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Papers in Evolutionary Economic Geography

22.11

Utrecht University Human Geography and Planning

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Abstract

Although technological change is widely credited as driving the last two hundred years of economic growth, its role in shaping patterns of inequality remains under-explored. Drawing parallels across two industrial revolutions in the United States, this paper provides new evidence of a relationship between highly disruptive forms of innovation and spatial inequality. Using the universe of patents granted between 1920 and 2010 by the U.S. Patent and Trademark Office, we identify disruptive innovations through their rapid growth, complementarity with other innovations, and widespread use. We then assign more- and less-disruptive innovations to subnational regions in the geography of the U.S. We document three findings that are new to the literature. First, disruptive innovations exhibit distinctive spatial clustering in phases understood to be those in which industrial revolutions reshape the economy; they are increasingly dispersed in other periods. Second, we discover that the ranks of locations that capture the most disruptive innovation are relatively unstable across industrial revolutions. Third, regression estimates suggest a role for disruptive innovation in regulating overall patterns of spatial output and income inequality

Keywords: technological change; regional development; industrial revolutions; innovation; inequality

JEL Codes: O30, O33, O51, J31.

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1 Introduction

Technological change has played a central role in two centuries of unprecedented growth in productivity, incomes, and world population (Maddison, 2007). The most important new technologies have not, however, trickled out at a constant pace. At certain moments, they have generated major waves of new outputs, industries, firms and types of work that together profoundly reshaped the economy (Bresnahan and Trajtenberg, 1995; Helpman, 1998). These periods of intense change are commonly described as industrial revolutions. The emergence of major technologies are also distinctively spatially unequal, both between and within countries (Mokyr, 2010). For example, the second industrial revolution unfolded in chiefly in Western Europe and North America during the second half of the 19th and early 20th centuries. Within leading economies, some subnational regions grew large and prosperous as they became centers of electrical and mechanical technologies (e.g. Lamoreaux et al., 2004). Technological leadership in these periods is also associated with a growing divergence between the incomes in emergent 'cores' and the rest of the world (Pomeranz, 2001). Gradually, major technologies of the second industrial revolution have spread out globally, if unevenly; with this diffusion has come a degree of catch-up in development (Comin and Hobijn, 2010; Kemeny, 2011).

Even as they now undergo worldwide diffusion, the key, disruptive technologies of the third industrial revolution – such as semiconductors, computers and related software – also originated from a relatively small set of locations in the 1970s, with a few American regions leading the way. It may therefore be no coincidence that, around the same time, after a long period of interregional wage compression, spatial income inequality started rising in the United States (Moretti, 2012; Manduca, 2019; Kemeny and Storper, 2020a; Gaubert et al., 2021). While accounts of the original causal determinants of this divergence vary, it is widely agreed that a proximate cause is the rising spatial concentration of college educated workers (Diamond, 2016; Giannone, 2017; Card et al., 2021) – those same workers whose productivity the new technologies are said to augment (Autor et al., 2008).

Nonetheless, the connections between geographical dimensions of technological change and the spatial organization of work and its rewards remain insufficiently well understood. In labor economists' work on skill biased technological change, the focus has been squarely on changes in the labor market. In this work, technologies are said to increase wage inequality, but their effects are mostly inferred rather than directly observed (i.e. Autor et al., 2003; Berger and Frey, 2016). Separately, innovation scholars and historians have sought to identify key disruptive technologies (i.e. Moser and Nicholas, 2004; Feldman and Yoon, 2012). But that work leaves the links between these technologies and the distribution of economic outcomes over time and space largely unexplored. These hitherto distinct bodies of scholarship could benefit from more interaction.

This paper fosters such interaction by directly linking patterns of spatial inequality in income and output to the geography of disruptive innovation in the United States. Building on an approach developed in Petralia (2020b), we draw on detailed data from the U.S. Patent and Trademark Office to distinguish more from less economically-disruptive innovations over the long period from 1920 to 2010. Inventor and assignee addresses on granted patents are used to geographically locate these innovations in counties and commuting zones. Crucially, unlike most work on subnational spatial inequality, our approach enables description of two key waves of disruption: the 1920s, in which key electrical technologies of the second industrial revolution began to profoundly reshape the U.S. economy (Field, 2003; David, 1990), as well as the post-1970 rise of the third industrial revolution.

The U.S. is a particularly good case for analyzing relationships between technology and spatial economic inequality. It has been a dynamic innovation economy since at least the mid-19th century, at the forefront of both the second and third industrial revolutions (Soskice, 2020). Through its frontier development and extension of infrastructure, it experienced vigorous integration of its internal markets, signalled by high rates of internal migration from 1880 to 1980, along with significant capital mobility and rapid and low-cost technology diffusion (Molloy et al., 2011; Ganong and Shoag, 2017). This integration should generate strong forces pushing for interregional convergence in productivity and wages. Hence, in seeking to better understand the role of new, key technologies in shaping spatial economic inequality, our approach offers key advantages: it affords opportunities for drawing parallels and contrasts between the current and prior revolutions, as well as a less disruptive period in between; it permits comparison between the time- and space-paths of most and least disruptive innovations; and it does so against a backdrop of a highly innovative and increasingly spatially integrated national economy.

Several of our findings are new to the literature. At moments of rising spatial income inequality, the most disruptive innovations – unlike the least disruptive innovations – concentrate in space; conversely, when inter-regional economic inequality is in decline, disruptive innovations are spreading out. We identify two historical episodes in which disruptive innovations undergo marked concentration in space: one between 1920 and 1930, the other between 1980 and 2010. Between these periods – at the time of the Great Leveling, when spatial economic and inter-personal income inequality underwent major declines – disruptive innovations spread out across the regions of the United States. Moreover, multivariate results are consistent with the idea that the spatial behavior of disruptive innovation plays an important role in shaping spatial inequality.

2 Disruptive innovation and economic inequalities: literature

The present study builds on a large and varied literature that explores links between technological change, the labor market and economic development. A first strand of research examines the process of technological change over the long run, starting with the European industrial revolution as a key turning point in modern economic history. Between roughly 1750 and 1820, a complex set of technological and organizational innovations enabled humanity to escape persistent cycles of Malthusian boom and bust with unprecedented and sustained growth in productivity, incomes and population, that have now lasted more than two centuries (Freeman and Soete, 1997; Landes, 2003; Maddison, 2007; Mokyr, 2010).[1]

Within this two-century period, however, there has not been a continuous flow of equally significant innovations. Specific major new technologies emerge periodically, and they set off chain reactions of spreading uses and additional innovations, as well as gradual spatial diffusion. These changes sweep across the economy and reshape employment, wages, skill requirements, and ways of life (Rosenberg and Nathan, 1982). Adopting biological metaphors, Mokyr (1990) distinguishes between two broad types of technological change: one marked by the gradual accretion of new ideas; and another emanating from comparatively rare, discontinuous mutations.

Attempts to capture empirically the distinction between major and less important innovations have opened a Pandora's Box of competing terminology and shifting emphases. Within this broad semantic field, our preferred term is 'disruptive' innovation, signalling technologies that generate major discontinuities in terms of the locations that produce them, and the skills and tasks for which they complement and substitute.[2] In the spirit of Mokyr's distinction described above, disruptive innovations punctuate equilibria, and set the economy on a new path. Historians sometimes label such technologies as 'general purpose' signalling their ability to spur a wide range of new uses, while also inspiring a chain of many further innovations (Bresnahan and Trajtenberg, 1995). Meanwhile, other strands of research favor different terms, such as 'radical' (Perez, 2010; Schumpeter, 1943); 'sleeping beauties' (Teixeira et al., 2017); 'unconventional' (Berkes and Gaetani, 2021); 'atypical' (Mewes, 2019); 'complex' (Balland and Rigby, 2017); 'breakthrough' (Phene et al., 2006; Esposito et al., 2021); and 'promiscuous' (Foster and Evans, 2019).

