	-0.003* (0.001)	-0.004** (0.002)	-0.001 (0.002)	-0.004** (0.002)
Employment/population	0.262* (0.150)	0.303** (0.154)	0.376** (0.156)	0.144 (0.156)	0.290* (0.163)
Yearly wages	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.005** (0.002)	-0.004** (0.002)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Priority year	-0.001 (0.000)	0.000 (0.001)	-0.001* (0.001)	0.001 (0.001)	-0.000 (0.001)
Constant	1.600* (0.855)	0.309 (3.226)	4.287 (2.883)	-1.001 (1.070)	1.197 (1.165)
Number of observations	251	247	233	218	229
Wald chi2	81.31	93.53	85.33	114.01	84.20
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a4: Regressions with dependent variable GINI with imputed rents using priority years

Variables/models	1	2	3	4	5
First lag of GINI with imputed rents	0.322*** (0.071)	0.283*** (0.069)	0.295*** (0.070)	0.252*** (0.068)	0.259*** (0.070)
First lag of innovativeness (in absolute values)	-0.056 (0.061)	-0.048 (0.060)	-0.019 (0.067)	-0.033 (0.059)	-0.059 (0.060)

Second lag of innovativeness (in absolute values)	-0.118 (0.091)	-0.096 (0.092)	-0.055 (0.092)	-0.071 (0.083)	-0.041 (0.083)
Third lag of innovativeness (in absolute values)	0.083 (0.085)	0.085 (0.087)	0.057 (0.086)	0.003 (0.083)	0.048 (0.081)
Population density	0.092* (0.053)	0.112* (0.061)	0.124** (0.059)	0.114** (0.052)	0.114** (0.053)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
GDP/population (in absolute values)	-0.004** (0.002)	-0.004** (0.002)	-0.004** (0.002)	-0.004** (0.002)	-0.004** (0.002)
Employment/population	0.320 (0.204)	0.438*** (0.156)	0.402* (0.226)	0.322** (0.155)	0.286 (0.227)
Yearly wages	-0.005* (0.002)	-0.003 (0.002)	-0.002 (0.002)	-0.004** (0.002)	-0.003 (0.002)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Priority year	-0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Constant	0.999 (1.623)	1.480 (1.811)	0.485 (2.364)	-2.449 (1.572)	-1.238 (1.828)
Number of observations	224	229	233	233	236
Wald chi2	101.48	80.93	80.40	90.89	89.08
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a5: Regressions with dependent variable quintile ratios using priority years

Variables/models	1	2	3	4	5
First lag of quintile ratios	0.458*** (0.078)	0.461*** (0.081)	0.453*** (0.082)	0.478*** (0.081)	0.433*** (0.084)
First lag of innovativeness (in absolute values)	-2.100 (2.505)	-1.939 (2.577)	-0.794 (2.703)	0.289 (2.869)	-1.124 (2.710)
Second lag of innovativeness (in absolute values)	-4.221 (3.428)	-3.719 (3.579)	-0.850 (4.207)	-4.850 (4.532)	-1.833 (4.239)
Third lag of innovativeness (in absolute values)	-1.721 (3.329)	-1.185 (3.625)	-5.636 (3.800)	-4.287 (4.142)	-7.014* (4.036)

Population density	1.634 (1.848)	1.432 (2.131)	1.823 (1.868)	1.956 (1.681)	1.675 (1.787)
Gross fixed capital formation	0.018 (0.017)	0.014 (0.019)	0.012 (0.017)	0.017 (0.018)	0.018 (0.018)
GDP/population (in absolute values)	0.013 (0.071)	0.014 (0.074)	-0.015 (0.076)	-0.006 (0.085)	0.015 (0.084)
Employment/population	-7.308 (6.884)	-7.197 (7.185)	-3.666 (7.088)	-4.952 (7.416)	-5.522 (7.747)
Yearly wages	0.067 (0.093)	0.073 (0.099)	0.048 (0.097)	0.031 (0.103)	0.039 (0.098)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Priority year	0.062*** (0.020)	0.070* (0.041)	0.083** (0.035)	0.066** (0.030)	0.052* (0.030)
Constant	-120.237*** (39.338)	-80.429 (146.505)	-121.134 (136.413)	-128.071** (60.663)	-100.660* (58.195)
Number of observations	231	229	216	202	214
Wald chi2	228.28	221.29	229.35	219.36	206.59
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a6: Regressions with dependent variable quintile ratios using priority years

Variables/models	1	2	3	4	5
First lag of quintile ratios	0.429*** (0.088)	0.451*** (0.082)	0.464*** (0.095)	0.455*** (0.089)	0.455*** (0.082)
First lag of innovativeness (in absolute values)	-1.584 (2.688)	-0.960 (2.782)	-2.709 (3.145)	-1.498 (2.803)	-2.194 (2.856)
Second lag of innovativeness (in absolute values)	-2.882 (4.087)	-2.144 (4.253)	-2.190 (4.429)	-2.285 (4.127)	-3.604 (3.922)
Third lag of innovativeness (in absolute values)	-6.370* (3.729)	-5.563 (3.908)	-7.385* (4.038)	-5.840 (3.869)	-6.635* (3.755)
Population density	0.501 (1.505)	1.503 (1.937)	1.648 (1.867)	1.180 (1.839)	2.398 (2.025)
Gross fixed capital formation	0.020 (0.017)	0.022 (0.017)	0.025 (0.019)	0.019 (0.017)	0.028 (0.017)

GDP/population (in absolute values)	-0.030 (0.079)	0.032 (0.083)	-0.037 (0.088)	-0.013 (0.080)	0.005 (0.019)
Employment/population	-0.204 (8.753)	-3.419 (7.284)	0.165 (11.478)	-4.715 (7.266)	-9.056 (10.974)
Yearly wages	0.057 (0.103)	0.037 (0.095)	0.065 (0.114)	0.039 (0.098)	-0.015 (0.103)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Priority year	0.023 (0.046)	0.067 (0.046)	0.037 (0.059)	0.052 (0.039)	0.011 (0.044)
Constant	-41.214 (91.940)	-130.448 (92.388)	-67.328 (120.137)	-98.850 (81.853)	-14.187 (87.954)
Number of observations	210	215	216	216	220
Wald chi2	253.88	223.21	213.85	214.00	227.58
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

In the regressions using the provincial level (model 2) we find different, and in some cases even opposite, results from the regressions at the regional level and even between the different dependent variables used: when the inequality variable used is the GINI, first and third lag of innovativeness (this one only when the year used is the filing one), population density, GDP per capita and the employment rate are all negatively and statistically significantly correlated with inequality (actually the only positive variables are the autocorrelation and the year), so the relationship is the same of the regional regressions for innovativeness and GDP per capita and the opposite for population density and the employment rate. The difficulty to interpret the results increases when the inequality variable is the top 10% share of income, even if in this case they are more in line with the theory: innovativeness is positively but not statistically correlated, population density is strongly and positively correlated with inequality, GDP per capita is positively correlated and the employment rate is negatively correlated. The magnitude of the effects, however, is not so high, as an increase of a standard deviation for population density increases inequality of less than half of a standard deviation and effects of other variables on inequality are lower.

There are several possible explanations for the differences between the results of the regional and provincial models: the first one is the different time period (2003-2015 for the regional data, 2000-2011 for the provincial data), the other differences may be explained by the different meaning of the dependent variables themselves, as GINI studies all the distribution, and top 10% (provincial) and quintile ratios (regional) only parts of it.

Table b1: Regressions at the provincial level using priority years				
Variables/models	1	2	3	4
Inequality variable used	Gini	Top 10%	Gini	Top 10%
Innovation and GDP/population variables used	Absolute values	Absolute values	Logarithms	Logarithms
First lag of inequality	0.394*** (0.032)	0.169*** (0.036)	0.383*** (0.032)	0.191*** (0.035)
First lag of innovativeness	-0.042*** (0.009)	0.647* (0.363)	-0.046*** (0.010)	0.787* (0.405)
Second lag of innovativeness	-0.012 (0.009)	0.394 (0.345)	-0.015 (0.009)	0.492 (0.386)
Third lag of innovativeness	-0.004 (0.009)	0.187 (0.369)	-0.004 (0.010)	0.266 (0.413)
Population density	-0.026*** (0.004)	1.168*** (0.136)	-0.025*** (0.004)	1.117*** (0.136)
GDP/population	-0.001*** (0.000)	0.035*** (0.010)	-0.019*** (0.007)	0.575** (0.246)
Employment/population	-0.051** (0.022)	-5.328*** (0.914)	-0.043** (0.022)	-4.468*** (0.920)
Priority year	0.000*** (0.000)	-0.006** (0.002)	0.000*** (0.000)	-0.007*** (0.002)
Constant	-0.405*** (0.115)	35.506*** (4.785)	-0.332*** (0.127)	35.750*** (5.154)
Number of observations	1167	1167	1167	1167
Wald chi2	1940.15	341.18	1966.22	331.23
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses				

