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Technological diversification of U.S. cities during the great historical crises

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Abstract

Regional resilience is high on the scientific and policy agenda. An essential feature of resilience is diversifying into new activities but little is known about whether major economic crises accelerate or decelerate regional diversification. This article shows how crises impact the development of new technological capabilities within U.S. metropolitan areas by examining three of the largest downturns in U.S. history, the Long Depression (1873–1879), the Great Depression (1929–1934) and the 1970s recession (1973–1975). We find that crises (i) reduce the pace of diversification in cities and (ii) narrow the scope of diversification to more closely related activities. This pattern seems general as it also holds for smaller, local crises. Evidence is presented that this general pattern of technological diversification strongly hampers employment growth. Additionally, we find that diverse cities generally diversify more strongly during times of crisis.

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1. Introduction

Large crises tend to have global economic consequences but are also characterised by strong local disparities in vulnerability (Martin, 2012; Odendahl and Springford, 2020). With the recent shocks following the COVID-19 pandemic and the war in Ukraine questions on how to prevent regions from entering crises and how to alleviate the impacts of crises on regions have returned to prominence on the research agenda. However, despite the wide interest, the literature on regional resilience is still largely considered work in progress (Boschma, 2015).

A crucial component of regional resilience is the ability of regions to diversify into new activities (Pike et al., 2010; Boschma, 2015; Xiao et al., 2018; Rocchetta et al., 2022). Since the work of Schumpeter (1942) it is clear that dynamics in innovation and economic crises are strongly connected (Filippetti and Archibugi, 2011). Crises are known to accelerate technological change because less competitive firms operating under outdated paradigms are more likely to shut down during negative demand shocks making adaptation necessary to employ productive sources set free (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). As similar industrial activities cluster in space, regions can be particularly badly affected by crises when their main industries are hit, which may make it crucial to develop new activities to speed up the recovery process. History is replete with cases in which adaptation to new circumstances was necessary to overcome crises (Grabher, 1993; Glaeser, 2005; Hill et al., 2012; Esposito, 2022). For example, Glaeser (2005) contrasts Boston's capability to reinvent itself during the computer revolution to the absence of this capacity in Detroit.

However, little is known about the nature of diversification within regions during periods of crisis. In the long-wave literature two different views are expressed on the relation between diversification and crises (Filippetti and Archibugi, 2011): some scholars claim major crises trigger technological breakthroughs because the opportunity costs of diversification decrease when previous activities are no longer profitable (Schumpeter, 1939; Kleinknecht, 1987), while others suggest that dramatic drops in demand prevent the investments necessary to introduce new (major) technologies during unsettled times (Schmookler, 1966; Scherer, 1982). Which of these theories prevails at the regional level remains unclear. Therefore, we formulate two research questions: do regions diversify more or less during crises;? and do regions diversify more or less into unrelated activities during crises?

Previously, empirical evidence on these questions relied primarily on case studies. More recent work by Hidalgo et al. (2007), Kogler et al. (2013), Boschma et al. (2015), Balland et al. (2015) and Rigby (2015), among others, made it possible to quantify the relatedness between technologies, permitting more systematic analyses. Advances in data availability complement this development. The HISTPAT U.S. patent data set (Petralia et al., 2016) reaches back to 1836. Patents yield insights into the evolution of regional knowledge stocks and hence how technological capabilities in regions adapt to crises. In this article, we focus on patterns of technological diversification within Metropolitan Statistical Areas (MSAs) during three of the most devastating economic shocks in U.S. history: the Long Depression, the Great Depression and the 1970s recession.[1]

The results are summarised here. First, we find that U.S. cities diversify less during crises. Second, in periods of crisis, cities diversify more in closely related activities than during periods of prosperity. More specifically, the probability that a region develops a new specialisation in a strongly related technology decreases by 11% during a crisis, while the probability of developing a specialisation in a strongly unrelated technology decreases by 51%. This helps to explain why so few regions experience a resurgence of economic activity after a downturn (see also Esposito, 2022). We find that the diversification pattern generally holds for each of the three major crises and smaller local crises, which suggests that the patterns found hold for crises in general.

Additionally, we analyse the effects of technological diversification on employment dynamics during the 1970s recession. We find that diversification is strongly beneficial for employment growth in regions in crisis, especially when new activities are unrelated. This is strong proof of the relevance of diversification in regional resilience claimed by Pike et al. (2010)

1 The recent crises and also the financial crisis (2007–2008) are too recent to be included in the analysis, as further explained in Section 3.

and Boschma (2015). We also consider the type of diversification during each of the crises separately and find that during the Long Depression and the 1970s recession, diversification focused more on specific upcoming technologies, respectively, in electrical and electronics and computers and communication. This is in line with the observation that these two crises occurred during industrial revolutions with radical technological change in these technological fields (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998; Boschma, 1999; Perez, 2009). Finally, we also find that more diverse cities have a higher probability of diversifying during crises than do specialised cities, which is in line with the findings by Castaldi et al. (2015). This suggests that actively diversifying technologies in regions may offer benefits that are in addition to the advantage of the portfolio effects that diverse cities already enjoy (Chinitz, 1961; Frenken et al., 2007).

The structure of the article is as follows. In Section 2, we discuss recent theorising on regional resilience and diversification, and how that is related to periods of crisis and technological change. Based on these theoretical considerations, we derive two hypotheses on diversification in times of crisis. In Section 3, we explain the data and the methodology used. In Section 4, we present the main empirical findings. Section 5 of the article offers a conclusion and a discussion of the findings pointing towards a future research agenda.

2. Resilience of regions and diversification in times of crisis

In recent years, studies have investigated the ability of regions to bounce back after a crisis (Martin, 2012; Balland et al., 2015; Dijkstra et al., 2015; Diodato and Weterings, 2015; Cuadrado-Roura et al., 2016; Crescenzi et al., 2016; Sedita et al., 2016; Bristow and Healy, 2018; Fratesi and Perucca, 2018; Rocchetta and Mina, 2019). The regional resilience literature is fundamentally interested in the capacity of regions to recover from a shock, and what processes drive that recovery. Many resilience studies follow an equilibrium approach, that is, looking at the ability of regions to return to a pre-existing equilibrium state after a shock or to move into a new equilibrium state (Fingleton et al., 2012). These studies tend to overlook the fact that a substantial part of the recovery process may depend on the ability of regions to develop new growing activities that offset processes of decline (Boschma, 2015; Balland et al., 2019; Xiao et al., 2018; Rocchetta et al., 2022). As such, tackling the question of regional resilience requires an understanding of how regions diversify into new activities.

A large empirical literature on diversification suggests that agents in regions do not start from scratch when diversifying: they tend to build on existing local capabilities, a process that has been labelled related diversification (Neffke et al., 2011; Boschma et al., 2015; Rigby, 2015; Hidalgo et al., 2018). This literature asserts that the capabilities of agents present in a region influence the type of new products and inventions that can be made because it is harder to learn new skills and ideas when these are less related to one's current capabilities. For example, Boschma and Wenting (2007) showed that during the early development of automobiles, entrepreneurs were more successful in the car industry when they previously had worked in related industries like bicycle and coach making or when their regions were specialised in these related industries. As a result, there is a strong path dependency in the industrial developments of a region in which the past strongly influences the future (Rigby and Essletzbichler, 1997). Note that this does not mean that unrelated diversification (i.e., the successful development of new activities unrelated to local activities) does not occur in regions, but it is found to be a rare phenomenon

(Hidalgo et al., 2007; Neffke et al., 2018; Pinheiro et al., 2021). However, this line of literature does not consider diversification during crises yet.