Semantics aside, there have been multiple technological-industrial revolutions since the 18th century, each corresponding to a wave of new, disruptive technologies. Thus, water power and textiles are linked to the first industrial revolution; steam power and railroads to a second revolution (though, for some this was a continuation of the first revolution); fossil fuels, electricity and mechanization are widely considered the heart of the second industrial revolution; and of course semiconductors, computers and related digital technologies are the enabling technologies of the third industrial revolution. Revolutions do not happen in an instant, of course. This means there can be considerable differences in how different scholars date the beginning and end of these waves.[3] Within each wave, a major new technology initially has a fallow period of slow productivity growth, later followed by a period of 'reaping,' as the disruptive innovation begins to intensively reshape economic activity (David, 1990; Helpman and Trajtenberg, 1998b; Lipsey et al., 2005). In the case of the second industrial revolution, David et al. (2005) and Petralia (2020a) find that the 1920s was the major reaping period for the electricity and related technologies that were initially invented between 1880 and 1910.[4] Similarly, researchers were at first perplexed by the 'missing' productivity effects of the major innovations of the 1970s and 1980s, but they subsequently started finding them from the 1990s onward (Bresnahan et al., 2002). Historians agree that, although the electrical dynamo was invented during the 1860s, and the 1880s witnessed the emergence of the first electrical power stations, it was not until the 1910s and 1920s that the effects of these innovations began to powerfully reshape the economy of the United States (Field, 2003; David, 1990; Freeman and Louçã, 2001). Similarly, though silicon semiconductors were conceptualized in the early 20th century, and key working transistors came out of Nobel-prize winning work at Bell Labs in the 1940s and 1950s, it was not until the late 1970s and 1980s that computers, and subsequently the internet, begin to transform the organizational patterns of economic activity in the United States.[5]

Just as these key technologies emerge unevenly in time, they also arise in specific national and sub-national locations. The first industrial revolution began with a major pulse of innovation – the factory system – in Europe during the 18th and early 19th centuries, and earliest in the English Midlands. World manufacturing then concentrated in Britain, and subsequently developed in a broad central arc of the European continent, as well as in the northeastern United States. Though there exist different views on why the first industrial revolution happened where it did (c.f. Mokyr, 2010; Allen, 2009), the consequences of the geographical concentration of industrial activity are clear: incomes in the industrialized West sharply diverged from the rest of the world (Pomeranz, 2001). Related work documents the subsequent diffusion of these and other key innovations, and their growth-enhancing effects (Keller, 2004; Kerr, 2008; Comin and Hobijn, 2010), noting that absorption, and thus catch-up, is conditional upon institutional and other features of lagging economies (Abramovitz, 1986; Kemeny, 2010).

While this first strand of work has largely focused on national economies, a second is explicitly concerned with subnational regional variation in the production and absorption of innovations. Much of this work has a shorter time frame, tracing the geography of the current revolution since the 1970s, within which it is clear that core technologies have emerged with a strongly spatially concentrated form (Saxenian, 1996; Storper, 1997; Duranton and Puga, 2004; Crescenzi et al., 2020). The important new technologies of the current period have emerged alongside major changes in the inter-regional sorting of labor and capital (i.e., Storper and Walker, 1989; Boschma and Van der Knaap, 1999; Rosenberg and Trajtenberg, 2004; Storper et al., 2015; Berger and Frey, 2016). Recent contributions along these themes have documented how new occupations and innovations that are disruptive and more complex have emerged in a highly geographically-concentrated manner, in locations marked by larger populations and dense hubs of educated workers (Lin, 2011; Balland et al., 2020; Bloom et al., 2021).

Although key innovations and the jobs linked to them may initially exhibit strong spatial concentration, Vernon's (1966) intuition that they may eventually disperse, driven by processes of maturation and standardization, is also supported by considerable research. Norton and Rees (1979) adapt the product-cycle framework, for example, to explain the mid-20th century rise of the Sunbelt and decline of former second industrial revolution hubs in the Midwest and Northeast. Bloom et al. (2021) observe that, as work activities linked to disruptive innovations spreads out over subnational space, they also become progressively de-skilled. Meanwhile, Griliches (1957), Pred (1975), Phene et al. (2006), and Feldman et al. (2015) trace the spread of knowledge and certain key technologies in sub-national space. One implication of this work is that technologies that are standardizing and spreading out will continue to yield new adaptive innovations. But, these innovations and their geography are likely to be different from those that are most disruptive.

A third major strand of relevant work, operating at a more microeconomic level, is concerned with the links between technological change and wage formation. Such studies, emerging chiefly from labor economics, start from a framework in which income or wage inequality is shaped by the introduction of new technologies. New technologies complement workers performing specific tasks or holding particular skills, while they act as a substitute for the jobs of others (Autor et al., 2003; Bresnahan et al., 2002; Gordon, 2017; Acemoglu and Restrepo, 2021). Changes in labor demand are in a race against the creation of the supply of workers with suitable skills, with levels of inequality hanging in the balance (Goldin and Katz, 2009). More macro-approaches look for other factors that can influence the overall income distribution, such as policy shifts, wars, international trade, urbanization, inter-regional integration, and the size of the financial sector (Lindert and Williamson, 2016). But these are debates about emphasis; there are basically no accounts in which technological change does not play a major role in shaping the income distribution through its influence on wages, as well as through other mechanisms such as returns to capital and changes in the distribution of capital ownership associated with new technologies (Bresnahan and Trajtenberg, 1995; Wright, 1990; Aghion and Howitt, 2000; Acemoglu, 2002; Helpman, 2009; Galor, 2011; Storper et al., 2015; Aghion et al., 2019). This body of theory and empirical work has added enormously to our understanding of inequality. And yet, in that part of it exploring skill-biased technological change, technologies are not observed directly, hence their links to wage formation remain oblique. Instead, their effects are said to be observed through the trace elements of educational attainment, occupational definitions, and task composition of work.

A fourth and final strand of relevant work is addressed specifically to the post-1980 rise in spatial income inequality in the U.S. (Drennan et al., 1996; Moretti, 2012; Kemeny and Storper, 2012; Ganong and Shoag, 2017; Manduca, 2019; Gaubert et al., 2021). One view postulates that spatial inequality is largely due to barriers to worker mobility, on the basis that frictionless mobility will generate a tendency towards inter-place equalization of real incomes. In some current versions of that perspective, limits on housing supply are the primary drivers (Gyourko et al., 2013; Ganong and Shoag, 2017), In this line of work, little attention is paid to changes in the spatial structure of labor demand (Roback, 1982; Glaeser and Gottlieb, 2006; Partridge, 2010). A contrasting argument is that recent spatial inequality is indeed strongly shaped by the geography of labor demand (Galbraith et al., 2014; Diamond, 2016; Autor, 2019). Connecting some of the strands reviewed thus far, this latter account can be considered as a spatialization of arguments around skill-biased technological change, in which the new technologies of the third industrial revolution spawned industries that are highly spatially concentrated, employing workers that enjoy task- and education premiums, with the overall result being rising spatial inequality (Berger and Frey, 2016; Giannone, 2017; Kemeny and Storper, 2020b). However, in empirical work on these themes, actual technologies remain under-explored. Moreover, almost all of the work remains narrowly focused on the recent period of divergence, leaving open how technology or other factors may have reduced inequality during the Great Leveling from 1940-1980, when regions of the U.S. were instead in a long period of income convergence.

This review motivates the priority tasks in the present research: identifying particular kinds of innovation that are likely to be economically disruptive; placing such technologies in space and time; tracing directly the relationship between the geographies of regional economic performance and disruptive innovations.