Table b2: Regressions at the provincial level using filing years				
Variables/models	1	2	3	4
Inequality variable used	Gini	Top 10%	Gini	Top 10%
Innovation and GDP/population variables used	Absolute values	Absolute values	Logarithms	Logarithms

First lag of inequality	0.400*** (0.030)	0.135*** (0.037)	0.390*** (0.031)	0.162*** (0.036)
First lag of innovativeness	-0.023** (0.009)	-0.149 (0.362)	-0.027*** (0.010)	-0.026 (0.405)
Second lag of innovativeness	-0.007 (0.008)	-0.061 (0.328)	-0.008 (0.009)	-0.001 (0.368)
Third lag of innovativeness	-0.030*** (0.008)	0.579* (0.343)	-0.032*** (0.009)	0.689* (0.386)
Population density	-0.028*** (0.004)	1.324*** (0.138)	-0.027*** (0.004)	1.266*** (0.138)
GDP/population	-0.001*** (0.000)	0.044*** (0.010)	-0.019*** (0.007)	0.732*** (0.244)
Employment/population	-0.043** (0.021)	-5.474*** (0.906)	-0.037* (0.022)	-4.433*** (0.916)
Filing year	0.000*** (0.000)	-0.004* (0.002)	0.000*** (0.000)	-0.005** (0.002)
Constant	-0.570*** (0.115)	33.378*** (4.812)	-0.499*** (0.128)	33.428*** (5.199)
Number of observations	1164	1164	1164	1164
Wald chi2	1854.34	345.70	1876.21	331.64
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses				

In the Dynamic Spatial Durbin Model regional regressions most associations disappear, and the only significant variables are the employment rate and the yearly wages. Both variables are negatively correlated confirming that a better labour market and a higher labour share of income decrease inequality. The effects of the spatial variables differ depending on the inequality variable used: when GINI without imputed rents is used there are no spatial variables with significant correlation, but the spatial rho has a very high value, this means that in this case probably the Dynamic Spatial Autoregressive model (DSAR) would have been better. When GINI with imputed rents is used, instead, the spatial time lag of inequality, and the spatial lag of both innovativeness (negatively), population density (positively) and yearly wages (positively but only when using filing years) are correlated with inequality. Finally, when quintile ratios are used the employment rate is not correlated and the spatial rho is not different from zero, so probably the true model may not be a spatial one. However, as stated when commenting the first model, the lack of association of the independent variables with quintile ratios may be caused by problems regarding the quality of data.

Table c1: Spatial regressions at the regional level using priority years						
Variables/Models	1	2	3	4	5	6
Inequality variable used	Gini without imputed rents	Gini with imputed rents	Quintile ratios	Gini without imputed rents	Gini with imputed rents	Quintile ratios
Innovation and GDP/pop variables	Absolute	Absolute	Absolute	Logarithms	Logarithms	Logarithms
Time lag of the inequality variable	0.208*** (0.054)	0.259*** (0.054)	0.408*** (0.057)	0.208*** (0.055)	0.256*** (0.054)	0.412*** (0.055)
Spatial time lag of the inequality variable	790.808 (3309.325)	14140.35*** (5018.509)	-5947.827 (4975.206)	806.025 (3365.109)	13357.84*** (5058.290)	-5834.298 (5268.467)
Innovativeness	-0.009 (0.033)	-0.014 (0.032)	1.755 (1.283)	-0.008 (0.037)	-0.013 (0.036)	1.872 (1.487)
Population density	-0.008 (0.232)	0.096 (0.239)	14.953 (11.211)	-0.020 (0.253)	0.055 (0.205)	14.525 (9.812)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.000)	-0.011 (0.025)	0.000 (0.000)	0.000 (0.000)	-0.007 (0.023)
GDP/population	0.000 (0.002)	0.000 (0.001)	-0.011 (0.050)	-0.009 (0.042)	-0.008 (0.040)	-1.044 (1.476)
Employment/population	-0.404*** (0.144)	-0.444*** (0.142)	-9.737 (8.227)	-0.393*** (0.144)	-0.421*** (0.146)	-8.780 (9.355)
Yearly wages	-0.005*** (0.001)	-0.005*** (0.002)	-0.161** (0.072)	-0.005*** (0.001)	-0.004*** (0.001)	-0.144* (0.074)
Priority year	0.001 (0.001)	-0.000 (0.001)	0.042 (0.083)	0.001 (0.001)	-0.000 (0.001)	0.042 (0.079)
Spatial lag of innovativeness	-1397.050 (1439.002)	-4125.501*** (1281.062)	-211.364 (52535.80)	-1539.472 (1639.569)	-4365.552*** (1462.619)	6668.361 (60224.78)
Spatial lag of population density	16623.26 (18865.12)	51104.05** (21802.69)	2202094* (1229075)	15771.93 (19950.58)	46353.20** (21319.57)	2068063 (1218834)
Spatial lag of gross fixed capital formation	-0.614 (57.282)	52.352 (58.354)	499.581 (1911.913)	1.597 (54.312)	51.992 (55.344)	769.734 (1780.639)
Spatial lag of GDP/population	14.135 (55.256)	13.033 (56.495)	2522.429 (2871.715)	435.055 (1612.254)	178.175 (1564.884)	74567.27 (78764.81)
Spatial lag of employment/population	5455.055 (6294.597)	7355.028 (5996.211)	-207736.9 (208174.3)	5178.063 (6546.936)	7448.676 (6348.339)	-246217.8 (241185.0)

Spatial lag of yearly wages	87.680 (64.068)	108.359** (51.114)	-4153.621* (2500.258)	84.144 (68.289)	106.304* (55.863)	-4711.211* (2801.098)
Spatial lag of priority year	-23.411 (23.406)	-7.408 (21.853)	-2271.480 (1416.972)	-22.352 (24.876)	-6.038 (23.187)	-2072.859 (1377.823)
Spatial rho	5423.123*** (1451.099)	4431.880*** (1705.752)	1351.419 (1859.606)	5226.125*** (1436.479)	4280.545** (1724.695)	1350.947 (1839.641)
Number of observations	252	252	231	252	252	231
R squared (within)	0.1020	0.1255	0.3146	0.1029	0.1286	0.3153
Log pseudolikelihood	763.5719	786.0205	-140.0383	763.6296	786.5413	-139.9648
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses						

Table c2: Spatial regressions at the regional level using filing years

Variables/Models	1	2	3	4	5	6
Inequality variable used	Gini without imputed rents	Gini with imputed rents	Quintile ratios	Gini without imputed rents	Gini with imputed rents	Quintile ratios
Innovation and GDP/pop variables	Absolute	Absolute	Absolute	Logarithms	Logarithms	Logarithms
Time lag of the inequality variable	0.199*** (0.057)	0.211*** (0.058)	0.420*** (0.055)	0.200*** (0.059)	0.210*** (0.059)	0.427*** (0.053)
Spatial time lag of the inequality variable	269.012 (3017.240)	5417.190 (4233.094)	-4263.257 (4907.294)	157.213 (3008.245)	4926.621 (4171.983)	-3843.620 (5179.269)
Innovativeness	-0.036 (0.046)	-0.048 (0.040)	-0.304 (1.193)	-0.039 (0.051)	-0.051 (0.046)	-0.415 (1.459)
Population density	0.082 (0.309)	0.123 (0.251)	19.631 (12.862)	0.047 (0.283)	0.087 (0.227)	17.550 (11.090)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.000)	-0.002 (0.026)	0.000 (0.000)	0.000 (0.000)	0.003 (0.024)
GDP/population	0.000 (0.002)	0.000 (0.001)	0.001 (0.057)	-0.001 (0.042)	-0.006 (0.040)	-0.962 (1.624)
Employment/population	-0.425*** (0.138)	-0.397*** (0.131)	-11.177 (9.071)	-0.420*** (0.141)	-0.389*** (0.142)	-9.634 (10.311)
Yearly wages	-0.005*** (0.001)	-0.004*** (0.002)	-0.175** (0.078)	-0.005*** (0.001)	-0.004*** (0.002)	-0.151* (0.083)