Connecting the diversification literature to the regional resilience literature has already been proposed by Boschma (2015). Inspired by scholars who advocate an evolutionary approach to regional resilience (e.g., Christopherson et al., 2010; Pike et al., 2010; Simmie and Martin, 2010; Martin and Sunley, 2015; Cainelli et al., 2018; Webber et al., 2018), he links resilience to the ability of regions to diversify and create new growth paths, to offset stagnation and decline during shocks. At the firm level, crises entail negative demand shocks that generally lead to the acceleration of technological change as less competitive firms operating under outdated paradigms close down and set labour and capital free (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). At the regional level, spatial clusters of firms within the same industrial sector mean that crises can be far-reaching and that a new phase of growth likely involves replacing old activities with new ones, as suggested by the adaptive regional life cycle model.

Diversification is even more important in major crisis periods as these are often associated with radical, disruptive kinds of technological change (Duijn, 1983; Boschma, 1999; Perez, 2009) that also form turning points in regional innovation cycles and geographies of prosperity (Dosi, 1984; Berger and Frey, 2016; Esposito, 2022). Case studies illustrate the importance of regional diversification during these technological revolution-induced crises. Glaeser (2005), for example, describes how Boston reinvented itself during the computer revolution of the 1970s by developing new leading industries when others faded. In contrast, Detroit appeared unable to develop new industries when its dominance in car-producing technology waned (Glaeser and Ponzetto, 2007; Hill et al., 2012).

However, more systematic evidence is missing to show how generalisable and accurate the diversification patterns from these examples actually are and whether they hold in all types of crises. Currently, it remains unknown whether crises speed up and extend the scope of innovation or do the opposite.

This topic has not received a lot of attention in the regional resilience literature. However, a related debate has been taking place in the long-wave literature for many years (Filippetti and Archibugi, 2011). Innovation theories, inspired by Schumpeter, that developed in the 1980s (Dosi et al., 1988) viewed radical innovations as clustering in waves rather than occurring randomly over time. However, much discussion arose on whether this 'swarming of innovations' occurred during the downswing period (crisis) or upswing period (growth) of the long wave. In this debate, Mensch (1975) and Kleinknecht (1981, 1987) supported the so-called depression trigger hypothesis, claiming that in periods of crisis, demand drops dramatically and returns on further improvements of mature products and technologies are low, and therefore the relative risk of introducing radical innovations for firms decreases. This incentive becomes even stronger when productive resources are set free during the downswing of the economy, leading to declining wages and lower capital costs, which makes it more attractive to invest (Krugman, 1993; Glaeser, 2005; Hershbein and Kahn, 2018). Moreover, many innovative breakthroughs are technologically related to each other, showing interdependencies and complementarities (Rosenberg, 1982; Carlsson and Stankiewicz, 1991) which makes them cluster in time (Rosenberg and Frischtak, 1983; Boschma, 1999). And, once radical innovations are introduced, they often attract new investments leading to a large stream of additional innovations, known as the 'bandwagon effect' (Clark et al., 1981).

Diametrically opposing this depression trigger hypothesis is the 'demand-pull' hypothesis suggesting that dramatic drops in demand during crises prevent the introduction of new (major) technologies (Schmookler, 1966; Freeman et al., 1982; Scherer, 1982). Freeman et al. (1982) argued that R&D activity is reduced considerably in long-wave depressions. Instead, the rise in demand during the upswing provides more favourable conditions for firms to introduce breakthroughs and major innovations (Geroski and Walters, 1995). Schmookler (1966) claimed that upswings in inventive activity followed upswings in demand (Coombs et al., 1987). Moreover, depression phases are characterised by a mismatch between major technologies and institutions (Perez, 1983; Dosi, 1984): the successful introduction and diffusion of major breakthroughs in the economic system require a set of new institutions that take a long time to develop (Freeman and Perez, 1988). The demand-pull model claims that new major technologies are more likely to enter the economy in the growth phase of the long wave.

Reformulating the neo-Schumpeterian ideas into the framework of the regional diversification literature, we might expect economic agents within regions to introduce and develop new activities during downswings as much as during upswings. Therefore, we develop a set of competing hypotheses on the adoption of new technologies within regions:

Hypothesis 1(a). Cities diversify more during crises than during non-crisis periods.

Hypothesis 1(b). Cities diversify less during crises than during non-crisis periods.

Hypothesis 1a builds on the depression trigger hypothesis, stressing that diversification is more likely to occur during periods of crisis. As stated above, economic agents might be more willing to take risks and try something new when current products and technologies show decreasing returns. Institutional agents (like regional governments) may see major enduring crises as windows of opportunity and are therefore more prone to promote new possibilities to end the crisis. In contrast, Hypothesis 1b builds on the demand-pull argument and states that diversification is even more unlikely to take place in regions during periods of crisis. Inventions have to wait until upswings in demand arise.

Furthermore, the contrasting Schumpeterian views on adopting new major technologies also yield different expectations on the level of unrelated diversification during crises, which are expressed in Hypothesis 2:

Hypothesis 2(a). Cities diversify more in less related technologies during crises than during non-crisis periods.

Hypothesis 2(b). Cities diversify more in related technologies during crises than during non-crisis periods.

On the one hand, the depression trigger hypothesis suggests that unrelated diversification is more likely as returns on related diversification have decreased. On the other hand, the demand-pull hypothesis suggests that related diversification is more likely as unrelated diversification would just add to the uncertainty of the crisis period. This uncertainty is likely higher for unrelated diversification that requires a transformation in existing capabilities, knowledge sets, skills and production techniques (Neffke et al., 2018).

Here, we are fundamentally interested in understanding how *capabilities* present in a region are adapted in response to a crisis. Our hypotheses focus on technologies because we rely on patent data. We believe patents to be a reasonable proxy for the capabilities present in a region as they capture the qualitative aspect of the know-how present and put to work in an area. This certainly holds for the time periods examined here when manufacturing, where patenting is more relevant than in services, occupied a more prominent place in the economy and product development and production generally took place within the same area (Duranton and Puga, 2005). The development of new technologies hence can be seen as a reasonable proxy for developments in the capabilities during crises within an area.

We do caution that new patenting activity does not necessarily lead to the successful commercialisation of additional capabilities in new growth sectors. The successful commercialisation of technologies depends on many more factors such as local market conditions, institutions, entrepreneurial ecosystems and competition (Saxenian, 1994; Boschma, 2015; Balland et al., 2019). Nonetheless, we do explore the link between technological diversification and employment growth in an extension to our main analysis, see Section 4.2 and Appendix 3.9.

To test our hypotheses we focus on the largest economic crises of their time periods, following the NBER: the Long Depression (1873–1879), the Great Depression (1929–1934) and the 1970s recession (1973–1975). There are two reasons for this choice to identify the link between patenting activity and economic activity, and to ascertain whether technological diversification is a relevant regional resilience strategy. The first relates to the fact that we have to rely solely on patent data to determine the size and type of activities in a region. A concern may be that a drop in regional patenting activity is not actually associated with a drop in economic activity, that is, a crisis, but to spurious patenting dynamics. The profound impact of the economic crises chosen here makes it much more likely that these drops in patenting activity are related to drops in economic activity. The second relates to the relevance of (technological) diversification. The time periods chosen also overlap with periods of great technological change that form turning points in regional economic history suggesting that diversification is a particularly relevant regional resilience strategy in these time periods (Duijn, 1983; Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998; Boschma, 1999; Perez, 2009; Berger and Frey, 2016). Note that our results greatly alleviate these two concerns.

The three crises do vary in the nature of technological change. We consider these differences in Appendix 3.10.