3 Data and Methods

3.1 Identifying disruptive innovations

We identify three features that distinguish more- from less-disruptive innovations, drawing on the extensive historical literature on general-purpose technologies (i.e., Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998b,a; Aghion and Howitt, 2000; David and Wright, 2003; Moser and Nicholas, 2004; Lipsey et al., 2005; Hall and Trajtenberg, 2006; Rosenberg and Trajtenberg, 2010; Feldman and Yoon, 2012).

1. ***Growth*:** Disruptive technologies have a particularly wide scope for improvement and elaboration, expressed as an intensive process through which technologies are further developed and perfected. Consider, for instance, Jack Kilby's 1958 invention of the first microchip while at Texas Instruments. The vast potential for improvement of this technology is evidenced by the enormous quantity of subsequent refinements – from Robert Noyce's more practical silicon version invented a year later, to contemporary neural-network-based chips. The effects of these improvements can be seen in dramatic increases in processing power that have enabled the modern information economy.

2. ***Innovation Complementarity*:** When disruptive technologies are introduced, they introduce a wide array of possibilities to complement with existing technologies. In a sequence of problem solving, they enable many technologies that are new to the world. Returning again to Kilby's integrated circuit, this technology opened up possibilities to innovate in products and services that didn't exist before, particularly around the creation of portable computing machines.

3. ***Use Complementarity*:** Disruptive technologies are also characterized by their widespread use throughout the economy, in products and processes. Electric power, for example, became widely used in an enormous range of products and processes: household appliances, transportation services, chemical reactions, information transmission. After its introduction, it gradually became a central input in nearly all manufacturing processes.

3.1.1 Operationalization

In order to identify disruptive technologies and their geography, we use historical patenting information provided by the United States Patent and Trademark Office (USPTO), which makes available the patent document for each patent it has granted since 1920.[6] We make use of several features of patent documents. First, we use the class structure built into the patent system in which each patent is assigned to at least one technology class.[7] There are currently more than 400 different technological classes in use in the U.S. Patent Classification, and whenever a new class is created, or an existing one redefined, all available patents are reclassified to maintain temporal consistency. Patent examiners are responsible for assigning each patent to at least one technology class, according to type of invention to which it claims rights. All patent classifications in each patent document are used, counting equally each appearance of a technological class.[8] In addition, we make use of the aggregation of classes into six broad economically-relevant categories: Chemical; Computers & Communications (C&C); Drugs & Medical (D&M); Electrical & Electronic (E&E); Mechanical; and Others.[9] We also leverage the information contained within each document's detailed description.

In each year, we identify a set of the most disruptive technologies, defined as patent classes in the USPTO terminology, based on class averages of Growth, Use Complementarity and Innovation Complementarity. Following Petralia (2020b), we operationalize these characteristics as follows:

1. ***Growth:*** To capture a technology's scope for improvement and elaboration, we measure growth rates over time of its patent class. This adapts an approach found in work by Hall and Trajtenberg (2006) who consider the growth of a specific subset of classes, and Moser and Nicholas (2004), who measure growth at the more aggregate category scale. Growth rates for patent class c will be calculated as $\Delta\ P_c = \frac{P_{c,t} - P_{c,t-5}}{P_{c,t-5}} - 1$, where P represents the number of patents in a given year t.

2. ***Innovation complementarity:*** We count the average number of patent classes with which each technology co-occurs in patent claims, ignoring co-occurrences within the same aggregate category (Chemicals, Mechanical, etc). Since patent claims identify the set of 'new to the

world' innovations in patent documents, technologies that co-occur with a wide and diverse set of claims within patent documents outside their category are considered to enable a wider range of innovation than classes with fewer co-occurrences.

3. ***Use complementarity:*** We exploit the high-dimensional information contained in patent descriptions in order to identify the uses of different technologies. For intuition, consider the case of technologies X and Y. While X and Y may not co-occur frequently with each other as described in the previous point, the detailed description of patents in technology X may nonetheless refer to core methods, concepts or notions of technology Y. In this case we would consider X to be a 'user' of Y. In this example, technology Y is not used by X to create something new to the world (they not co-occur in patent claims), however, some of the core methods, concepts or notions of technology Y enable technology X. We operationalize this intuition by developing a set of technology-specific keywords, using a data-driven algorithm that identifies keywords (2-grams) that distinctively represent specific classes of patents. Then, we trace these technology-specific keywords within the detailed texts of individual patents in other technologies. Technology X is defined as a user of Y if it has a sufficient number of patents mentioning at Y keywords. To arrive at a measure of the use complementarity of Y, we then count all the technologies (classes) that are users of Y.[10]

Each of these three characteristics is a necessary but insufficient indicator a technology's disruptiveness. For instance, a mature technology might be pervasive and thus have high levels of use complementarity, while having exhausted its capacity for growth and innovation. Similarly, a technology that grows quickly but has little scope for complementarity will not produce economy-wide disruptive effects. We therefore consider as disruptive only those technologies that rank above average in all three criteria. Note that patent classes contain substantial heterogeneity – not all within can be expected to be equally disruptive. Technologies least likely to be disruptive will be found in those classes that score below average in all three characteristics. This leaves a third, more indeterminate middle category of innovations that may be above average in certain features and below average in others. In the empirical work that follows, we mainly draw on the contrast between the two categories at the extremes - the most and least disruptive.

The result is a classification that identifies disruptive innovations relative to other innovations that have emerged at the same time. Our approach allows cross sectional comparisons to other technologies, but it does not track changes over time in the overall quantity of disruptiveness present in the economy. Hence, with this measure we cannot directly validate historians' claims of bursts of particularly disruptive innovation, though we do explore how such arguments fit with the shifting geography of disruptive innovation over our study period.

[Table 1 about here.]

Table 1 provides a snapshot of the most and least disruptive technology classes in 1925-1930 and 2005-2010, with rankings based on the average values of the indicators, normalized by demeaning and dividing by the standard deviation. The table offers a view of disruptive innovation that is consistent with existing historical and anecdotal evidence, where the 1920s are dominated by mechanical and electrical categories and the most recent period by computers and electronics (i.e. Freeman and Louçã, 2001). Individual disruptive technology classes can be seen to be clustered together. Recently most of the highly disruptive electrical and electronic technologies listed in the lower half of the table – such as those related to the production of solid state devices – are linked to computers, broadly conceived. Least disruptive technologies in the 1920s include scaffolding, wooden receptacles, and railway draft appliances; in 2005-2010 scaffolding again appears, alongside several technology classes related to paper goods.

3.2 Locating disruptive innovations in subnational space

Patent documents list address information for inventors and/or assignees. We obtain this information from two data sources: For the 1920 to 1975 period, we rely on the HistPat dataset, which contains county-level information identifying the location of the inventor(s) and/or assignee(s) for 99.3% of all patents granted between 1836 and 1975 (Petralia et al., 2016).[11] For the period from 1975 to 2010, we use similar information obtained directly from the USPTO.[12] Individual patents are then assigned to geographical locations.[13]

As noted, we aim to identify the economic effects of disruptive innovations at the scale of local labor markets. The spatial extent of local labor markets has profoundly changed over the nearly century-long study period. In 1920, there was less than one car for every 10 people in the United States (Mom, 2014), and as recently as 1911, horses outnumbered cars in New York City (Morris, 2007). By contrast, by 2010, the country contained almost as many highway vehicles as people (U.S. Department of Transportation, 2021). The study period also includes the rollout of the interstate highway system, which is widely credited as having revolutionized patterns of settlement as well as economic activity (Baum-Snow, 2007; Michaels, 2008; Allen and Arkolakis, 2014). The suburbanization that emerged in part through these changes in trade costs expanded the spatial extent of local labor markets, generating sprawling and integrated regional economies. This means that, in earlier portions of the period under investigation, smaller spatial units are most likely to capture the concept of interest; this is reflected in the large volume of empirical work examining the 19th and early 20th century in the U.S. focused at the scale of counties (i.e. Kim, 2007; Fishback and Cullen, 2013; Abramitzky and Boustan, 2017; Akcigit et al., 2017). Closer to the present, meanwhile, larger units will be optimal for measurement, reflecting the sprawl mentioned above. This presents empirical challenges: we can either use the same spatial units over the 90 years under investigation, which risks introducing potentially significant measurement error at one end of the full study period or the other, or we can use one set of units to track changes in one sub-period and a different set for the other. We prefer the latter. We use units that best fit the spatial extent of local labor markets in each period in question, though at specific points in this paper when our analysis demands common units, we make use of them.