Filing year	0.001 (0.001)	-0.001 (0.001)	0.056 (0.083)	0.001 (0.001)	-0.001 (0.001)	0.058 (0.079)
Spatial lag of innovativeness	-2211.162 (1735.232)	-3935.846*** (1324.878)	-45163.66 (51039.63)	-2227.970 (1956.660)	-3991.841*** (1520.214)	-36854.44 (55416.88)
Spatial lag of population density	29577.32 (20061.02)	45119.24** (21564.41)	3046714** (1405301)	27027.26 (21890.58)	40674.66* (22053.77)	2761127 (1378277)
Spatial lag of gross fixed capital formation	-4.799 (50.365)	-5.477 (47.299)	1059.252 (1859.502)	2.211 (49.033)	1.156 (44.537)	1381.133 (1765.013)
Spatial lag of GDP/population	41.381 (46.208)	60.106 (46.088)	2354.158 (2719.554)	1061.701 (1371.364)	1509.218 (1280.320)	58939.73 (73325.49)
Spatial lag of employment/population	3750.170 (6594.696)	4153.800 (6208.877)	-229132.8 (205100.5)	3252.645 (6843.786)	3519.055 (6460.860)	-236779.9 (233524.4)
Spatial lag of yearly wages	72.816 (60.656)	69.554 (48.125)	-3586.339 (2377.145)	63.897 (63.496)	59.711 (51.512)	-3882.417 (2518.895)
Spatial lag of filing year	-33.016 (23.481)	-16.807 (21.766)	-3242.699** (1494.751)	-30.617 (25.379)	-13.536 (24.301)	-2981.128** (1472.588)
Spatial rho	4743.916*** (1497.940)	3241.488* (1842.103)	2038.410 (1777.985)	4779.249*** (1486.283)	3289.001* (1838.561)	2115.190 (1789.179)
Number of observations	252	252	231	252	252	231
R squared (within)	0.1191	0.1443	0.3099	0.1183	0.1439	0.3094
Log pseudolikelihood	764.6027	789.1718	-140.5976	764.6022	789.2208	-140.6921
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses						

In the Dynamic Spatial Durbin Model provincial regressions, the only variables strongly correlated with inequality are its time lag and its spatial time lag, and the correlation of the spatial time lag is negative and thus different from the correlation that has at the regional level, this is probably due to people at the tails of the distribution moving between provinces within the same region. The employment rate is weakly correlated only when innovativeness and GDP per capita are calculated in absolute values. Correlations are quite different when filing years are used instead of the priority ones: the spatial lag of innovativeness is positively correlated with inequality and when the dependent variable is the GINI, the spatial lag of GDP per capita is negatively correlated with inequality.

Table d1: Spatial regressions at the provincial level using priority years				
Variables/Models	1	2	3	4
Inequality variable used	Gini	Top 10	Gini	Top 10
Innovation and GDP/pop variables	Absolute values	Absolute values	Logarithms	Logarithms
Time lag of the inequality variable	0.649*** (0.032)	0.671*** (0.045)	0.640*** (0.032)	0.672*** (0.044)
Spatial time lag of the inequality variable	-1501.101*** (110.120)	-1237.099*** (166.189)	-1512.881*** (111.507)	-1246.496*** (169.098)
Innovativeness	-0.006 (0.007)	0.008 (0.364)	-0.007 (0.008)	0.050 (0.406)
Population density	0.010 (0.010)	1.293* (0.747)	0.012 (0.010)	1.366* (0.744)
GDP/population	-0.000 (0.000)	0.014 (0.011)	-0.008 (0.005)	-0.031 (0.267)
Employment/population	-0.026** (0.013)	-1.286* (0.735)	-0.011 (0.014)	-0.540 (0.730)
Priority year	0.000 (0.000)	-0.015 (0.009)	0.000 (0.000)	-0.016* (0.009)
Spatial lag of innovativeness	52.099 (81.178)	4705.462 (4608.833)	60.859 (90.515)	5391.290 (5224.085)
Spatial lag of population density	-234.989 (211.978)	-1307.680 (11572.38)	-264.818 (211.231)	-2440.126 (11641.65)
Spatial lag of GDP/population	-0.958 (0.700)	32.921 (42.843)	-19.093 (19.145)	1450.830 (1141.265)
Spatial lag of employment/population	-25.471 (52.005)	-7673.106* (4239.131)	-35.763 (50.774)	-8783.773** (4457.381)
Spatial lag of priority year	-0.285 (0.599)	27.511 (33.668)	-0.160 (0.605)	30.120 (34.467)
Spatial rho	1956.983*** (37.878)	1853.075*** (51.665)	1945.722*** (40.737)	1857.734*** (51.490)
Number of observations	1210	1210	1210	1210
R squared (within)	0.4288	0.3844	0.4390	0.3778
Log pseudolikelihood	5416.3929	544.6317	5420.9502	542.9179
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses				

Table d2: Spatial regressions at the provincial level using filing years				
Variables/Models	1	2	3	4
Inequality variable used	Gini	Top 10	Gini	Top 10
Innovation and GDP/pop variables	Absolute values	Absolute values	Logarithms	Logarithms
Time lag of the inequality variable	0.636*** (0.033)	0.672*** (0.045)	0.626*** (0.033)	0.673*** (0.044)
Spatial time lag of the inequality variable	-1518.808*** (105.112)	-1326.941*** (135.553)	-1519.430*** (106.337)	-1338.106*** (137.863)
Innovativeness	-0.003 (0.008)	0.331 (0.417)	-0.002 (0.009)	0.461 (0.450)
Population density	0.011 (0.010)	1.409* (0.755)	0.013 (0.010)	1.494** (0.749)
GDP/population	0.000 (0.000)	0.014 (0.011)	-0.007 (0.005)	-0.022 (0.269)
Employment/population	-0.028** (0.013)	-1.291* (0.733)	-0.013 (0.014)	-0.568 (0.729)
Filing year	0.000 (0.000)	-0.016* (0.009)	0.000 (0.000)	-0.017* (0.009)
Spatial lag of innovativeness	273.953*** (91.852)	8042.956 (4900.685)	318.139*** (101.823)	9340.806* (5367.414)
Spatial lag of population density	-270.675 (222.492)	-2816.844 (11800.16)	-272.058 (222.876)	-3254.438 (11891.87)
Spatial lag of GDP/population	-2.967*** (1.030)	-23.683 (60.367)	-69.020** (26.697)	1.144 (1498.159)
Spatial lag of employment/population	-41.974 (53.448)	-6462.901 (3807.394)	-56.249 (52.242)	-7416.497* (4021.903)
Spatial lag of filing year	-0.701 (0.625)	19.802 (34.136)	-0.626 (0.636)	21.034 (34.778)
Spatial rho	1950.978*** (34.735)	1851.563*** (49.365)	1937.461*** (38.259)	1853.416*** (50.276)
Number of observations	1210	1210	1210	1210
R squared (within)	0.4236	0.3764	0.4448	0.3738
Log pseudolikelihood	5423.2411	546.5371	5428.8888	545.4721

Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses

To sum up correlations between independent variables and inequality change between the various specifications of the models, for this reason we can affirm that different aspects of inequality seem to be differently associated with each variable, creating confusion, and this is probably also one of the reasons why results not only differ in our study but also between the various studies examined in the introduction.

Conclusions

In this paper we have analysed the relationship between innovations and income inequality in the Italian regions between 2003 and 2015 and provinces between 2000 and 2011. We have employed four models: two (one regional and one provincial) using the Arellano-Bover/Blundell-Bond estimator, and two (one regional and one provincial) using the Dynamic Spatial Durbin Model.

We have found that innovations are in most cases not correlated with income inequality and inequality of taxpayers and there are no differences between the years of lag, so direct and indirect effects, if present, are similar.

Population density, our second variable of interest, tends to be positively correlated with inequality, but in most cases not statistically significant and in the provincial regressions of the second model the correlation with GINI is high and negative.

Our main finding is probably the high heterogeneity of results between and even within the same models, as only the autoregressive parameter maintains the same association with income inequality (and if it had been different, it would have been very strange), these differences may be due either to problems of data or to different relationship with the various kinds of inequalities. The first model, which is the most complete, shows that most employment and education variables are not correlated with inequality and don’t change the results. The spatial models confirm the presence of this heterogeneity also in the spatial lags of the variables.

This high heterogeneity and the low significance of the innovativeness variable make hard to predict which policies related to innovation are the best to decrease inequality, so we cannot advise anything in this regard, and this is probably the main limitation of our study. We can however suggest other policies (listed in detail in Franzini et al. 2017), and among them active labour policies and investments in infrastructures that increase employment of low skilled people, minimum wages, minimum incomes, and an increase in competition to limit rents are probably the most related to our study. As Lazio and the south are chronically more unequal and less innovative than the rest of Italy, it is very hard to radically change their characteristics, but we think it is not impossible and it could unite a historically, politically and economically divided country.