3. Data and methodology

The hypotheses outlined above are tested with a unique dataset of U.S. patents covering the period 1836–2002. Although we are aware of the limitations of patent records (Griliches, 1981), patents hold a wealth of information regarding the process of invention and the nature of additions to the expanding stock of knowledge. The patent data from 1836 to 1974 were developed by Petralia et al. (2016) and patents since 1974 are available through the NBER (Hall et al., 2001).

Diversification in an MSA is captured by the development of a comparative advantage in a new technology within that MSA.[2] MSAs are defined by the U.S. Census Bureau as core areas with at least 50,000 inhabitants and adjacent countries that are socially and economically integrated, as measured through commuting patterns. As these commuting patterns do not necessarily hold for the same areas as 100 years ago, we also run robustness checks using county-level data. We use the Metropolitan Core-Based Statistical Areas delimitations of 2013 as the definition of MSAs. As agents interact within these areas,

2 We note that if a region diversifies in activities where patenting is uncommon this will not be captured by our methodology.

then MSAs also capture the spaces within which technological knowledge circulates and within which resources set free during crises find new purposes, see Boschma (2015) and Rigby (2015). We remain agnostic on which agents within an MSA are involved in the development of new technological specialisations, this topic is studied elsewhere, see Neffke et al. (2018). We do introduce measures below that capture the linkages between MSAs through inventors, as innovation does not necessarily take place in isolation and global pipelines matter (Bathelt et al., 2004; van der Wouden and Rigby, 2019).

We restrict our sample to MSAs within the contiguous USA. We also impose a minimum of 10 patents per year for a time period for an MSA to be included and a minimum of 0.5 patents[3] per year in a certain primary technology class. As a result, data are drawn from a sample of 274 MSAs and 2,171 MSA-time periods. Technologies are represented by the 438 different primary classes of the U.S. Patent and Trademark Office (USPTO) patent classification system.[4] Below, we introduce our definitions and measurements of crises, diversification, relatedness and diversity.

3.1. Crises

Following Balland et al. (2015), we build on trends in patenting per region to indicate when regions are in crisis, as patent counts are highly correlated with economic performance (Glaeser and Ponzetto, 2007; Rothwell et al., 2013). As said, we focus on the great historical crises of the USA.

Each nationwide crisis is regarded as a shock at the regional level. A metropolitan area can then either enter into a crisis or not. At the regional level, the emergence and the duration of crises are identified from patent records using an adapted version of the business cycle algorithm of Harding and Pagan (2002), after Balland et al. (2015). We follow the definition of technological crises by (Balland et al., 2015, 6) as sustained periods of negative growth in patent activity: ‘more formally, a time series recording yearly patenting activity can be defined as a continuum of local maxima (peaks) and minima (troughs) that divide the series into periods of technological growth from trough to peak and technological crisis from peak to trough’.

The algorithm to detect business cycles ‘identifies potential turning points as the local minima (trough) and maxima (peak) in the series. Let p_t be a patent count yearly series. A trough is identified as $\left(p_{(t-j)},\ldots,p_{(t-1)}\right) > p_t^{trough} < \left(p_{(t+1)},\ldots,p_{(t+j)}\right)$ while a peak follows the condition that $\left(p_{(t-j)},\ldots,p_{(t-1)}\right) < p_t^{\text{peak}} > \left(p_{(t+1)},\ldots,p_{(t+j)}\right)$’. (Balland et al., 2015, 172). To prevent ‘noise’ due to years of random growth or decline, two extra conditions are imposed: ‘The phases (technological growth or technological crisis) should be at least 2 years long, while complete cycles (the period between 2 peaks or between 2 troughs) should be at least 5 years long’.

As a result of this procedure, time periods are defined separately for each MSA and therefore do not necessarily match or have the same duration. For each MSA, all periods of crisis and growth are identified between 1836 and 2002. Crises that do not overlap with one of the three great U.S. crises or have a decrease in the patenting activity of less

3 Patents that are assigned to inventors in multiple MSAs, only count as 1 divided by the number of MSAs on that patent for each of the MSAs.

4 Primary technology classes are comparable over time as the USPTO reclassifies all patents when new class definitions are introduced.

than 35% during the crisis are ignored. Note that in Section 4.2, we show that using different thresholds and including local crises leads to similar results. Regional periods of growth are kept regardless of when they occur. We give further detail on the dynamics of regional patenting during the great historical crises in Appendix 1.

3.2. Diversification

We use the notion of Revealed Comparative Advantage (RCA) (Hidalgo et al., 2007) to identify in which technologies each MSA is specialised over time. In Equation (1), x represents the number of patents, c denotes the city-region (MSA), i is the primary technology class and t indicates the time period. RCA values are bounded on the left by zero. An RCA value of 1 indicates that an MSA has the same share of patenting activity in a particular technology class as the national average. RCA values of 1 or greater indicate regional specialisation in a technology. A technology enters the technological portfolio of an MSA when an MSA develops a specialisation in a technology class that it did not have in the previous time period, indicating it has diversified. To account for spurious entries of technologies, we add the condition that an entering technology has to remain present in the portfolio of a MSA (with RCA => 1) for at least two time periods. This condition also increases the likelihood that patenting activity is actually turned into profitable economic activity, as unprofitable patenting activity would likely not be sustained over a longer time.

$$\mathrm{RCA}_{cit} = \frac{\dfrac{x_{cit}}{\sum_{i=1}^{I} x_{cit}}}{\dfrac{\sum_{c=1}^{C} x_{cit}}{\sum_{c=1}^{C}\sum_{i=1}^{I} x_{cit}}} \tag{1}$$

3.3. Relatedness

Technologies that are not in the technological portfolio of an MSA in time period $t-1$ (those for which the RCA value is below one) enter or do not enter in time period t. An important predictor of the entry of a technology within an MSA is how closely related it is to technologies already present in the region (Boschma et al., 2015; Balland et al., 2019). This notion of relatedness is essential for Hypothesis 2, where we focus on less related diversification. The relatedness between *technologies* is measured by examining the frequency with which two technology classes co-occur on patent documents compared to a random distribution. The formula for relatedness, outlined by van Eck and Waltman (2009) and improved by Steijn (2021), is reported in Equation (2). Where C_{ijt} is the number of co-occurrences between technology i and technology j in time period t. S_{it} and S_{jt} is the number of co-occurrences involving respectively technology i and technology j in time period t, N is the total number of technologies and m is the total number of co-occurrences.

$$\mathrm{TR}_{ijt} = \frac{C_{ijt}}{\left(\frac{S_{it}}{\sum_{n=1}^{N} S_n}\frac{S_{jt}}{(\sum_{n=1}^{N} S_n)-S_{it}} + \frac{S_{jt}}{\sum_{n=1}^{N} S_n}\frac{S_{it}}{(\sum_{n=1}^{N} S_n)-S_{jt}}\right)m} \tag{2}$$

Building on relatedness, relatedness density (RlD; see Hidalgo et al., 2007) measures the relatedness of a *region* to a *technology* that is not yet present in its technological portfolio. RlD is equal to the sum of relatedness values of the technologies in the region to the potential entering technology divided by the sum of relatedness values of all technologies to this potential new technology class, as can be seen in Equation (3).

$$\text{Rel.density}_{cit} = \frac{\sum_{j \in c, j \neq i} \text{TR}_{ijt}}{\sum_{j \neq i} \text{TR}_{ijt}} \tag{3}$$

3.4. Control variables

3.4.1. Presence of technology in neighbouring MSA

Other factors that are correlated with our variables of interest may influence the development of a new technological specialisation within an MSA. Having MSAs nearby that have an RCA in a technology can be expected to positively influence the entry of that technology to the technological portfolio of a city because knowledge flows tend to be geographically conditioned (Rigby, 2015; Boschma, 2017). Therefore, we develop a spatial weight matrix using the inverse distance for the presence of technology in neighbouring MSAs.