For the period covering the second industrial revolution (1920 to 1930), we use counties as our unit of analysis. Meanwhile, for the 1980-2010 period, we adopt commuting zones as our primary spatial unit. Commuting zones are groups of counties that are linked through the intensity of travel patterns, and distinguished by weak inter-area commuting; they therefore effectively represent functionally-integrated economic units (Tolbert and Sizer, 1996). Commuting zones offer concrete advantages over other competing measures: unlike metropolitan Core Based Statistical Areas, they can be constructed for the full study period as needed; they cover the entire, contiguous 48 states; they also avoid problems of incomplete identification present in metropolitan areas in public use data since 1980. For this latter period, we adopt 1990-vintage commuting zone definitions, consisting of 726 local labor markets.

3.3 Exploring the relationship between disruptive innovation and spatial inequality

In addition to univariate descriptive analyses, we also estimate a series of simple panel regression models predicting changes in local growth in either per capita manufacturing output or income. Across these models, the independent variable of interest is local disruptive innovation. Our aim in these estimates is to consider how the marginal disruptive innovation may be related to patterns of growth in output or income. We estimate variants of the following baseline equation:

$$y_{c,t} = d_{c,t} + ld_{c,t} + X'_{c,t} + u_{c,t} \tag{1}$$

where y is log per capita output or income for location c in time t. The log of the number of local patents in the most disruptive classes taken out in either the most recent 5 or 10 years is captured by d. Similarly, ld represents log of counts of local patents in classes that are deemed least likely to be disruptive over the same period. X' is a vector of location-specific features, and u is the standard disturbance term. In X' we include some measures likely to be related to the dependent variable that are common to both periods, like population. We also include some control variables that are period-specific. To identify any in-built catch-up effects, as in a conventional convergence model, we include a one-period lag of the dependent variable.

For the observed decade during the second industrial revolution, estimates are generated by differencing values of the dependent variable and patent measures between 1920 and 1930, with covariates set to initial-period values. For the more recent period, a decadal panel spanning 1980 to 2010 allows estimation of a two-way fixed effects model, in which we include time-varying controls; location-specific fixed effects that will absorb bias from unobserved, but relatively stationary features of each local economy, including their overall propensity to be innovative; and year fixed effects that can account for unobserved national-level dynamics, such as business cycles. In each time period, the key independent variable of interest is d; all else equal, we expect changes in d to be positively related to changes in local levels of output or income per capita.

The long run timeframe of this study entails some compromises in terms of measuring our dependent variable of interest.[14] Recall that the theoretical motivation is to capture spatial economic inequalities, by which we mean indicators of inequalities in development. In the economic development literature generally, development is almost always operationalized through per capita output, incomes or wages, acting as proxies for productivity and well-being. For the period around the second industrial revolution, we use information from historical iterations of the Census of Manufactures made available by Haines (2005), as a means of constructing measures of local manufacturing output per head.[15] They key innovations in this period were largely in electrical and mechanical areas related to manufacturing activity, hence, this indicator should reasonably accurately gauge their economic impacts. Over the 1980 to 2010 period, we again cannot directly measure per capita gross domestic product, but we follow common practice in the literature on regional convergence (i.e., Barro and Sala-i Martin, 1991; Carlino and Mills, 1993; Drennan and Lobo, 1999), proxying development performance by using income-side data from the National Income and Product Accounts (NIPA), made available by the Bureau of Economic Affairs.[16] We aggregate per capita personal income (PCPI) to the commuting zone level, and adjust it for inflation to constant 2010 dollars using the Bureau of Labor Statistics' Consumer Price Index for All Urban Consumers (CPI-U).

We supplement our key dependent and independent variables with other measures of local economic structure. In both periods, we account for differences in industrial structure and population. In the period spanning the second industrial revolution these data are again drawn from Haines (2005). From that source we also include a measure of the urban population share in each county, on the basis that the shift from rural to a more urban manufacturing pattern could partially explain growth accelerations (Atack and Bateman, 1999; Kim, 2005). Additional measures from Haines (2005) include the share of foreign born in 1920 in each county, motivated by a range of potentially beneficial effects, including entrepreneurship, innovation; and labor market recomposition (Hunt and Gauthier-Loiselle, 2010; Ottaviano and Peri, 2012; Rodriguez-Pose and Von Berlepsch, 2014). Furthermore, we include a variable measuring the availability and exploitation of natural resources, the share of primary inputs used in manufacturing (PI), since natural resource exploitation during this period is often mentioned as crucial factor of the early US development process Wright (1990). We use additional sources of data to account for specific factors that may have played a role in the early development of regions in the 1920s. Following Acemoglu et al. (2016), to capture variation in local state capacity, we include information on the number of post offices per county.[17] Furthermore, since it has been argued that the presence of a university in a city has a considerable impact on local wages and capabilities (Moretti, 2004), we count the local presence of land-grant colleges.

[Table 2 about here.]

In the later period, control variables are largely drawn from public use extracts of population censuses, harmonized and made available to the public via IPUMS (Ruggles et al., 2021). These data are drawn from the largest available public use sample in each available year; this means five percent samples for 1980, 1990 and 2000, and a three percent sample covering 2009-2011 (which for convenience we call 2010). Adapting the probabilistic method described by Dorn (2009), we assign fractions of individuals in the Census to 1990-vintage commuting zones based on the proportion of each County Group (1980) or Public-Use Microdata Area (PUMA – 1990-2010) that belongs in each commuting zone. From the resulting data, we measure the share of local workers having attained at least four years of college education; as well as employment shares in computer and data processing sectors; in finance, insurance, and real estate (FIRE) and manufacturing.

Table 2 presents summary statistics, separated by major period. In the period spanning the 1920s, the average county was granted 145 patents, though the large standard deviation indicates the considerable dispersion of this indicator. The average county generated 28 more-disruptive patents and 10 least-disruptive. In the more recent period, the average commuting zone had a decadal patent rate of over one thousand, again with the standard deviation indicating the presence of major geographical variation. The most- and least-disruptive patents follow a similar pattern. There is a strong, substantive logic to the abundance of the most disruptive patents relative to the least. These most disruptive patents should be strongly growing in importance and number. Meanwhile, the least disruptive technologies are by definition nearing a stage of saturation, hence their size should be comparatively diminutive. The average county in 1920 had 47,000 residents; between 1980 and 2010, the average commuting zone had around ten times that population. In each case there are major differences in population indicated by the dispersion in the series. In practical terms, commuting zones include locations as small as Murdo, South Dakota, with a population of under 1,000, and as large as Los Angeles, at over 15 million residents in 2010. Other features of regional economies appear distributed as expected, including meaningful variation around educational attainment, industrial structure, immigration, and of course output and income.