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Appendix

Table 1: summary of variables, time periods and sources of the regional dataset		
Variables	Original time periods	Sources
Innovation variables	1980-2016	TechEvo database
Socioeconomic variables	1980-2015	ARDECO database
Education variables	2000-2019	EUROSTAT
Employment variables	2000-2019	EUROSTAT
Area	2013	EUROSTAT
GINI with and without imputed rents	2003-2018	ISTAT
Quintile ratios	2004-2019	EUROSTAT
As each variable covers different time periods, we consider only the 2003-2015 period (2004-2015 for quintile ratios), except for innovativeness (at most 2000-2015 using three lags)		

Table 2: summary of variables, time periods and sources of the provincial dataset		
Variables	Original time periods	Sources
Innovation variables	1980-2016	TechEvo database
Socioeconomic variables	1980-2015	ARDECO database
Metropolitan area	2013	TechEvo
Area	2013	EUROSTAT
GINI and top 10% share of taxpayers	2000-2011	Acciari and Mocetti 2013
As each variable covers different time periods, we consider only the 2000-2011 period, except for innovativeness (1997-2011 using three lags)		

Table a7: Regressions with dependent variable GINI without imputed rents using priority years					
Variables/models	1	2	3	4	5
First lag of GINI without imputed rents	0.214*** (0.066)	0.188*** (0.068)	0.245*** (0.072)	0.245*** (0.068)	0.242*** (0.066)
First lag of innovativeness (in logarithms)	-0.099 (0.070)	-0.101 (0.070)	-0.023 (0.075)	-0.146** (0.074)	-0.039 (0.072)
Second lag of innovativeness (in logarithms)	-0.084 (0.092)	-0.104 (0.093)	-0.099 (0.113)	-0.010 (0.114)	-0.168 (0.110)
Third lag of innovativeness (in logarithms)	-0.028 (0.091)	-0.057 (0.093)	0.005 (0.105)	-0.109 (0.101)	0.039 (0.106)
Population density	0.141** (0.059)	0.132** (0.063)	0.085 (0.058)	0.091** (0.046)	0.108** (0.052)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
GDP/population (in logarithms)	-0.105** (0.050)	-0.107** (0.050)	-0.145** (0.057)	-0.094 (0.058)	-0.146*** (0.052)
Employment/population	0.414** (0.186)	0.463** (0.189)	0.535*** (0.197)	0.388* (0.202)	0.517*** (0.187)
Yearly wages	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Priority year	-0.000 (0.000)	0.001 (0.001)	-0.002** (0.001)	0.001 (0.001)	-0.001 (0.001)
Constant	1.310 (0.991)	-0.162 (3.461)	5.827* (3.213)	-0.964 (1.295)	1.726 (1.379)
Number of observations	251	247	233	218	229
Wald chi2	66.38	77.50	72.61	88.80	73.81
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a8: Regressions with dependent variable GINI without imputed rents using priority years					
Variables/models	1	2	3	4	5
First lag of GINI without imputed rents	0.279*** (0.069)	0.266*** (0.068)	0.279*** (0.071)	0.232*** (0.067)	0.235*** (0.069)

First lag of innovativeness (in logarithms)	-0.065 (0.077)	-0.045 (0.075)	-0.033 (0.084)	-0.008 (0.074)	-0.057 (0.075)
Second lag of innovativeness (in logarithms)	-0.162 (0.114)	-0.165 (0.112)	-0.066 (0.114)	-0.097 (0.107)	-0.081 (0.102)
Third lag of innovativeness (in logarithms)	0.089 (0.108)	0.134 (0.107)	0.058 (0.108)	0.005 (0.103)	0.024 (0.099)
Population density	0.100* (0.057)	0.092 (0.060)	0.125** (0.059)	0.118** (0.055)	0.133** (0.054)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)	0.000 (0.000)
GDP/population (logarithms)	-0.145** (0.058)	-0.125** (0.056)	-0.146** (0.062)	-0.135** (0.058)	-0.153*** (0.056)
Employment/population	0.520** (0.220)	0.581*** (0.190)	0.559** (0.241)	0.475** (0.202)	0.528** (0.243)
Yearly wages	-0.002 (0.003)	-0.002 (0.002)	-0.001 (0.003)	-0.003 (0.002)	-0.002 (0.002)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Priority year	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)
Constant	1.784 (1.778)	3.176 (2.008)	-0.338 (2.751)	-1.765 (1.852)	-0.251 (2.104)
Number of observations	224	229	233	233	236
Wald chi2	81.56	77.33	65.80	75.59	75.76
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a9: Regressions with dependent variable GINI with imputed rents using priority years

Variables/models	1	2	3	4	5
First lag of GINI with imputed rents	0.234*** (0.066)	0.184*** (0.067)	0.264*** (0.070)	0.290*** (0.070)	0.248*** (0.066)
First lag of innovativeness (in logarithms)	-0.144** (0.060)	-0.148** (0.060)	-0.054 (0.066)	-0.154** (0.066)	-0.051 (0.065)
Second lag of innovativeness (in logarithms)	-0.009 (0.081)	-0.023 (0.083)	-0.059 (0.101)	-0.006 (0.102)	-0.109 (0.100)

Third lag of innovativeness (in logarithms)	0.032 (0.081)	0.008 (0.083)	0.034 (0.093)	-0.051 (0.091)	0.070 (0.097)
Population density	0.170*** (0.060)	0.175*** (0.063)	0.111* (0.058)	0.085** (0.041)	0.114** (0.052)
Gross fixed capital formation	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
GDP/population (in logarithms)	-0.086** (0.043)	-0.088** (0.043)	-0.126** (0.050)	-0.054 (0.051)	-0.115** (0.048)
Employment/population	0.334* (0.171)	0.371** (0.174)	0.453** (0.180)	0.225 (0.184)	0.350* (0.180)
Yearly wages	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.004** (0.002)	-0.004* (0.002)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Priority year	-0.001* (0.000)	0.000 (0.001)	-0.002** (0.001)	0.000 (0.001)	-0.001 (0.001)
Constant	2.073** (0.912)	1.355 (3.224)	5.383* (2.891)	-0.570 (1.202)	1.729 (1.231)
Number of observations	251	247	233	218	229
Wald chi2	82.82	94.72	86.09	115.47	85.62
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a10: Regressions with dependent variable GINI with imputed rents using priority years					
Variables/models	1	2	3	4	5
First lag of GINI with imputed rents	0.315*** (0.071)	0.278*** (0.069)	0.289*** (0.070)	0.246*** (0.068)	0.246*** (0.070)
First lag of innovativeness (in logarithms)	-0.071 (0.068)	-0.061 (0.067)	-0.026 (0.075)	-0.042 (0.065)	-0.071 (0.067)
Second lag of innovativeness (in logarithms)	-0.126 (0.101)	-0.110 (0.101)	-0.066 (0.101)	-0.075 (0.095)	-0.033 (0.091)
Third lag of innovativeness (in logarithms)	0.103 (0.095)	0.118 (0.096)	0.071 (0.096)	0.012 (0.092)	0.067 (0.089)
Population density	0.112** (0.055)	0.132** (0.062)	0.145** (0.061)	0.145*** (0.054)	0.148*** (0.054)

Gross fixed capital formation	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
GDP/population (in logarithms)	-0.117** (0.052)	-0.114** (0.049)	-0.118** (0.054)	-0.111** (0.052)	-0.119** (0.048)
Employment/population	0.384* (0.212)	0.491*** (0.177)	0.403* (0.227)	0.387** (0.185)	0.306 (0.224)
Yearly wages	-0.004* (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.004* (0.002)	-0.003 (0.002)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Priority year	-0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Constant	1.155 (1.619)	2.748 (1.906)	1.166 (2.422)	-1.922 (1.648)	-0.709 (1.871)
Number of observations	224	229	233	233	236
Wald chi2	104.07	81.42	80.60	91.00	91.01
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a11: Regressions with dependent variable quintile ratios using priority years

Variables/models	1	2	3	4	5
First lag of quintile ratios	0.458*** (0.078)	0.461*** (0.081)	0.454*** (0.082)	0.476*** (0.081)	0.430*** (0.084)
First lag of innovativeness (in logarithms)	-2.266 (2.758)	-2.064 (2.842)	-0.536 (3.004)	0.653 (3.190)	-0.872 (3.011)
Second lag of innovativeness (in logarithms)	-4.792 (3.748)	-4.187 (3.913)	-0.975 (4.650)	-5.528 (5.036)	-2.161 (4.712)
Third lag of innovativeness (in logarithms)	-1.834 (3.600)	-1.124 (3.966)	-6.078 (4.170)	-4.822 (4.579)	-8.026* (4.445)
Population density	1.612 (1.863)	1.402 (2.139)	1.782 (1.879)	1.968 (1.689)	1.632 (1.798)
Gross fixed capital formation	0.019 (0.018)	0.014 (0.019)	0.012 (0.017)	0.017 (0.018)	0.018 (0.018)
GDP/population (in logarithms)	0.434 (2.138)	0.712 (2.232)	-0.119 (2.178)	-0.167 (2.318)	0.867 (2.270)