3.4.2. Population

We also include the average population of MSAs in the time periods based on census data.

3.4.3. Diversity

Some scholars argue that it is the diversity of capabilities in a city that is more important than the size of a city. The regional resilience literature argues that variety is crucial for resilience because it can accommodate sector-specific shocks (Essletzbichler, 2007, 2015; Diodato and Weterings, 2015; Rocchetta et al., 2022). This is in line with numerous case studies on specialised regions that showed structural problems of adjustment (Boschma and Lambooy, 1999; Pike et al., 2010). Specialised regions may have a low capacity to diversify in new activities, because they are cognitively, socially and politically locked-in (Grabher, 1993; Hassink, 2005).

To control for this, we follow Duranton and Puga (2000) who propose a simple diversity index, known as the relative diversity index (RDI). The intuition is that if the relative distribution of patenting activity over technology classes in an MSA resembles the national distribution, then the city is relatively diverse. On the other hand, when the patents of an MSA cluster are strongly above the national average in a few classes then it is seen as specialised.

Following Duranton and Puga (2000) the formula for the RDI is provided in Equation (4), where the definitions are the same as above. A value close to zero denotes a specialised city, whereas the larger the value the more diverse a city is.

$$\text{RDI}_{ct} = \frac{1}{\sum_{i=1}^{I} \left| \frac{x_{cit}}{x_{ct}} - \frac{x_{it}}{x_t} \right|}. \tag{4}$$

3.4.4. Degree centrality

Agents in regions may also have strong connections external to their area that are not fully captured by adding a variable on the presence of a technology in neighbouring cities. For example, multinational corporations are known to be more capable of wielding knowledge from distant areas (Iammarino and McCann, 2013). To somewhat control for the extent to which diversification within and outside of crises may be influenced by these so-called 'pipelines' (Bathelt et al., 2004; van der Wouden and Rigby, 2019), we use the degree centrality of MSAs in the collaboration network of inventors of patents.

3.4.5. Fixed effects

We further reduce the risk of confounding variables by the inclusion of fixed effects at the level of the time period, technology and MSA.

Table 1 gives the descriptive statistics of our variables.

3.5. Empirics

Entry models are a common tool in the literature that yield insight into the role of relatedness in diversification (e.g., Boschma et al., 2015; Balland et al., 2019). Despite the popularity, some underestimation of risks exists concerning two particular traits in this type of analysis, namely, the extreme right skewness of its main variables of interest: entry and RlD. This means that often-used linear probability models (LPMs) do not lead to correct estimations and that the coefficient is strongly influenced by outliers. Therefore, we choose to use a logit model and substitute the continuous RlD variable for an ordered categorical variable by creating dummy variables for each quantile of RlD values, see for more details Appendix 2.

Equation (5) gives our preferred regression formula for Hypotheses 1 and 2 and is in line with previous work like Boschma et al. (2015). If a technology i enters the technological portfolio of city c in time period t, the value of the dependent variable is 1. If it was not in the portfolio of city c and it did not enter its value is 0. The dependent variable is regressed on the RlD of the technology class to the portfolio of each city in the previous time period, on a dummy variable which indicates if a city is experiencing a crisis (Crisis) or not, on the interaction between these first two terms (RlD × Crisis), city characteristics (City) at time t, which consist of the RDI, population and degree centrality and on the presence (Pr) of technology i in the technological portfolio of neighbouring MSAs

Table 1. Descriptive statistics

Statistic	*N*	Mean	St. Dev.	Min	Max
Entry	724,752	0.031	0.174	0	1
Crisis	724,752	0.141	0.348	0	1
RlD	724,752	0.089	0.126	0.000	1.000
Population	724,752	416,093.600	961,537.100	20,402	17,019,060
Present×**W**	724,752	0.00003	0.00003	0.00000	0.0003
Diversity	724,752	1.086	0.303	0.255	1.833
Degree centrality	724,752	60.002	250.444	0.000	8460.667

multiplied by a spatial weight matrix **W**, a city-fixed effect (ϕ), a technology-fixed effect (θ) and a time-fixed effect (τ).

$$\begin{aligned}\text{Entry}_{cit} = {} & \sum_{k=1}^{5}\alpha_k \text{RID}_{cit-1,k} + \beta\text{Crisis}_{ct} + \sum_{k=1}^{5}\gamma_k\text{RID}_{cit-1,k} \times \text{Crisis}_{ct} \\ & +\delta City_{ct} + \eta\text{Pr}_{it} \times \mathbf{W} + \phi_c + \theta_i + \tau_t + \epsilon_{cit}.\end{aligned} \tag{5}$$

To facilitate interpretation we standardise the RDI, population, degree centrality and Present×**W** to have 0 mean and a standard deviation of 1 and use sum-to-zero contrasts for the fixed effects. As such, converting the intercept to probabilities gives the probability of entry at the average of all cities, technologies and time periods instead of the reference category for each dummy variable.

Based on Equation (5), we can calculate the marginal effect of crisis per RlD group to see if Hypothesis 1 and 2 can be accepted or rejected.[5]

We note that this empirical strategy aims at *describing* how regions diversify during crises and does not allow us to ascertain that crises *cause* these changes.

4. Results

4.1. Diversification in times of crisis

Table 2 gives the marginal effects based on the results for specification 5. The full regression results can be consulted in Table A2 of the Appendix. The first and second columns give the marginal effects for a specification without fixed effects, and in the case of Column (1) also without interaction terms. These results are highly similar to the preferred specification given in Column (3). Note that the parentheses give the 95% confidence interval.[6]

The key variable of interest here is crisis, for which the marginal effect is negative and significant. The coefficient on the crisis variable indicates that on average the probability of entry decreases by 0.32% in crisis for the reference category, according to the full specification in Column (3). This effect is substantial considering that the development of a new specialisation by a region is a rare event. The probability of entry is on average only 0.63% outside of crises for technologies that fall in the reference category of the lowest 0–20% RlD values. This means that a crisis leads to a reduction of $0.32/0.63 \approx 51\%$. Even though technological diversification within cities is a rare event overall, it becomes significantly more rare during crises.

Cities also diversify less when entering a crisis in the other RlD values than those of the reference category of the 20% lowest RlD values, as shown in Appendix 3.1. This rejects the depression trigger Hypothesis 1a and confirms the demand-pull Hypothesis 1b

5 For this calculation, we developed and published a R-package called fastlogitME, which uses less CPU and is compatible with speedglm.

6 We prefer to give the 5th and 95th percentile instead than a to probabilities converted standard error as the response scale (probabilities) is linear whereas the scale of the underlying link function is non-linear. When using a standard error derived from bootstrapping or the delta-method it may result in a confidence interval that exceeds the range of 0% to 100% entry probability, which is technically impossible and the reason in the first place to use logit models instead of linear models.