4 Results: geographies of technological disruption and development

4.1 Disruptive technologies concentrate in space in periods of industrial upheaval

Figure 1 displays the evolution of geographic concentration in patents that fall into patent classes we consider disruptive, with variation in disruptiveness defined on the basis of methods described in section 3.1. The leftmost panel of Figure 1 displays the evolution of Gini coefficients, Theil indices and coefficients of variation, each describing how patterns of disruptive technologies across counties have changed over the 1920s. The three measures present largely consistent but slightly different pictures of the location of new, disruptive technologies. The Theil index presents a somewhat turbulent narrative in which concentration rises between 1920 and 1925, then falls up to 1929, and then begins to rise again. Over the same period, the Gini coefficient and coefficient of variation both suggest that disruptive innovations are progressively concentrating at the county level over the decade.

[Figure 1 about here.]

The right panel of Figure 1 displays the analogous evolution of the geography of disruptive innovation for the 1980-2010 period, at the level of commuting zones. Across the different measures of spatial inequality, each series rises quite consistently over the 30-year period. Over this recent period in which new, key technologies are believed to be most profoundly disrupting economic activity in the United States, they are emerging in an increasingly selective regional geography.

One might reasonably wonder whether such geographical patterns are, as we suggest, cyclical. A competing possibility is that the growing geographical clustering of disruptive innovations merely reflects more fundamental shifts in patterns of settlement and overall economic activity. On that logic, since 1980 at least, the U.S. has been experiencing growing concentration of population and output in larger urban centers (Black and Henderson, 2003; Balland et al., 2020). In reality, these processes are likely to be endogenously related to one another, with innovation as both outcome and driver of agglomeration (Duranton and Puga, 2001; Gordon and McCann, 2005; Asheim et al., 2011). Consideration of these relationships during the second industrial revolution is illuminating. Over the late 19th and early 20th centuries, the U.S. urban system had not yet fully completed its frontier transition (Leyk et al., 2020). The settler population was actively expanding and spreading toward the West and South, widening markets as well as the range of feasible locations for many traded goods to be produced (Kim, 1995). In this light, the patterns in Figure 1 indicating a growing concentration of disruptive innovations are all the more striking. Technological concentration in one period marked by dispersal in population, employment and output hints at the existence of a distinctive and powerful logic shaping the geography of these innovations.

In Figure 2 we seek to further contextualize these findings, revisiting the geography of innovation shown in Figure 1 with some significant differences. First, Figure 2 describes changes in the location of innovation across the entire 90-year study period – a shift that necessitates consistent spatial units (in this case, commuting zones). Second, while the left panel visualizes changes in the geography of the most disruptive innovations, for contrast the right panel shows the spatial evolution of the least disruptive new technologies.

Comparing across the two panels, Figure 2 shows that the most and least disruptive innovations exhibit strongly differentiated locational patterns. The leftmost panel captures the rising spatial concentration of disruptive innovations over the 1920s, with some of the instability seen at the county scale in the Theil series, but also the broadly rising pattern of concentration; this is followed by a gradual spreading out of disruptive innovations from the mid-1930s to approximately 1980, after which we observe once again the spatial concentration during the third industrial revolution.

We interpret this to mean that innovations with greater disruptive potential follow a wave-like pattern of rising and then falling spatial concentration that mirrors temporal patterns that economic historians highlight as peaks and troughs of industrial revolutions.

[Figure 2 about here.]

Examining the right panel of Figure 2, we observe that technologies that have the least potential for disruption appear to be spreading out over space over the entire 90-year period. This hints at a deepened diffusion process for the creation of new ideas whose underlying concepts and knowledge bases are more peripheral to the overall technological frontier. As we have seen that some of the least disruptive innovations involve 'mature' technologies, it suggests these became more easily accessible, perhaps driven by the wider settlement process underway in the United States. Nonetheless, it is striking that the progressive dispersal of such innovation in an ever-widening circle of locations proceeds even during periods of peak technological upheaval, and even when indicators of population and output grow increasingly concentrated.

4.2 Waves of concentrated disruptive innovation reshape the ranks of regional technological leadership

In this section we explore which cities have become sites of concentrated disruptive innovation. We also consider whether holding a leadership position in disruptive innovation in one period leads to being a leader in a subsequent one.

In a five year window within each industrial revolution, Table 3 lists the top 25 regions based on counts of disruptive innovation per thousand inhabitants. It lists counties that are hubs of disruptive innovation in 1925-30, while for the later period it lists commuting zones. Over the 1925-30 period, leading disruptive technology regions were mostly concentrated in the Northeast and Midwest – the old industrial heartland of the electrical-mechanical age. The distribution of disruptive innovations per thousand across these centers is relatively even, such that those in the middle of the list generate about a third of the number of disruptive innovations per capita as those at the very top. At the very top of the list is Schenectady, home of General Electric, as well as the American Locomotive Company, the latter focused on steam and diesel locomotives, as well as steel production. Larger counties on the list, like Lucas, Hamilton, New York, Allegheny, and Cook each represent significant industrial cities of the second industrial revolution: respectively, Toledo, Cincinnati, New York, Pittsburgh and Chicago. Though we show measures scaled to population in Table 3, absolute counts of disruptive innovation over this period favor large locations, including many of the biggest urban counties such as Wayne (Detroit); Los Angeles; Cuyahoga (Cleveland); Philadelphia, Milwaukee, St. Louis and San Francisco.

[Table 3 about here.]

The list describing the 2005-2010 period looks different in a number of ways. It is more consistently made up of large population centers, which are also drawn from a wider range of regions of the United States. Almost a quarter lie on the Pacific coast, and Sunbelt cities like Austin and Raleigh bring in the Old South. Regional economies known for leadership in high-technology sectors of the third industrial revolution appear on the list, including San Francisco, San Jose, Austin, Boston, and Seattle. Among the smaller places Rochester, Minnesota and Poughkeepsie, New York both host large IBM research and design facilities. One difference between the two periods is the degree of concentration of disruptive patents in the more recent period, with San Jose having generated approximately 1.6 times as many disruptive patents as the second-place location, and almost seven times as many as the middle of the list. By contrast, over the 1925-1930 period, the leading county had 1.2 times as many as the second place location, and less than three times as many as the middle of the list.

Based on this picture, we can ask whether the same regional economies are hubs of innovation across the two study periods. To respond to this question, we again require consistent units. Hence, in Table 4, we aggregate up to the level of 1990-vintage commuting zones. Only four regions that out of the top 25 most disruptive locations in 1925-1930 remain so in 2005-2010. The overwhelming majority of leading places are leaders in only one period. A similar picture emerges if we measure total patents, such that only half the locations that are in the top 25 in the 1920s remain so in the 2000s. This greater intertemporal consistency no doubt emerges as a consequence of the fact that big populations exhibit greater long-run persistence.

[Table 4 about here.]

Being at the top in per capita terms means being a center of the disruptive technologies of the specific industrial revolution at hand. There is substantial turbulence or difference in regional leadership of disruptive technological change from one revolution to another. On a total patenting basis, however, there is less volatility over time, perhaps reflecting some long-term advantage of being a large city-region in the urban system in successfully transitioning as a technology center from one period to another. Still, almost half of the leaders in the 2000s were not to be found there during the the second industrial revolution, reflecting the entrance of major new innovation centers as new technologies rely less on the innovators and inputs from previous rounds, creating what has been termed a 'window of locational opportunity' (Scott and Storper, 1987; Storper and Walker, 1989). Long-run stability is most evident among the non-innovative laggards.

4.3 Spatially concentrated disruptive innovation is associated with greater spatial economic inequalities

[Table 5 about here.]

Next we turn to regression estimates measuring the association between disruptive innovation and either output or income. Table 5 reports estimates for variants of equation (1), which relates changes in location-specific measures of disruptive innovation to changes in local per capita output. In both industrial revolutions, we detect a robust, positive relationship between the marginal instance of local disruptive innovation and economic performance. Models 1 and 2 are differenced between 1920 and 1930, such that the dependent variable is the change in log manufacturing output per worker. In Model 1, innovative output, as represented by total patents, is positively and significantly linked to growth in per capita output in manufacturing. Controls behave approximately as expected, including a lagged dependent variable that is negatively and significantly linked to output, indicating a conditional convergence dynamics that fit with State-level evidence on income spanning this period (Barro, 1991). Model 2 disaggregates total patents, with key predictors capturing additional patents granted in the most and least disruptive technology classes over the study period. Disruptive patents remain positively and significantly associated with growth in output per worker. Meanwhile, the addition of least disruptive patents is not significantly related to changes in manufacturing output over this period.