Employment/population	-7.593 (7.841)	-8.242 (8.151)	-4.487 (7.863)	-4.804 (8.099)	-6.926 (8.370)
Yearly wages	0.063 (0.102)	0.063 (0.107)	0.042 (0.105)	0.031 (0.107)	0.025 (0.106)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Priority year	0.063*** (0.021)	0.074* (0.043)	0.084** (0.036)	0.067** (0.031)	0.056* (0.031)
Constant	-122.958*** (43.259)	-88.215 (148.145)	-125.819 (138.555)	-129.494** (64.631)	-109.285* (61.516)
Number of observations	231	229	216	202	214
Wald chi2	228.24	221.42	229.19	219.96	207.11
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a12: Regressions with dependent variable quintile ratios using priority years					
Variables/models	1	2	3	4	5
First lag of quintile ratios	0.423*** (0.088)	0.450*** (0.082)	0.459*** (0.094)	0.455*** (0.089)	0.452*** (0.082)
First lag of innovativeness (in logarithms)	-1.409 (2.990)	-0.702 (3.104)	-2.664 (3.507)	-1.357 (3.117)	-2.242 (3.157)
Second lag of innovativeness (in logarithms)	-3.546 (4.529)	-2.470 (4.715)	-3.035 (4.867)	-2.698 (4.577)	-4.208 (4.313)
Third lag of innovativeness (in logarithms)	-7.122* (4.119)	-6.448 (4.296)	-8.283* (4.481)	-6.400 (4.255)	-7.413* (4.135)
Population density	0.569 (1.507)	1.489 (1.941)	1.711 (1.890)	1.105 (1.844)	2.482 (2.068)
Gross fixed capital formation	0.019 (0.017)	0.023 (0.017)	0.026 (0.019)	0.019 (0.017)	0.028 (0.017)
GDP/population (in logarithms)	-0.908 (2.197)	0.944 (2.332)	-0.388 (2.391)	0.201 (2.291)	-0.095 (2.259)
Employment/population	0.621 (9.393)	-3.860 (8.093)	1.521 (11.295)	-6.250 (8.208)	-8.467 (10.685)
Yearly wages	0.060 (0.106)	0.029 (0.103)	0.049 (0.117)	0.027 (0.106)	-0.008 (0.108)

Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Priority year	0.024 (0.046)	0.071 (0.047)	0.039 (0.060)	0.055 (0.039)	0.010 (0.044)
Constant	-42.061 (93.751)	-140.748 (95.329)	-71.063 (122.032)	-105.010 (83.599)	-12.516 (89.687)
Number of observations	210	215	216	216	220
Wald chi2	255.72	223.65	214.56	214.22	228.34
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a13: Regressions with dependent variable GINI without imputed rents using filing years

Variables/models	1	2	3	4	5
First lag of GINI without imputed rents	0.215*** (0.070)	0.211*** (0.072)	0.225*** (0.073)	0.281*** (0.073)	0.237*** (0.070)
First lag of innovativeness (in absolute values)	-0.079 (0.076)	-0.061 (0.079)	-0.076 (0.090)	-0.102 (0.084)	-0.116 (0.085)
Second lag of innovativeness (in absolute values)	-0.161** (0.079)	-0.181** (0.080)	-0.093 (0.105)	-0.066 (0.110)	-0.084 (0.105)
Third lag of innovativeness (in absolute values)	0.139 (0.086)	0.134 (0.089)	0.043 (0.106)	-0.003 (0.103)	0.020 (0.101)
Population density	0.122** (0.057)	0.133** (0.063)	0.066 (0.057)	0.076* (0.046)	0.090* (0.051)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
GDP/population (in absolute values)	-0.002 (0.002)	-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.004** (0.002)
Employment/population	0.241 (0.160)	0.307* (0.167)	0.342** (0.174)	0.297* (0.177)	0.427** (0.171)
Yearly wages	-0.003 (0.002)	-0.004** (0.002)	-0.004* (0.002)	-0.001 (0.002)	-0.003 (0.002)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Filing year	-0.000 (0.000)	0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.000 (0.001)

Constant	0.923 (0.874)	0.581 (3.541)	4.916 (3.310)	0.053 (1.209)	0.900 (1.288)
Number of observations	252	248	233	219	230
Wald chi2	69.36	76.39	65.89	78.38	66.18
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a14: Regressions with dependent variable GINI without imputed rents using filing years					
Variables/models	1	2	3	4	5
First lag of GINI without imputed rents	0.271*** (0.073)	0.228*** (0.070)	0.263*** (0.075)	0.221*** (0.070)	0.232*** (0.071)
First lag of innovativeness (in absolute values)	-0.141 (0.090)	-0.137 (0.088)	-0.084 (0.090)	-0.078 (0.086)	-0.080 (0.085)
Second lag of innovativeness (in absolute values)	0.013 (0.112)	-0.000 (0.109)	-0.045 (0.108)	-0.034 (0.105)	-0.038 (0.096)
Third lag of innovativeness (in absolute values)	-0.084 (0.109)	-0.026 (0.108)	0.027 (0.107)	-0.037 (0.105)	-0.033 (0.100)
Population density	0.072 (0.056)	0.068 (0.061)	0.111* (0.058)	0.094* (0.054)	0.103* (0.053)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)	0.000 (0.000)
GDP/population (in absolute values)	-0.004** (0.002)	-0.003 (0.002)	-0.005** (0.002)	-0.004* (0.002)	-0.004* (0.002)
Employment/population	0.451** (0.213)	0.429** (0.169)	0.531** (0.241)	0.335** (0.165)	0.429* (0.252)
Yearly wages	-0.002 (0.003)	-0.003 (0.002)	-0.001 (0.003)	-0.004* (0.002)	-0.003 (0.002)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Filing year	-0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Constant	1.711 (1.806)	0.837 (1.948)	-1.055 (2.634)	-2.615 (1.898)	-1.582 (2.028)
Number of observations	224	229	233	233	236
Wald chi2	76.36	68.60	63.91	70.13	69.71
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a15: Regressions with dependent variable GINI with imputed rents using filing years					
Variables/models	1	2	3	4	5
First lag of GINI with imputed rents	0.252*** (0.073)	0.230*** (0.074)	0.273*** (0.075)	0.307*** (0.074)	0.279*** (0.074)
First lag of innovativeness (in absolute values)	-0.061 (0.067)	-0.050 (0.069)	-0.064 (0.081)	-0.112 (0.075)	-0.069 (0.077)
Second lag of innovativeness (in absolute values)	-0.096 (0.071)	-0.114 (0.072)	-0.085 (0.096)	-0.071 (0.099)	-0.069 (0.098)
Third lag of innovativeness (in absolute values)	0.103 (0.078)	0.103 (0.080)	0.045 (0.096)	0.030 (0.094)	0.032 (0.094)
Population density	0.139** (0.059)	0.160** (0.064)	0.087 (0.057)	0.073* (0.042)	0.097* (0.052)
Gross fixed capital formation	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
GDP/population (in absolute values)	-0.003* (0.001)	-0.003* (0.001)	-0.004** (0.002)	-0.003 (0.002)	-0.004** (0.002)
Employment/population	0.283* (0.150)	0.346** (0.156)	0.419** (0.165)	0.231 (0.161)	0.415** (0.169)
Yearly wages	-0.004* (0.002)	-0.004** (0.002)	-0.004* (0.002)	-0.002 (0.002)	-0.004** (0.002)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Filing year	-0.001* (0.000)	0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Constant	1.786** (0.829)	1.216 (3.367)	4.248 (3.067)	0.719 (1.152)	1.161 (1.187)
Number of observations	252	248	233	219	230
Wald chi2	81.07	89.75	80.78	95.16	75.28
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a16: Regressions with dependent variable GINI with imputed rents using filing years					
Variables/models	1	2	3	4	5

First lag of GINI with imputed rents	0.337*** (0.077)	0.290*** (0.074)	0.305*** (0.078)	0.279*** (0.075)	0.282*** (0.075)
First lag of innovativeness (in absolute values)	-0.102 (0.080)	-0.079 (0.080)	-0.058 (0.080)	-0.068 (0.078)	-0.043 (0.077)
Second lag of innovativeness (in absolute values)	-0.020 (0.103)	-0.033 (0.101)	-0.050 (0.099)	-0.040 (0.096)	-0.019 (0.089)
Third lag of innovativeness (in absolute values)	-0.033 (0.099)	-0.011 (0.100)	0.030 (0.097)	-0.045 (0.097)	0.039 (0.092)
Population density	0.082 (0.054)	0.113* (0.064)	0.135** (0.061)	0.112** (0.054)	0.112** (0.054)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
GDP/population (in absolute values)	-0.004** (0.002)	-0.004** (0.002)	-0.005** (0.002)	-0.004** (0.002)	-0.004** (0.002)
Employment/population	0.428** (0.212)	0.493*** (0.163)	0.495** (0.233)	0.391** (0.158)	0.323 (0.237)
Yearly wages	-0.004* (0.002)	-0.004* (0.002)	-0.002 (0.003)	-0.004** (0.002)	-0.003 (0.002)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Filing year	-0.001 (0.001)	0.000 (0.001)	-0.000 (0.001)	0.001* (0.001)	0.001 (0.001)
Constant	1.237 (1.668)	-0.060 (1.903)	0.175 (2.383)	-2.858 (1.745)	-2.163 (1.838)
Number of observations	224	229	233	233	236
Wald chi2	92.79	72.63	77.36	83.03	82.64
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a17: Regressions with dependent variable quintile ratios using filing years					
Variables/models	1	2	3	4	5
First lag of quintile ratios	0.508*** (0.078)	0.520*** (0.083)	0.512*** (0.086)	0.527*** (0.084)	0.498*** (0.085)
First lag of innovativeness (in absolute values)	-1.643 (3.093)	-1.097 (3.311)	1.344 (3.682)	-1.716 (3.644)	-0.056 (3.667)