Table 2. Marginal effects (Hypotheses 1 and 2)

Dependent variable: entry of technology class *i* in the technological portfolio of city *c* at time *t*

	Naive specification (1)	+ crisis × relatedness density (2)	+ fixed effects (3)
RlD (20–40%)	0.0033***	0.0034***	0.0027***
	(0.0024, 0.0043)	(0.0024, 0.0044)	(0.0019, 0.0035)
RlD (40–60%)	0.0102***	0.0105***	0.0074***
	(0.0088, 0.0116)	(0.0091, 0.0120)	(0.0063, 0.0085)
RlD (60–80%)	0.0222***	0.0223***	0.0150***
	(0.0201, 0.0244)	(0.0201, 0.0245)	(0.0134, 0.0167)
RlD (80–100%)	0.0428***	0.0414***	0.0293***
	(0.0394, 0.0463)	(0.0381, 0.0450)	(0.0266, 0.0322)
Crisis	−0.0023***	−0.0053***	−0.0032***
	(−0.0026, −0.0021)	(−0.0063, −0.0040)	(−0.0042, −0.0019)
Diversity	0.0034***	0.0035***	0.0023***
	(0.0033, 0.0035)	(0.0034, 0.0036)	(0.0021, 0.0025)
Population	0.0001	0.0001	0.00004
	(−0.0001, 0.0003)	(−0.0001, 0.0002)	(−0.0001, 0.0002)
Present × **W**	0.0032***	0.0033***	0.0020***
	(0.0032, 0.0033)	(0.0033, 0.0034)	(0.0018, 0.0021)
Degree centrality	−0.0012***	−0.0012***	−0.0005***
	(−0.0014, −0.0010)	(−0.0014, −0.0010)	(−0.0007, −0.0004)
Time fixed effects	No	No	Yes
Technology fixed effects	No	No	Yes
MSA fixed effects	No	No	Yes
Observations	724,752	724,752	724,752

Notes: The RlD groups and crisis are dummy variables with as reference category, respectively, the 20% lowest RlD values and non-crisis time periods; $^{***}p<0.01$, $^{**}p<0.5$, $^{*}p<0.10$.

suggesting that when a crisis hits agents in cities see their resources to develop new activities diminish and cities end up diversifying less.

Before turning to the results of Hypothesis 2, we will consider the results of the other variables. The marginal effect of RlD values falling between the 20% and 40% lowest values in Column (3) indicates that technologies within this category are 0.27% more likely to enter the technological portfolio of a city than those of the reference category with the lowest 20% of RlD values *ceteris paribus*.

The probability of entry increases with RlD as can be seen by the increase in coefficient size up to 0.0293 with each step in RlD. This indicates that a region is more likely to develop a specialisation in a technology that is more strongly related to its technological portfolio, which is in line with the literature (e.g., Boschma et al., 2015; Hidalgo et al., 2018).

The marginal effect of technological diversity, as measured by the RDI, is positive and significant. The effect on entry is 0.23% is substantial and of a similar size of increasing RlD from the 0–20% quantile to the 20–40% quantile.[7] This is the first systematic

7 The reference categories for which the marginal effects are calculated are non-crisis periods but results are similar when this is switched to crisis periods.

evidence corroborating earlier suggestions based on case studies (Grabher, 1993; Boschma and Lambooy, 1999; Hassink, 2005; Pike et al., 2010; Boschma, 2015; Neffke et al., 2018), which claim that there is more to diverse cities that makes them open and interested in developing new activities. In such diverse settings, there is a lower probability that established industries and vested interests that dominate the institutional and policy network can block new key developments. This comes on top of the advantage that diverse cities have by virtue of their larger technological portfolio and therefore increased RlD to potential entering technologies, see also Balland et al. (2015) and Boschma (2015). Note that a larger technological portfolio also has a 'hedging' advantage when entering a crisis (Chinitz, 1961; Frenken et al., 2007).

Contrary to expectation, the marginal effect of population size is insignificant and virtually zero and the marginal effect of degree centrality is even significantly negative. However, when the diversity variable is omitted from the regression the population variable is positive and statistically significant and when also the population variable and fixed effects are dropped also the degree centrality variable turns positive and statistically significant. This suggests that the industrial composition, proxied by diversity, is more important for the development of new specialisations than just agglomeration size, proxied by population or having a central position in inventor networks, proxied by degree centrality.

The positive marginal effect of Present $\times$ $\mathbf{W}$ indicates that the presence of the technology in nearby cities increases the likelihood that said technology enters the technological portfolio of a city, which is in line with Rigby (2015) and Boschma et al. (2017).

4.1.1. The nature of diversification during crises

For Hypothesis 2, on how crises impact the RlD of the technologies that cities enter, we turn to Figure 1. Figure 1 illustrates the relative size of the marginal effect of entering a crisis compared to the average probability of entry outside of a crisis per RlD group. As said, the probability of entry of a technology decreases by $0.32/0.63 \approx 51\%$ when entering a crisis for the lowest RlD values, whereas, for technologies with RlD values in the highest quintile, the entry probability is only about 11% smaller during crises, see Appendix 3.1 for more details. Hence, Figure 1 confirms Hypothesis 2b: cities diversify more in related technologies during crises. This likely reflects the uncertainty of economic agents in terms of future technological development during the highly turbulent phases of major crises, following the demand-pull hypothesis.

Interestingly it seems that during periods of radical technological change local economies that enter a crisis switch to more conservative, that is, related, diversification. This may give insight into why industrial revolutions shift prosperity from certain cities to other cities (Glaeser and Ponzetto, 2007; Berger and Frey, 2016) and the finding of Esposito (2022) that only very few cities manage to overcome a period of decline and move into a new growth path.

4.2. Robustness and extensions

The results presented should be interpreted as being descriptive and not indicating causality. Nevertheless, to check and expand on the results, we briefly discuss results derived from other specifications in this section, while the full results can be consulted in Appendix 3.1.

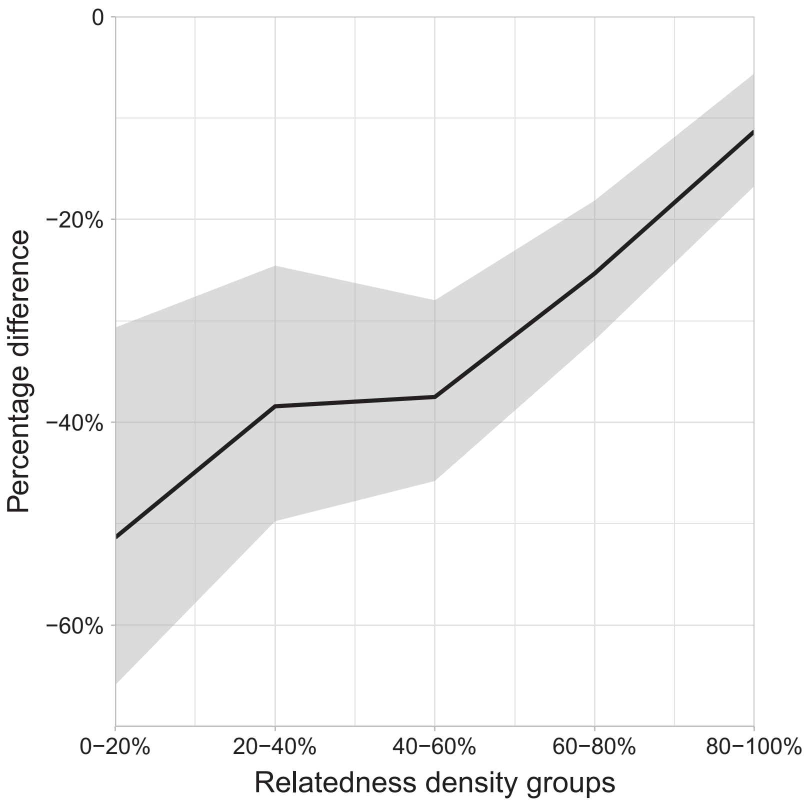

Figure 1. Percentage difference in probability of entry between crisis and no crisis across quintile groups.

We show that similar results are found when the threshold of crisis depth is increased or lowered, in Appendix 3.2; when entries are not defined by the RCA passing the threshold of one but when larger steps are necessary, in Appendix 3.3; when also smaller crisis periods outside of the great historical crises are taken into account, in Appendix 3.4; when looking at the county level instead of the MSA level, in Appendix 3.5; when entering technologies are compared to the previous technological portfolio of a region, instead of the idiosyncratically varying boom–bust-cycle-based time periods, in Appendix 3.6; when crisis and non-crisis periods of cities within the great historical crises are considered within equal time periods while controlling for observables and certain unobservables through fixed effects, in Appendix 3.7, which approximates a difference-in-difference approach; and when looking at each of the historical crises separately in Appendix 3.8.