Based on a decadal panel specification with two way fixed effects, results for the more recent period up to 2010 track the relationship between changes in disruptive innovation and log per capita personal income. The inclusion of local fixed effects should absorb bias that arises from differences in overall innovative capacity, as long as this characteristic is relatively stationary; it also accounts for other unmeasured but relatively non-dynamic features of locations. As in Model 1 for the 1920s, Model 3 confirms that, over this more recent period, increases in local patenting are linked to rising output per head, significant against a threshold of 0.05. Mirroring the estimates for the second industrial revolution shown in Model 2, in Model 4 we decompose total patents into their extremes: patents in the most disruptive classes, and those in classes deemed to be least likely to be disruptive. The coefficient on disruptive patents is positive and statistically significant at a 0.01 percent level, the greater precision in the estimate as compared to all patents in Model 3 indicating the greater clarity offered by a focus on disruptive innovation. In keeping with Model 2, the addition of new, least-disruptive patents are unrelated to changes in per capita personal income. Meanwhile, the β-convergence process detected in the early period is no longer in evidence.[18]

Overall then, for each of the key periods in two industrial revolutions, the regressions in table 5 suggest that the relationship between overall local patenting and local output or income is partly a function of those innovations that are most disruptive. Considering these relationships in light of the distinctive patterns of geographical concentration of disruptive innovations we document in Figure 1 suggests that disruptive innovation acted as a force spurring growing regional inequalities, whether in terms of manufacturing output per capita in the 1920s, or per capita personal incomes as the third industrial revolution unfolded.

[Figure 3 about here.]

Exploring this idea further, Figure 3 visualizes changes in spatial inequality that emerge from predicted values of local per capita personal income that emerge from Model 4, Table 5, setting all independent variables to 1980 mean levels, except for disruptive innovation, which we allow to change according to actual values. These predictions are then used to build standard inequality indices used earlier in the paper. This figure is not meant to be interpreted as a direct gauge of disruptive innovation's marginal effects, rather it represents a counterfactual scenario that more directly highlights the how the growing concentration of disruptive innovations in space yields tangible increases in spatial inequality.

5 Conclusion: the future of disruption and its geographies

Over the past century, disruptive innovations in the United States follow alternating wave-like patterns of rising and falling spatial concentration that closely mimic peak and trough periods of industrial revolutions (Field, 2003; David, 1990). The least disruptive innovations, by contrast, were quite consistently spreading out over the regional geography of the country. Further, there was only partial overlap in the geography of disruptive innovations across the two industrial revolutions, with turbulence in the ranks of the most innovative places and thus limited path dependence in disruptive innovation. In contrast, there was mostly stability in the geography of places excluded from the business of leading in the generation of the most disruptive innovations. Finally, we found a robust association between regional disruptive innovation and measures of economic performance. This relationship remains after accounting for the influence of a host of other factors shaping such outcomes, including other markers of innovative effort. Taken together, these results are consistent with the idea that disruptive innovation has played an important role in shaping patterns of spatial economic inequality over the past century.

Still, much more work is required to understand the links between technology and the geography of inequality. It would be particularly interesting to understand more precisely the nature and geography of technology during the peak spatial and inter-personal convergence period of the American economy from 1940 to 1960. What we do not know from this analysis is the precise extent to which the technological contribution to the 1940-1980 Great Leveling in both regional development and income inequality was due to the spatial deconcentration of disruptive innovations; to an overall decline in disruptiveness; to a decline in the skill-bias of disruptive innovations; or to some as yet unobserved quality of disruptiveness that may have changed between the two high inequality and concentration periods and the intervening Great Leveling. These questions are therefore urgent for further research that would build upon the present results.

Building such an understanding is particularly urgent as we appear to be on brink of a fourth industrial revolution, perhaps based upon breakthroughs in robotics, artificial intelligence, genomics, and decarbonization technologies. Historical research, such as we report on in this paper, does not promise prediction of future processes, but provides a useful framework of questions to ask as such processes begin to unfold. In particular, as these technologies emerge from their current experimental phase, we should carefully consider whether they manifest analogous forms of geographical concentration to their forebears, reinforcing 'superstar' agglomerations of knowledge workers, major firms and supply chains, and incomes, but also possibly generating some new superstars in the urban-regional system (Kemeny and Storper, 2020a). In this case, then the contemporary geography of regional economic divergence may be a prelude to another round of uneven development within innovative countries. At the global scale, the current period is different from the great divergence of the first industrial revolution, as East Asia has now arisen as a third great pole of innovation and world economic growth, and – at least among the three poles of North America, Western Europe and East Asia, per capita incomes are converging. And yet within that third great pole of the world economy, the subnational geography of innovation is highly concentrated. On the other hand, if the upcoming waves of technological disruption are more similar to the disruptions of the Great Leveling, the future of interpersonal and spatial development indicators might look more egalitarian. The social, economic, political and cultural consequences of more versus less egalitarian technological disruption processes are profound; hence, it behooves us to continue deepening the historical understanding of why some disruptions are more spatially concentrated and inegalitarian than others, and to be highly attentive to how the now-unfolding new waves of innovation fit in this picture.

Notes

[1]While some eschew the term 'revolution', preferring instead an image of gradual unfolding, it is widely agreed that a major phase change occurred with early industrialization (Crafts, 2004).

[2]The term 'disruptive' is itself highly polysemic, used by varied strands of academic work, as well as by journalists, pundits, and tech entrepreneurs, through which it has entered the general lexicon. In academic work, a literature in business studies aims to explore the positions of firms whose practices or products disrupt existing industries and markets (such as Bower and Christensen, 1995; Christensen et al., 2018). In economics, it is used mostly to characterize major effects on the economy as a whole, wrought through changes in employment, industry structure, productivity, incomes, wages, overall growth, and geography (i.e., Bloom et al., 2021). As our review makes clear, the research reported in this paper is situated within this latter tradition.

[3]For instance, Lindert and Williamson (2016) date the start of the second industrial revolution at around 1870 and the end around 1920, whereas Jovanovic and Rousseau (2005) argue it spanned the period 1889 to 1929.

[4]Field (2003) has a different, but partially overlapping formulation, one that puts greater emphasis on the 1929-1941 period.

[5]While it is worth noting the lively debate around the measurement of the productivity effects of the digital revolution (i.e., Brynjolfsson and Hitt, 1996; Gordon, 2000), there remains little dispute about the broad timing with which information technologies began to restructure the U.S. economy.

[6]All patent documents granted since 1920 can be accessed at: `https://bulkdata.uspto.gov`

[7]`http://www.uspto.gov/learning-and-resources/electronic-bulk-data-products`

[8]Each class appearance counts as one – there are no fractional counts. However, as explored in Petralia (2020b), an alternate strategy that uses fractional counts produces material similar results.

[9]See Hall et al. (2001) for details. The concordance is available at `http://www.nber.org/patents/`.

[10] Our implementation is identical to the one described in Petralia (2020b), please refer to its Appendix B for a detailed explanation of the procedure.

[11]The latest version of thisHistPat can be downloaded at `https://dataverse.harvard.edu/dataverse/HistPat`. Petralia et al. (2016) contains a detailed documentation of the methodology used to create it and a set of tests to discard the existence of potential biases using manually collected data.