Second lag of innovativeness (in absolute values)	-1.790 (3.337)	-1.398 (3.493)	-4.761 (4.253)	-4.599 (4.681)	-5.758 (4.478)
Third lag of innovativeness (in absolute values)	-3.027 (3.529)	-2.540 (3.741)	-0.174 (4.522)	0.408 (4.697)	0.714 (4.507)
Population density	1.552 (1.862)	1.344 (2.157)	1.484 (1.915)	1.057 (1.711)	1.365 (1.823)
Gross fixed capital formation	0.019 (0.017)	0.013 (0.019)	0.011 (0.017)	0.014 (0.018)	0.012 (0.018)
GDP/population (in absolute values)	-0.016 (0.069)	-0.011 (0.072)	-0.040 (0.078)	0.001 (0.087)	0.006 (0.084)
Employment/population	-6.375 (6.604)	-6.712 (6.913)	-3.791 (7.201)	-7.208 (7.420)	-5.214 (7.636)
Yearly wages	0.148* (0.087)	0.161* (0.093)	0.134 (0.092)	0.064 (0.101)	0.127 (0.093)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Filing year	0.062*** (0.020)	0.062 (0.044)	0.073** (0.036)	0.058* (0.030)	0.031 (0.030)
Constant	-121.827*** (39.611)	-62.146 (152.783)	-115.274 (140.220)	-113.166* (60.004)	-60.316 (58.934)
Number of observations	231	229	216	202	214
Wald chi2	227.29	219.30	217.54	207.98	194.83
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a18: Regressions with dependent variable quintile ratios using filing years

Variables/models	1	2	3	4	5
First lag of quintile ratios	0.435*** (0.086)	0.518*** (0.085)	0.515*** (0.097)	0.502*** (0.091)	0.499*** (0.083)
First lag of innovativeness (in absolute values)	-0.897 (3.412)	-0.383 (3.677)	-0.648 (3.814)	-0.037 (3.631)	-1.435 (3.530)
Second lag of innovativeness (in absolute values)	-5.756 (4.214)	-4.853 (4.579)	-4.976 (4.523)	-4.645 (4.454)	-2.134 (4.054)
Third lag of innovativeness (in absolute values)	-0.028 (4.250)	0.815 (4.600)	-0.800 (4.768)	-0.662 (4.592)	-3.703 (4.300)

Population density	-0.258 (1.495)	1.426 (1.992)	1.156 (1.924)	1.081 (1.865)	2.468 (2.072)
Gross fixed capital formation	0.022 (0.016)	0.016 (0.017)	0.021 (0.019)	0.015 (0.017)	0.022 (0.018)
GDP/population (in absolute values)	-0.066 (0.076)	0.023 (0.084)	-0.054 (0.088)	-0.040 (0.080)	-0.033 (0.080)
Employment/population	1.557 (8.646)	-3.360 (7.282)	0.790 (11.601)	-4.209 (7.092)	-8.666 (10.865)
Yearly wages	0.115 (0.099)	0.136 (0.090)	0.128 (0.115)	0.097 (0.097)	0.099 (0.101)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Filing year	0.005 (0.045)	0.066 (0.047)	0.048 (0.059)	0.057 (0.043)	0.014 (0.043)
Constant	-5.799 (90.242)	-130.817 (93.682)	-91.736 (119.449)	-110.872 (90.711)	-22.644 (87.280)
Number of observations	210	215	216	216	220
Wald chi2	258.49	209.33	203.64	203.88	210.14
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a19: Regressions with dependent variable GINI without imputed rents using filing years

Variables/models	1	2	3	4	5
First lag of GINI without imputed rents	0.217*** (0.070)	0.212*** (0.072)	0.227*** (0.073)	0.280*** (0.072)	0.228*** (0.069)
First lag of innovativeness (in logarithms)	-0.085 (0.085)	-0.064 (0.089)	-0.078 (0.102)	-0.110 (0.096)	-0.132 (0.096)
Second lag of innovativeness (in logarithms)	-0.169** (0.085)	-0.194** (0.087)	-0.092 (0.115)	-0.074 (0.121)	-0.090 (0.116)
Third lag of innovativeness (in logarithms)	0.147 (0.093)	0.136 (0.097)	0.048 (0.115)	-0.003 (0.112)	0.033 (0.110)
Population density	0.140** (0.058)	0.144** (0.063)	0.092 (0.059)	0.087* (0.047)	0.114** (0.053)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)

GDP/population (in logarithms)	-0.093* (0.048)	-0.094* (0.048)	-0.129** (0.057)	-0.121 (0.059)	-0.132** (0.052)
Employment/population	0.395** (0.182)	0.445** (0.187)	0.502** (0.200)	0.440** (0.201)	0.515*** (0.186)
Yearly wages	-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.000 (0.002)	-0.002 (0.002)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Filing year	-0.001 (0.000)	0.000 (0.001)	-0.002* (0.001)	-0.000 (0.001)	-0.001 (0.001)
Constant	1.541 (0.954)	1.648 (3.563)	6.038* (3.328)	1.041 (1.394)	1.474 (1.351)
Number of observations	252	248	233	219	230
Wald chi2	72.05	78.68	68.69	81.24	68.74
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a20: Regressions with dependent variable GINI without imputed rents using filing years

Variables/models	1	2	3	4	5
First lag of GINI without imputed rents	0.267*** (0.072)	0.228*** (0.070)	0.261*** (0.075)	0.220*** (0.070)	0.229*** (0.071)
First lag of innovativeness (in logarithms)	-0.163 (0.102)	-0.155 (0.100)	-0.103 (0.101)	-0.084 (0.098)	-0.079 (0.096)
Second lag of innovativeness (in logarithms)	0.020 (0.123)	0.009 (0.120)	-0.051 (0.119)	-0.033 (0.115)	-0.029 (0.105)
Third lag of innovativeness (in logarithms)	-0.081 (0.118)	-0.022 (0.118)	0.043 (0.117)	-0.028 (0.115)	-0.035 (0.109)
Population density	0.087 (0.057)	0.081 (0.062)	0.127** (0.059)	0.118** (0.055)	0.128** (0.054)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)	0.000 (0.000)
GDP/population (in logarithms)	-0.131** (0.056)	-0.106* (0.056)	-0.132** (0.061)	-0.122** (0.057)	-0.133** (0.057)
Employment/population	0.511** (0.220)	0.527*** (0.192)	0.529** (0.240)	0.441** (0.195)	0.471* (0.245)

Yearly wages	-0.002 (0.003)	-0.002 (0.002)	-0.001 (0.003)	-0.003 (0.002)	-0.002 (0.002)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Filing year	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Constant	1.776 (1.800)	2.038 (2.059)	-0.300 (2.739)	-1.927 (1.992)	-0.870 (2.092)
Number of observations	224	229	233	233	236
Wald chi2	78.70	70.57	63.98	71.51	72.00
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a21: Regressions with dependent variable GINI with imputed rents using filing years

Variables/models	1	2	3	4	5
First lag of GINI with imputed rents	0.250*** (0.073)	0.227*** (0.074)	0.268*** (0.075)	0.301*** (0.074)	0.265*** (0.073)
First lag of innovativeness (in logarithms)	-0.066 (0.075)	-0.054 (0.077)	-0.074 (0.091)	-0.126 (0.086)	-0.083 (0.087)
Second lag of innovativeness (in logarithms)	-0.096 (0.077)	-0.120 (0.078)	-0.088 (0.105)	-0.080 (0.109)	-0.078 (0.108)
Third lag of innovativeness (in logarithms)	0.112 (0.085)	0.106 (0.088)	0.061 (0.104)	0.035 (0.102)	0.046 (0.102)
Population density	0.161*** (0.060)	0.173*** (0.064)	0.118** (0.060)	0.087** (0.043)	0.126** (0.053)
Gross fixed capital formation	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
GDP/population (in logarithms)	-0.082* (0.043)	-0.083* (0.043)	-0.116** (0.052)	-0.094* (0.052)	-0.117** (0.049)
Employment/population	0.351** (0.171)	0.400** (0.175)	0.483** (0.188)	0.322* (0.185)	0.454** (0.186)
Yearly wages	-0.003 (0.002)	-0.003* (0.002)	-0.003 (0.002)	-0.002 (0.002)	-0.004* (0.002)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet

Filing year	-0.001** (0.000)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Constant	2.293** (0.892)	2.233 (3.379)	5.340 (3.067)	1.407 (1.300)	1.555 (1.242)
Number of observations	252	248	233	219	230
Wald chi2	82.07	90.30	81.43	96.91	76.05
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a22: Regressions with dependent variable GINI with imputed rents using filing years