These results, in particular the ones for smaller local crises, show that the drop in diversification activity and a stronger focus on related technologies during crises is a general pattern that holds for all economic downturns in general. This also suggests that, in spite of earlier concerns, patenting activity is a reasonable measure of economic activity and that diversification is similar during and outside periods of much technological change.

Table 3. Regression results—entry and employment dynamics

Dependent variable:	Employment growth in:					
	Percentages between 1975 and 1989		between 1970 and 1989	between 1970 and 1978	between 1975 and 1978	Log levels between 1975 and 1989
	(1)	(2)	(3)	(4)	(5)	(6)
Entry	0.085**	0.087**	0.107**	0.078***	0.047***	0.079**
	(0.037)	(0.035)	(0.052)	(0.030)	(0.014)	(0.036)
Rel. dens. of entry	0.014*	0.013*	0.044***	0.016***	–0.002	0.012*
	(0.007)	(0.007)	(0.010)	(0.006)	(0.003)	(0.007)
Crisis	−0.143***	−0.114***	−0.167***	−0.088***	−0.064***	−0.084***
	(0.007)	(0.006)	(0.009)	(0.005)	(0.003)	(0.007)
Entry × crisis	0.162**	0.134*	0.044	–0.054	0.027	0.109
	(0.079)	(0.074)	(0.109)	(0.063)	(0.030)	(0.076)
Rel. dens. of entry × crisis	−0.053***	−0.048***	−0.061***	−0.014	−0.014***	−0.036***
	(0.013)	(0.012)	(0.018)	(0.010)	(0.005)	(0.012)
Log employment	−0.101***	−0.111***	−0.178***	−0.095***	−0.023***	−0.225***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)
Diversity	−0.104***	−0.111***	−0.147***	−0.029***	−0.005***	−0.133***
	(0.004)	(0.003)	(0.005)	(0.003)	(0.001)	(0.004)
Population	0.046***	0.021**	0.052***	0.068***	0.042***	0.103***
	(0.009)	(0.009)	(0.013)	(0.007)	(0.003)	(0.009)
Present × **W**	−0.060***	−0.140***	−0.212***	−0.106***	−0.040***	−0.136***
	(0.003)	(0.005)	(0.007)	(0.004)	(0.002)	(0.005)
Degree centrality	−0.076***	−0.037***	−0.069***	−0.073***	−0.048***	−0.080***
	(0.011)	(0.011)	(0.015)	(0.009)	(0.004)	(0.011)
Constant	0.634***	0.672***	1.070***	0.590***	0.204***	1.027***
	(0.009)	(0.009)	(0.011)	(0.006)	(0.004)	(0.009)
Technology fixed effects	No	Yes	Yes	Yes	Yes	Yes
Observations	57,847	57,847	57,847	57,847	57,847	57,847
R^2	0.113	0.113	0.087	0.074	0.066	0.220

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.2.1. Entry and employment dynamics

We also consider some extensions to the main results. First, we evaluate the impact of technological diversification on local employment dynamics for the 1970s recession by measuring the impact of the entry of technologies on the changes in the number of employees working with those technologies. More detail on the analysis and results can be found in Appendix 3.9. Here, we focus on the most relevant results in Column (2) of Table 3.

These results suggest that a city's entry into a new technology class between 1972 and 1976 is associated with an increase of 8.7% in employment for those working with that technology between 1975 and 1989 for the reference category, that is, regions that are not in crisis during the 1970s recession. A region that is in crisis during the 1970s recession experiences an additional increase in the employment growth rate of 13.4% when a new technology class is entered. Interestingly, regions that are not in a crisis see a stronger increase of 1.3% in employment growth rates when the technology that enters is a standard deviation more strongly related to their portfolio, but regions that are in crisis actually see their employment growth rate decrease by 4.8% when the entering technologies are more related.

This is a first strong proof that more technological diversification, in particular in less related activities, is beneficial to overcome crises, as was suggested earlier by Pike et al. (2010) and Boschma (2015). Strikingly, our main results show that regions tend to show the opposite of this ideal diversification behaviour when entering the crisis, that is, less diversification focused on more related activities.

4.2.2. Crises, diversification and technological change

In Appendix 3.10, we explore the technological variation between crises by classifying technologies as upcoming or outdated according to the respective time periods. For example, electrical and electronics are considered upcoming technologies during the electric revolution that coincides with the Long Depression but become outdated when the computer revolution emerges shortly after the 1970s recession.

On the one hand, we find that in the time periods of the Long Depression and the 1970s recession upcoming technologies have a larger probability of entry, during and outside of crises, which is consistent with the characterisation of these time periods as industrial revolutions. On the other hand, outdated technologies are less likely to enter, except during the Long Depression. We also find that outdated technologies see a larger drop in the probability of entry, particularly when less related. Upcoming technologies show a much smaller decrease in the probability of entry. This suggests that the type of technology does matter for diversification during crises.

4.2.3. Diversity and diversification

Finally, we further explore the finding of the main results that diverse cities have a strong advantage in diversifying into new technologies. In Appendix 3.11, we show that diverse cities in spite of diversifying more do not have a stronger tendency to focus on unrelated diversification when entering a crisis compared to more specialised cities.

5. Conclusion

In this article, we provide systematic evidence on the diversification patterns of regions in times of major crisis. Diversification is considered to be a crucial part of regional resilience, as developing new capabilities may allow regions to overcome crises. For a long time, questions like the ones asked here relied on case studies, which although insightful were difficult to generalise. Combining developments in data availability and in methods to quantify relatedness, we were able to examine the technological diversification of cities during crises by building on U.S. data for the Long Depression, the Great Depression and the 1970s recession.

We found that crises have (i) a strong dampening effect on diversification and (ii) that diversification in less related technologies is sharply reduced in crises relative to more prosperous times, which is in line with the demand-pull hypothesis (Schmookler, 1966; Freeman et al., 1982; Scherer, 1982). This is a general pattern as we find that it holds for each of the three great historical crises and also for smaller local crises. This finding may help to explain why so few cities manage to reinvent themselves when declining (Esposito, 2022).

Additionally, we find that successful technological diversification during crises is strongly associated with employment growth, in particular when the new technologies are less related to previous activities. This provides evidence that diversification into unrelated activities can contribute to overcoming crises and technological lock-in, as suggested by Grabher (1993), Pike et al. (2010) and Boschma (2015). This also suggests a possible role for policy-makers. Our main results showed that regions tend to show the exact opposite of the diversification behaviour that leads to more employment growth during crises, that is, diversifying less instead of more and in more related instead of unrelated activities. This suggests that a policy to stimulate diversification into less related activities during crises may be necessary.

Also, we find that the diversification of regions in crisis during the Long Depression and the 1970s recession does focus relatively strong on a particular set of technologies, respectively, those in electrical and electronic and in computers and communication. This is in line with these crises being in the time periods of, respectively, the electrical revolution and the computer revolution (Duijn, 1983; Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998; Boschma, 1999; Perez, 2009).

Furthermore, we also show that diverse cities manage to diversify more than their specialised counterparts during crises, which is in line with suggestions that there are less vested interests in the policy and institutional context that block new developments (Boschma, 2015; Castaldi et al., 2015; Neffke et al., 2018). This comes on top of the advantage that diverse cities have because of increased technological proximity to more technologies due to their larger technological portfolio and a smaller chance of entering a deep crisis as not all industries are generally hit at the same time (Chinitz, 1961; Frenken et al., 2007). However, these advantages seem overlooked in policy as improving diversity is currently generally not part of diversification policies, such as the Horizon 2020 and Smart Specialization strategy of the European Union.