[12]Data is available at: `https://www.patentsview.org/download/`

[13]Note that we assign patents to locations without taking into consideration the share of inventors per location. For instance, if a patent contains three inventors from Boston and one from Los Angeles we assign 1 count to each location. We do this for two reasons, on the one hand, this procedure help us netting out the effect of inventive activity becoming more collaborative over time. Using this procedure prevents more populous locations from receiving a disproportionate amount of patent counts. Additionally, disregarding fractional counts makes the comparison between HistPat and more recent data possible. This is because the HistPat database identifies locations in patents but not the inventors,

making it impossible to weight contributions.

[14]These limitations mean that we cannot simply run one model that spans the entire 90-year study period.

[15]ICPSR 2896 is available at https://www.icpsr.umich.edu/icpsrweb/

[16]At a detailed subnational scale, information on per capita GDP are only available after 2000.

[17]Original records available at: https://catalog.hathitrust.org/Record/002137107

[18]Concerned with the possibility that our inclusiuon of a lagged dependent variable might render our estimated standard errors inconsistent, in the Appendix we report a version of Model 4 using the Arellano-Bond estimator. Results remain materially consistent with those presented in the main table.

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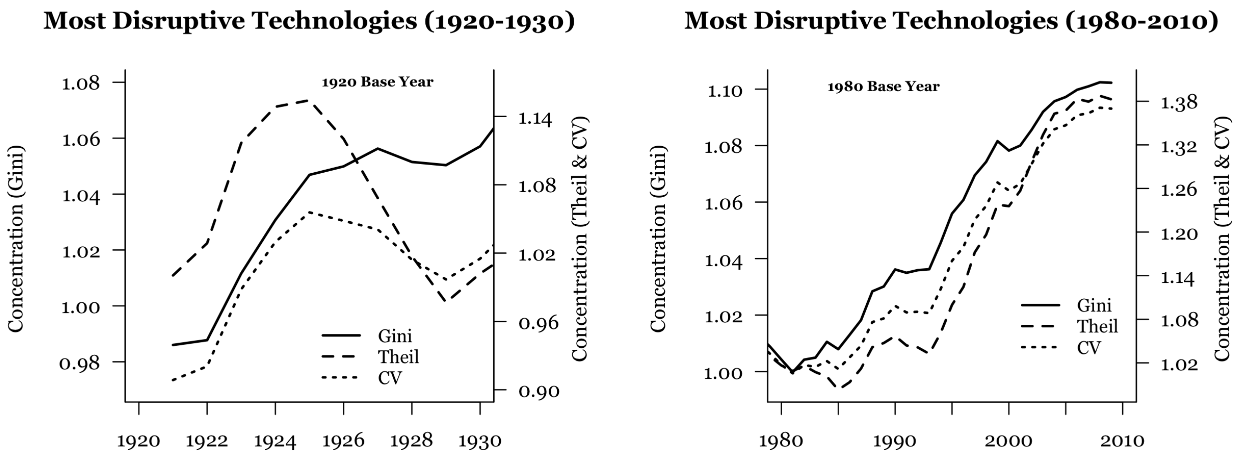
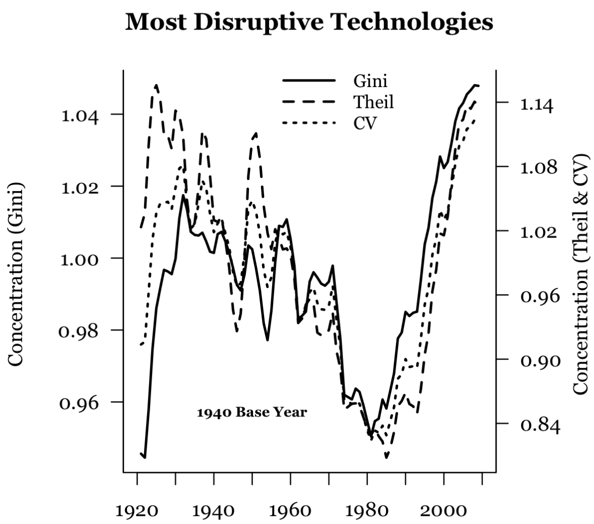
List of Figures

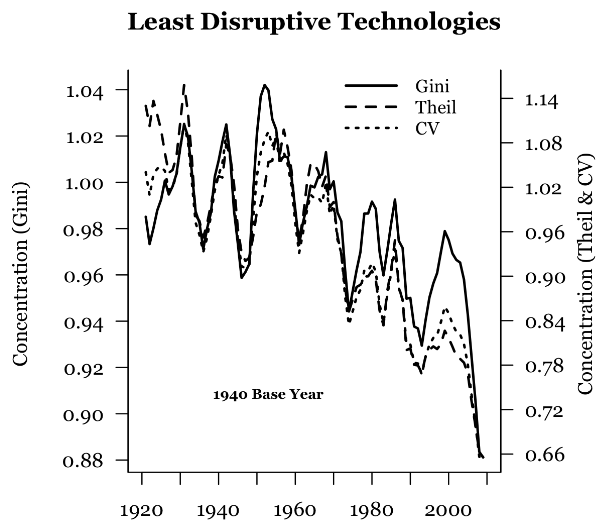
Figure 1: Tracing the geographical concentration of disruptive innovation in the United States, 1920-1930 and 1980-2010



Source: Authors' elaboration based on HistPat & Lai Database. Geographic units are counties in the left panel, and commuting zones in the right panel. Consult Section 3.2 in the text for a detailed discussion of geographic definitions.

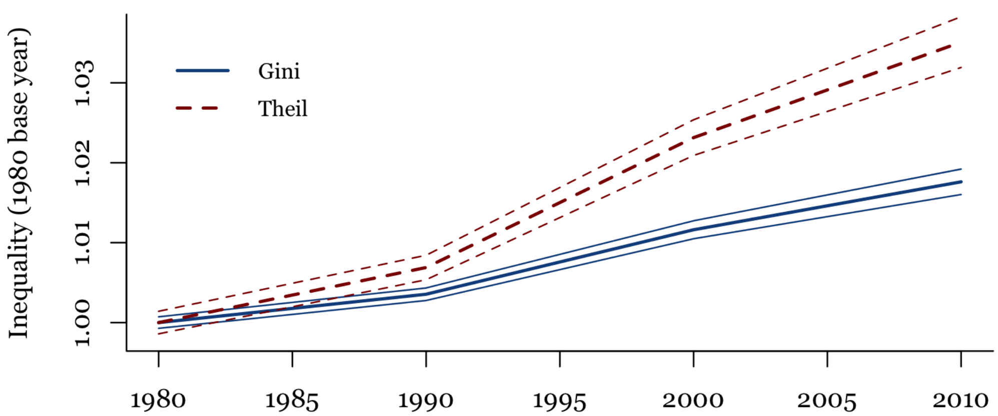
Figure 2: Tracing the geographical concentration of more and less disruptive innovation in the United States, 1920-2010





Source: Authors' elaboration based on HistPat & Lai Database. Geographic units are commuting zones. Consult Section 3.2 in the text for a detailed discussion of geographic definitions.

Figure 3: A counterfactual scenario relating disruptive innovation and spatial inequality, 1980-2010



Note: Figure traces changes in per capita personal income inequality based on Model 4, Table 5, except with all predictors except the most disruptive innovations set to 1980 means.