Variables/models	1	2	3	4	5
First lag of GINI with imputed rents	0.330*** (0.076)	0.284*** (0.074)	0.297*** (0.078)	0.273*** (0.074)	0.272*** (0.075)
First lag of innovativeness (in logarithms)	-0.119 (0.091)	-0.097 (0.090)	-0.075 (0.091)	-0.082 (0.088)	-0.039 (0.087)
Second lag of innovativeness (in logarithms)	-0.019 (0.113)	-0.029 (0.111)	-0.059 (0.108)	-0.045 (0.106)	-0.008 (0.097)
Third lag of innovativeness (in logarithms)	-0.028 (0.107)	0.004 (0.109)	0.044 (0.106)	-0.037 (0.106)	-0.042 (0.100)
Population density	0.098* (0.057)	0.130** (0.065)	0.155** (0.063)	0.142** (0.056)	0.144** (0.056)
Gross fixed capital formation	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
GDP/population (in logarithms)	-0.113** (0.052)	-0.113** (0.051)	-0.126** (0.055)	-0.108** (0.052)	-0.112** (0.051)
Employment/population	0.449** (0.220)	0.521*** (0.184)	0.475** (0.233)	0.435** (0.186)	0.320 (0.233)
Yearly wages	-0.004* (0.002)	-0.003 (0.002)	-0.002 (0.003)	-0.004* (0.002)	-0.003 (0.002)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Filing year	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Constant	1.152 (1.664)	1.138 (2.008)	0.841 (2.457)	-2.442 (1.819)	-1.857 (1.880)
Number of observations	224	229	233	233	236

Wald chi2	94.02	72.06	77.12	82.87	83.76
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

Table a23: Regressions with dependent variable quintile ratios using filing years					
Variables/models	1	2	3	4	5
First lag of quintile ratios	0.506*** (0.078)	0.519*** (0.083)	0.512*** (0.086)	0.526*** (0.084)	0.496*** (0.086)
First lag of innovativeness (in logarithms)	-1.808 (3.467)	-1.272 (3.700)	1.685 (4.173)	-1.816 (4.144)	0.096 (4.187)
Second lag of innovativeness (in logarithms)	-2.006 (3.629)	-1.554 (3.824)	-5.407 (4.688)	-5.189 (5.178)	-6.582 (4.947)
Third lag of innovativeness (in logarithms)	-3.162 (3.834)	-2.670 (4.078)	0.114 (4.924)	0.488 (5.101)	0.765 (4.907)
Population density	1.602 (1.874)	1.338 (2.167)	1.521 (1.924)	1.112 (1.718)	1.412 (1.832)
Gross fixed capital formation	0.019 (0.018)	0.013 (0.019)	0.010 (0.018)	0.013 (0.018)	0.011 (0.018)
GDP/population (in logarithms)	-0.362 (2.035)	0.050 (2.139)	-1.055 (2.187)	-0.358 (2.321)	0.097 (2.243)
Employment/population	-6.448 (7.424)	-7.643 (7.761)	-3.595 (7.844)	-5.997 (7.980)	-4.881 (8.105)
Yearly wages	0.149 (0.093)	0.156 (0.098)	0.141 (0.098)	0.075 (0.105)	0.131 (0.099)
Education variables used	None	Education 25-64	Education 30-34	Early leavers	Neet
Filing year	0.062*** (0.021)	0.063 (0.045)	0.071* (0.037)	0.056* (0.031)	0.030 (0.031)
Constant	-120.710*** (43.318)	-63.448 (155.010)	-111.401 (142.003)	-109.240* (64.343)	-59.949 (61.799)
Number of observations	231	229	216	202	214
Wald chi2	227.71	219.43	217.82	208.48	195.43
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

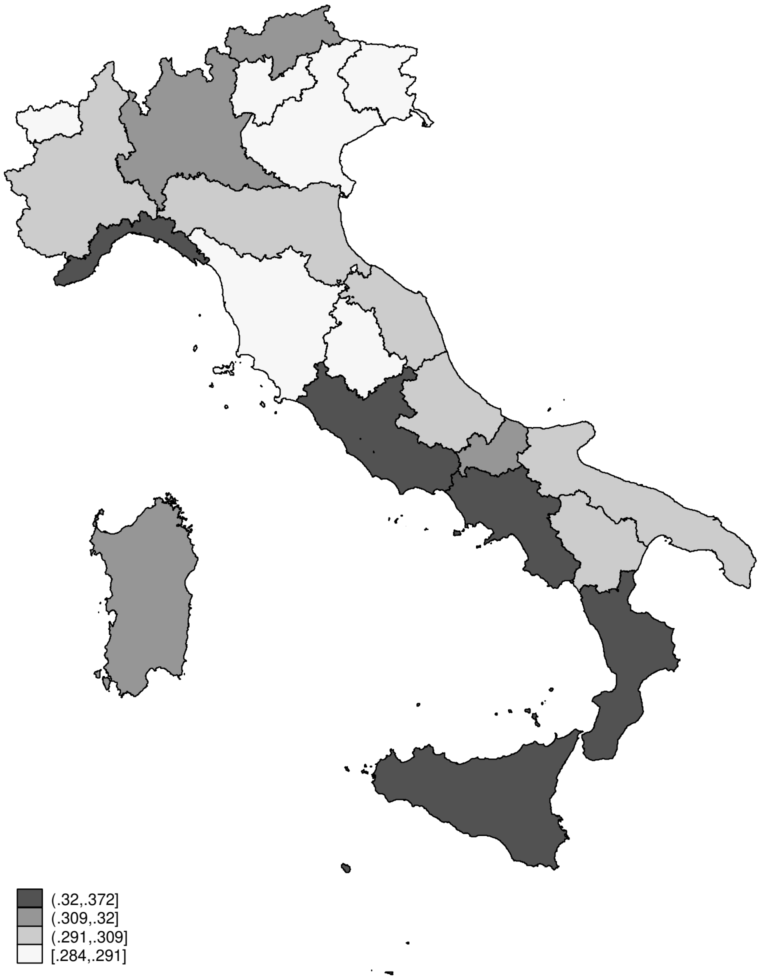
Table a24: Regressions with dependent variable quintile ratios using filing years

Variables/models	1	2	3	4	5
First lag of quintile ratios	0.427*** (0.087)	0.516*** (0.085)	0.512*** (0.097)	0.501*** (0.091)	0.495*** (0.083)
First lag of innovativeness (in logarithms)	-0.801 (3.875)	-0.362 (4.187)	-0.866 (4.302)	0.091 (4.128)	-1.573 (3.972)
Second lag of innovativeness (in logarithms)	-6.765 (4.645)	-5.562 (5.079)	-6.025 (4.987)	-5.448 (4.928)	-2.461 (4.445)
Third lag of innovativeness (in logarithms)	0.379 (4.622)	0.781 (5.041)	-0.636 (5.229)	-0.368 (5.007)	-3.975 (4.680)
Population density	-0.201 (1.496)	1.457 (1.996)	1.242 (1.948)	1.108 (1.867)	2.657 (2.119)
Gross fixed capital formation	0.019 (0.016)	0.016 (0.017)	0.020 (0.019)	0.014 (0.017)	0.021 (0.018)
GDP/population (in logarithms)	-2.340 (2.056)	0.514 (2.344)	-1.182 (2.368)	-1.047 (2.231)	-1.011 (2.245)
Employment/population	4.186 (9.123)	-3.143 (7.974)	0.063 (11.350)	-3.892 (7.842)	-8.828 (10.507)
Yearly wages	0.134 (0.100)	0.137 (0.097)	0.123 (0.116)	0.102 (0.103)	0.107 (0.104)
Employment variables used	Employment by education	High tech or skilled	Employment by age	Hours worked	Full time or part time
Filing year	0.001 (0.045)	0.067 (0.048)	0.047 (0.060)	0.056 (0.043)	0.014 (0.043)
Constant	5.780 (91.963)	-134.256 (96.007)	-87.716 (121.765)	-107.930 (92.418)	-21.048 (88.419)
Number of observations	210	215	216	216	220
Wald chi2	261.02	209.83	204.14	204.33	210.81
Notes: *** indicates p<0.01, ** indicates 0.01<p<0.05, * indicates 0.05<p<0.1, standard errors in parentheses					

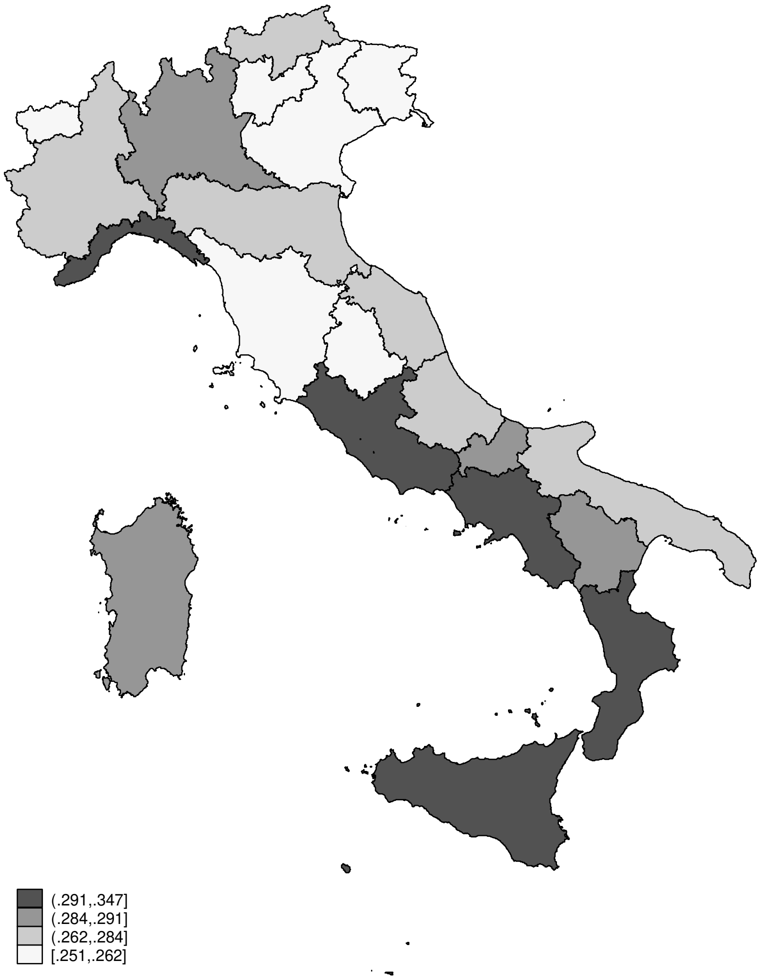
Innovativeness (patents per capita) by Italian region in 2004