These results give a detailed description of the diversification of regions during major crises. However, the study remains largely descriptive, causal mechanisms can be suggested from theory but are not tested directly. Future research could develop on the micro-mechanisms that influence diversification. For example, by using this framework to retrace previous case studies, such a Glaeser (2005).

Furthermore, this article found a relation between (technological) diversification and employment dynamics. However, there is still much room for improving our understanding of the exact ways in which inventions are transformed into successful industries during crises as this depends on many more factors than just the ability to patent, such as local market conditions, institutions, entrepreneurial ecosystems and competition (Saxenian, 1994; Boschma, 2015; Balland et al., 2019). The lack of data for many of these dimensions remains a challenge to our understanding of the mechanisms at hand.

This study is limited by its focus on diversification based on patent data. To get a more comprehensive picture of the resilience of cities, it is important to account for other forms of knowledge, which are not captured by patent data, such as in tertiary activities (Xiao et al., 2018).

Finally, a possible improvement for future research would be to include the role of institutions in regional resilience research (Boschma, 2015). Recent research has shown that regional institutions like bridging social capital matter for the ability of regions to diversify (Cortinovis et al., 2017). In the end it is institutional agents that renew economies, adapt institutions and develop new activities (Freeman and Perez, 1988; Amable, 2000; Hall and

Soskice, 2001). This matters even more in crises that are shown in this article to impact strongly on diversification and therefore possible avenues for recovery.

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Appendix A

A.1. Background information on crises

This section presents more information on (changes in) patent dynamics during the great historical crises. Figure A1 depicts the number of MSAs entering a period of growth in green, respectively, a period of crisis in red per year, during the time periods associated with each of the great historical crises. The impact of the crises on patenting activity is clearly visible in the number of MSAs that start a period of crisis in red, in the lower-segment of the graph, compared to those that start a period of growth in green, in the upper-segment of the graph. This suggests that patenting is a suitable proxy for regional economic activity.

One can also note a small time lag between the actual start of the great historical crises and MSAs entering a period of downturn in patenting for the first two major crises whereas the effect of the 1970s recession is immediately noticeable.[8] Because of the time lag in the reaction of patenting activity, we retain the regional crises that start in years when the number of MSAs that enter a crisis period is larger than the number of MSAs that enter a period of growth. For the Long depression, this is 1876 to 1878, for the Great depression 1932 to 1938 and for the 1970s recession 1972–1976. All other crisis periods are dropped from the sample. Regional periods of growth are kept regardless of when they occur.

Table A1 shows the strong impact of the great historical crises on the patent production at the regional level. Affected MSAs, in the second column, indicates the number of MSAs that enter a crisis that meets the aforementioned requirements and respective time period. Unaffected MSAs are MSAs that were in a growth phase before the start of the crisis and remain so over the course of the crisis. #MSAs give the total number of MSAs that meets the requirement of producing on average ten patents per year in that time period. This is not equal to the sum of unaffected MSAs and affected MSAs as MSAs could already be in crisis upon entering the respective time periods or could enter a crisis in which the requirement of losing more than 35% of patenting activity is not met. The last two columns, respectively, give the average duration of the crises, and the average percentage of patent activity lost at the trough compared with the peak for the affected MSAs. In these respects, the Great Depression stands out as the heaviest crisis.

A.2. Background information empirics

8 Note that the years indicate the end year of the previous cycle period and the start year of the next cycle period. For example, a period of crisis starting in 1972 indicates that the peak was in 1972 and the first year of downturn is 1973.

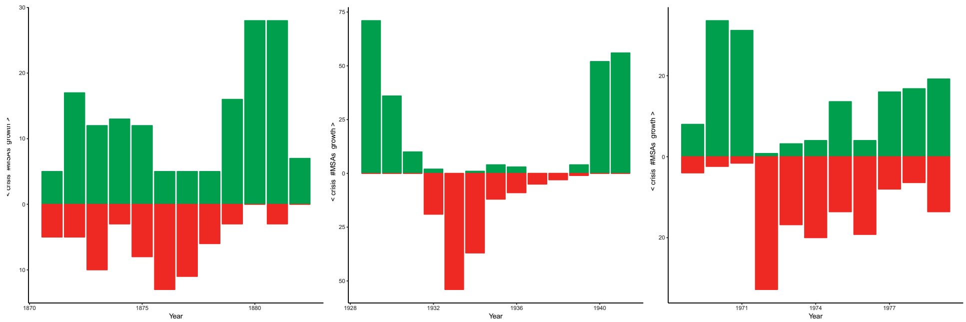

Figure A1. Number of MSAs starting a period of growth (green in upper-segment of the graph) versus a period of crisis (red in the lower-segment of the graph).

Table A1. The regional impact of the great historical crises

Crisis	Aff. MSAs	Unaff. MSAs	#MSAs	Avg. crisis length	Avg. crisis depth
Long depression	30	19	101	~3.7 years	~−53.6%
Great depression	139	2	205	~6.4 years	~−74.3%
70 s recession	128	44	252	~6.7 years	~−59.4%

In this section, we further provide information on two underestimated risks in the empirics of the widely used entry models. First, the dependent variable entry is strongly right-skewed, that is, there are very few incidences of successful entries (values of 1) compared with technologies that do not enter (values of 0). Second, the independent variable RID is strongly right skewed, that is, values range from 0 to 1 but are more strongly concentrated to the left of the mean, as can be seen in Figure A2.

The first has already been noticed by Boschma et al. (2015), referring to work by King and Zeng (2001). They argue that the coefficient estimates of nonlinear models might not be consistent when there are too many zeros in the dependent variable. They, therefore, use an OLS to estimate the entry model. The use of such an LPM has certain risks that can be considered to be outweighed by the benefits of easier interpretation (see Hellevik, 2009). However, when the probability of 'success' of the dependent variable is on the extreme ends of the distribution, as is the case here, the slope of a logit or probit is not well approximated by the slope of a linear regression and the flaw of the LPM in predicting probabilities outside the possible range of 0 to 1 generally becomes apparent. Von Hippel (2015) suggests that probabilities of success should be in the range of 20–80% for logit and linear models to be used interchangeably.

Therefore, a logistic regression seems more appropriate.[9] As said, this is not without risk as King and Zeng (2001) warn for inconsistent estimates when probabilities are extremely low. King and Zeng (2001) also provide guidelines when this risk is more likely to exist. They show in a simulation that the inconsistency tends to zero as the sample size tends to infinity and/or the percentage of ones tend to 50%. In our data, there are 724,752 observations and an average probability of entry of 3.1%. Following guidelines and simulation results of

9 Note that Boschma et al. (2015) do run a logit model as a robustness check, which confirms their results.

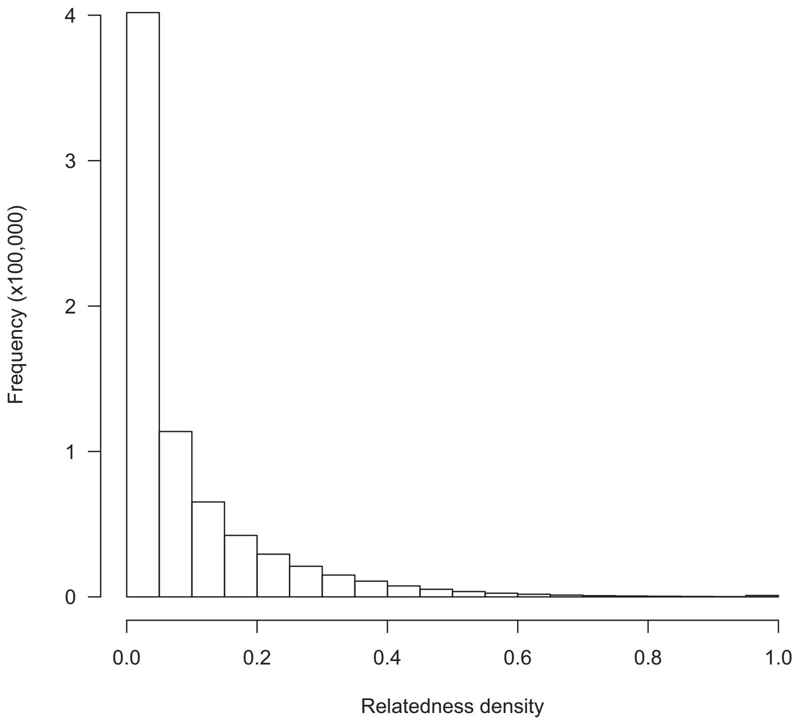

Figure A2. Histogram of RlD.