List of Tables

Table 1: Most and least disruptive patent classes in key periods of each industrial revolution

Period	Disruptiveness	Category	Class
1925-1930	Most	Electrical and Electronic	Electricity: circuit makers and breakers
		Mechanical	Clutches and power-stop control
		Mechanical	Brakes
		Others	Liquid heaters and vaporizers
		Mechanical	Plastic and nonmetallic article shaping or treating
		Others	Refrigeration
		Mechanical	Movable or removable closures
		Mechanical	Glass manufacturing
		Electrical and Electronic	Electric lamp and discharge devices
		Electrical and Electronic	Inductor devices
	Least	Others	Hydraulic and earth engineering
		Others	Fire escape, ladder, or scaffold
		Drugs and Medical	Dentistry
		Chemical	Ammunition and explosives
		Chemical	Fluid reaction surfaces (i.e., impellers)
		Mechanical	Railway draft appliances
		Mechanical	Vehicle fenders
		Mechanical	Ordnance
		Mechanical	Elongated-member-driving apparatus
		Others	Wooden receptacles
2005-2010	Most	Computers and Communications	Communications: electrical
		Electrical and Electronic	Radiant energy
		Electrical and Electronic	Active solid-state devices
		Electrical and Electronic	Chemistry: electrical current producing apparatus
		Computers and Communications	Optical waveguides
		Electrical and Electronic	Illumination
		Electrical and Electronic	Television
		Computers and Communications	Telecommunications
		Electrical and Electronic	Measuring and testing
		Mechanical	Optical: systems and elements
	Least	Others	Horizontally supported planar surfaces
		Chemical	Organic compounds – part of the class 532-570 series
		Mechanical	Manufacturing container or tube from paper
		Others	Excavating
		Chemical	Coating implements with material supply
		Others	Tent, canopy, umbrella, or cane
		Others	Harvesters
		Others	Fire escape, ladder, or scaffold
		Chemical	Organic compounds – part of the class 532-570 series
		Others	Envelopes, wrappers, and paperboard boxes

Table 2: Summary statistics for disruptive innovation and other key variables

	1920–1930		1980–2010	
	Mean	Standard Deviation	Mean	Standard Deviation
Total patents	145	1,037	1,126	6,075
Most disruptive Patents	28	200	586	2,995
Least disruptive Patents	10	70	66	207
Per capita manufacturing output, 1850$	112	159	–	–
Per capita personal income, 2010$	–	–	29,848	6,755
Population (000s)	47	151	464	1,120
Share urban population	0.07	0.2	–	–
Share foreign-born	0.05	0.06		
Number of post offices	18	14	–	–
Land grant university	0.03	0.16	–	–
Share of primary inputs	0.54	0.151		
Share 4+ years of college	–	–	0.20	0.07
Share computer industry employment	–	–	0.007	0.01
Share manufacturing industry employment			0.20	0.09
Share FIRE industry employment	–	–	0.05	0.02
Observations	2,438		2,236	
Locations	2,438		655	

Note: Units of observation in the 1920-1930 period are counties; in the 1980-2010 period they are commuting zones. During the 1920-30 period, all patenting variables are described in terms of decadal flows; in the 1980-2010 period they are measured in terms of 5-year flows. FIRE refers to industries classed as finance, insurance or real estate. See text for more detailed description of variables.

Table 3: Top 25 most disruptive places in each period, according to the number of disruptive patents per thousand inhabitants

1925-1930			2005-2010		
County	Disruptive Patents/000	Population	Largest city in Commuting Zone	Disruptive Patents/000	Population
Schenectady, NY	3.111	125,021	San Jose, CA	14.453	2,521,876
Branch, IN	2.463	23,950	Boise City, ID	8.863	645,142
Sullivan, NH	2.347	24,286	Burlington, VT	6.951	334,495
Lucas, OH	1.585	347,709	Fort Collins, CO	4.998	582,859
Coos, NH	1.489	38,959	San Francisco, CA	4.783	4,896,022
Warren, OH	1.463	27,348	Rochester, MN	4.649	253,379
New York, NY	1.458	1,867,312	Poughkeepsie, NY	4.238	931,061
Hamilton, OH	1.435	589,356	Austin, TX	3.952	1,779,457
Rock, WI	1.267	74,306	Lawton, OK	3.299	183,112
Essex, MA	1.179	498,040	Portland, OR	2.803	2,133,238
Knox, OH	1.125	39,338	San Diego, CA	2.679	3,104,346
Essex, NJ	1.103	833,513	Elmira, NY	2.599	350,074
Brule, SD	1.079	7,416	Boston, MA	2.561	5,163,543
Washington, CO	1.043	9,591	Raleigh, NC	2.508	1,876,821
Allegheny, PA	1.038	1,374,410	Palm Bay, FL	2.424	682,251
Union, NJ	1.032	305,209	Minneapolis, MN	2.303	3,197,939
Fairfield, CT	0.996	386,702	Albany, NY	2.231	1,112,237
Cook, IL	0.967	3,982,123	Seattle, WA	2.181	4,285,519
Hartford, CT	0.962	421,097	Eugene, OR	2.122	1,045,295
Bossier, LA	0.951	28,388	Buffalo, NY	2.095	2,353,374
Fairfax, VA	0.950	25,264	Binghamton, NY	2.014	294,870
Hampton, VA	0.940	6,382	Manchester, NH	1.982	1,271,163
Erie, OH	0.902	42,133	Brick Township CDP, NJ	1.909	1,208,464
Westchester, NY	0.898	520,947	Pullman, WA	1.901	82,075
Richland, OH	0.895	65,902	Cedar Rapids, IA	1.878	274,746

Table 4: Turbulence in the leadership ranks of commuting zones across the 1925 to 2010 period.

			2005-2010	
			Not in Top 25	Top 25
Disruptive patents/capita	1925-1930	Not in Top 25	527	21
		Top 25	19	4
Total Disruptive patents	1925-1930	Not in Top 25	534	12
		Top 25	12	13

Note: Because of the need for consistent units in this analysis, we aggregate counties over the 1925-30 period up to the level of commuting zones.

Table 5: Local disruptive innovation and development indicators for the second and third industrial revolution, 1920-1930, and 1980-2010

	2nd Industrial Revolution		3rd Industrial Revolution	
	Differenced Δy_c		Decadal FE Panel	
	(1)	(2)	(3)	(4)
All patents (log)	0.085***		0.011*	
	(0.018)		(0.005)	
Most disruptive patents (log)		0.054***		0.011**
		(0.020)		(0.0043)
Least disruptive patents (log)		0.036		0.0059
		(0.02)		(0.0034)
Population (log)	0.074*	0.094*	-0.072	-0.102
	(0.037)	(0.042)	(0.024)	(0.027)
Urban Population share	0.00003	-0.00001		
	(0.0001)	(0.0001)		
Foreign-born share	-0.0001	-0.0002		
	(0.0005)	(0.0005)		
Primary inputs	0.914***	0.922***		
	(0.172)	(0.174)		
Land grant university	-0.052	-0.045		
	(0.062)	(0.064)		
Post offices	-0.004**	-0.005**		
	(0.002)	(0.002)		
$y_{c,t-1}$	-0.204***	-0.199***	-0.049	-0.041
	(0.028)	(0.029)	(0.023)	(0.026)
4+ Years College share			0.146	0.078
			(0.108)	(0.116)
Computer employment share			0.279	0.308
			(0.339)	(0.339)
FIRE employment share			2.66***	2.853***
			(0.371)	(0.461)
Manufacturing employment share			0.397***	0.447***
			(0.073)	(0.086)
Period	1920-1930	1920-1930	1980-2010	1980-2010
State FEs	Yes	Yes	No	No
CZ FEs	No	No	Yes	Yes
Year FEs	No	No	Yes	Yes
Observations	2,438	2,438	2,900	2,900
R^2	0.148	0.146	0.934	0.904

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Panel models report cluster-robust (CZ-level) standard errors in parentheses. The 1920-30 period reports cluster-robust (State-level) standard errors in parentheses. Unit of observation in models 1-2 is the county; in 3-4 it is the commuting zone. Dependent variable in models 1 and 2 is change in log manufacturing output per worker. Dependent variable in models 3-4 is log per capita personal income (PCPI). PCPI is inflation-adjusted to constant 2010 dollars.