Innovativeness (patents per capita) by Italian region in 2015

GINI without imputed rents by Italian region in 2004

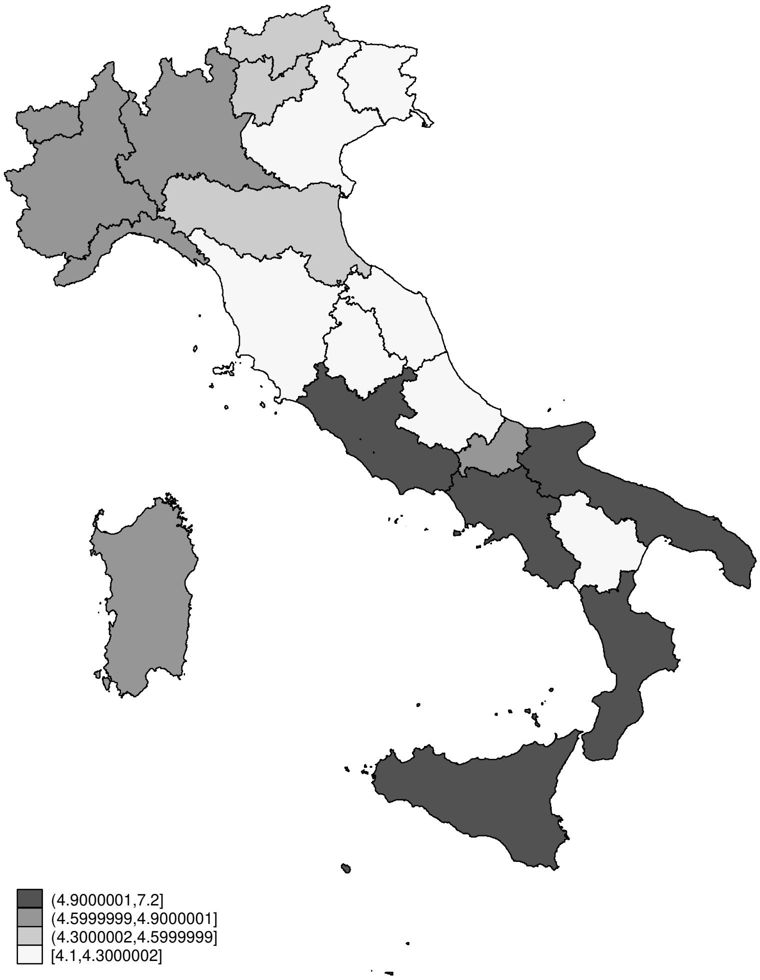


GINI without imputed rents by Italian region in 2015



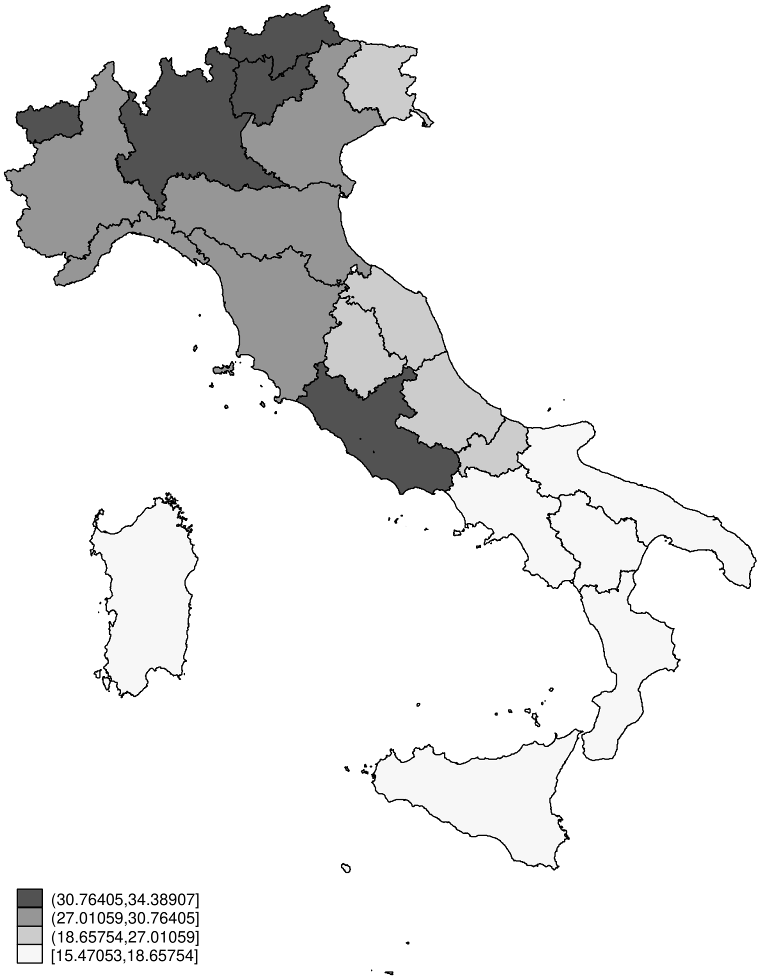
GINI with imputed rents by Italian region in 2004

GINI with imputed rents by Italian region in 2015

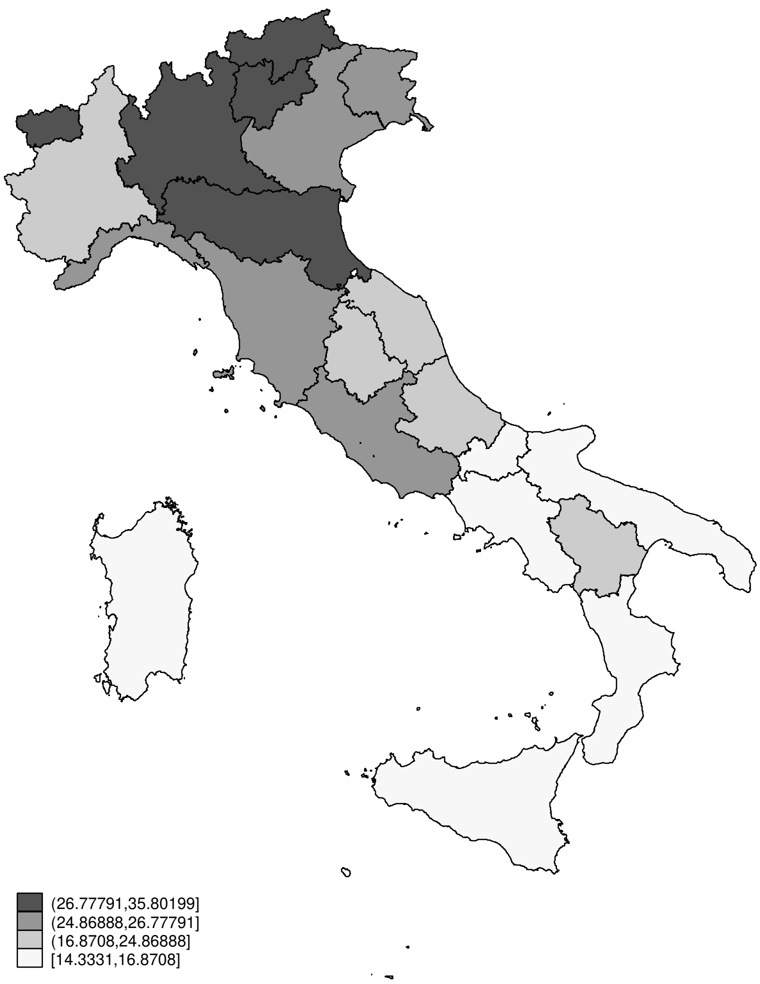


Quintile (80/20) ratios by Italian region in 2004

Quintile (80/20) ratios by Italian region in 2015



GDP per capita by Italian region in 2004



GDP per capita by Italian region in 2015