King and Zeng (2001), the risk can be assumed to be negligible. We, therefore, argue that a logit model is the appropriate method to estimate the entry model.

Then there is the second issue related to the main variable of interest: RlD. As it is strongly right-skewed there is a sizeable risk that outliers exert a strong influence on the estimated coefficient on RlD.

Therefore, we substitute the continuous RlD variable for an ordered categorical variable by creating dummy variables for each quantile of RlD values. That is, we rank the RlD values and create five dummy variables so that each designates a fifth of these values from the 20% lowest values to the 20% highest values. The categorisation of RlD also has the added benefit that it controls for the possibility of this variable having a non-linear relation in log odds with the dependent entry variable.[10]

A.3 Supplementary material to the main results

A.3.1 Additional results

10 Note that we did explore several monotonic transformations to reduce the risk of outliers but found these to be unfruitful. The most common option, a log transformation, cannot be applied because there are zeros among the values. Other common transformation methods, which are able to deal with zeros, for example, box-cox, taking the square or an inverse hyperbolic sine, also fail to give a distribution in which a strong influence of outliers can be ruled out. This is likely due to that an impressive 12.9% of observations involve zero RlD.

The marginal effects estimated in the main results of Table 2 are based on the regression results presented below in Table A2.

As the marginal effects in the main results of Table 2 only holds for the reference category of the 20% lowest RlD values and some of the interaction terms between crisis and RlD values in Table A2 are positive and significant, we show the marginal effects for other RlD values in comparison to the average probability of entry outside of crises in Figure A3.

Here the sample average probability of entry per RlD group outside of crises is given in blue. For the first group of RlD values, the probability of entry is, as said in the main text, 0.63%.[11] The red line gives the marginal effect of crisis and its 95% confidence intervals vis-à-vis the blue baseline. As the marginal effect of crisis is minus 0.32% for the first RlD group the probability of entry is about 0.31% during crises.

Clearly, the red line is significantly lower than the blue line across all RlD groups, which indicates that the marginal effect of crisis is statistically significant for all RlD values. This confirms that the probability of an MSA entering a new technological specialisation is lower during a crisis regardless of RlD.

Figure A3 also gives insight on the foundation of Figure 1 in the main text, which is based on the difference expressed in percentages between the blue line and the red line and its confidence intervals.

A.3.2. Crisis depth variations

A first interesting check is to see how the depth requirement of the crisis impacts the results. In the main analysis, regions had to lose at least 35% of patenting activity during one of the major crises to be taken into account. In Figure A4(a and b), we reproduce Figure 1 putting the depth requirement at, respectively, at least 25% and at least 45%.

In the former case, the loss during crises in entry probability is reduced across all RlD groups, which suggests that diversification patterns during smaller crises are similar to that outside of crises, which is to be expected. Although we have to note that these results are not statistically significantly different from those with a 35% depth requirement. The crises with a 45% depth requirement show a similar reduction in entry probability as the main results.

A.3.3. Entry with variations in RCA threshold

Another interesting check is to see if the entry variable is influenced notoriously differently during crisis compared to non-crises due to the choice in the threshold of RCA, which we use to define entry. In the main results, an entry is seen as an increase in the RCA from below 1 to above 1. This means that a change from 0.99 to 1.01 is seen as an entry even though it is a negligible change in the technological portfolio of a region. Although this issue plays a role both in crisis and in non-crisis periods and therefore may not directly impact the difference in diversification patterns between these types of time periods, we explore how the results would be when defining entry only when larger changes in RCA are observed, respectively, from 0.9 to 1.1 and from 0.75 to 1.25. The results are shown in Figure A5.

These results are highly similar to the main results depicted in Figure 1, reproduced by the red line. We do notice that there are more small movements in RCA during crisis periods for the most related technologies because when these are left out the drop in entry probability

11 This average probability is equal to the intercept in Column (3) of Table A2 converted to probabilities as population and Present$\times$**W** have been scaled to have a mean of zero and we use sum-to-zero contrasts for the fixed effects. Note that there is obviously also a margin of error to this estimate but this is not shown in the figure as we are interested in the marginal effect of crisis with respect to the average probability of entry outside of crises.

Table A2. Regression results (Hypotheses 1 and 2)

Dependent variable: entry of technology class i in the technological portfolio of city c at time t			
	Naive specification (1)	+ crisis×RlD (2)	+ fixed effects (3)
RlD (20–40%)	0.340***	0.335***	0.357***
	(0.042)	(0.044)	(0.045)
RlD (40–60%)	0.814***	0.811***	0.779***
	(0.039)	(0.040)	(0.042)
RlD (60–80%)	1.328***	1.307***	1.229***
	(0.037)	(0.038)	(0.041)
RlD (80–100%)	1.866***	1.811***	1.758***
	(0.036)	(0.037)	(0.041)
Crisis	−0.334***	−0.988***	−0.724***
	(0.022)	(0.178)	(0.182)
Diversity	0.412***	0.414***	0.366***
	(0.006)	(0.006)	(0.013)
Population	0.012	0.009	0.007
	(0.010)	(0.010)	(0.014)
Present × **W**	0.396***	0.396***	0.312***
	(0.005)	(0.005)	(0.009)
Degree centrality	−0.145***	−0.142***	−0.081***
	(0.011)	(0.011)	(0.012)
RlD (20–40%) × crisis		0.321	0.236
		(0.205)	(0.206)
RlD (40–60%) × crisis		0.332*	0.249
		(0.191)	(0.194)
RlD (60–80%) × crisis		0.548***	0.426**
		(0.183)	(0.187)
RlD (80–100%) × crisis		0.821***	0.600***
		(0.180)	(0.184)
Constant	−4.790***	−4.757***	−5.057***
	(0.033)	(0.034)	(0.444)
Time fixed effects	No	No	Yes
Technology fixed effects	No	No	Yes
MSA fixed effects	No	No	Yes
Observations	724,752	724,752	724,752
Log-likelihood	−87,613	−87,568.1	−81,544.2
Akaike Inf. Crit.	175,246	175,164.2	164,552

Notes: The RlD groups and crisis are dummy variables with as reference category, respectively, the 20% lowest RlD values and non-crisis time periods.
***$p < 0.01$, **$p < 0.5$, *$p < 0.10$.

becomes larger when entering a crisis, as indicated by the difference between the red and the green line for the 80–100% most related technologies.

A.3.4. Diversification during local crises

Another data choice in this study was to only retain downturns in patenting activity as periods of crisis when they occurred during one of the three great historical crises to ascertain that these local downturns were not due to changes in patent activity unrelated to actual

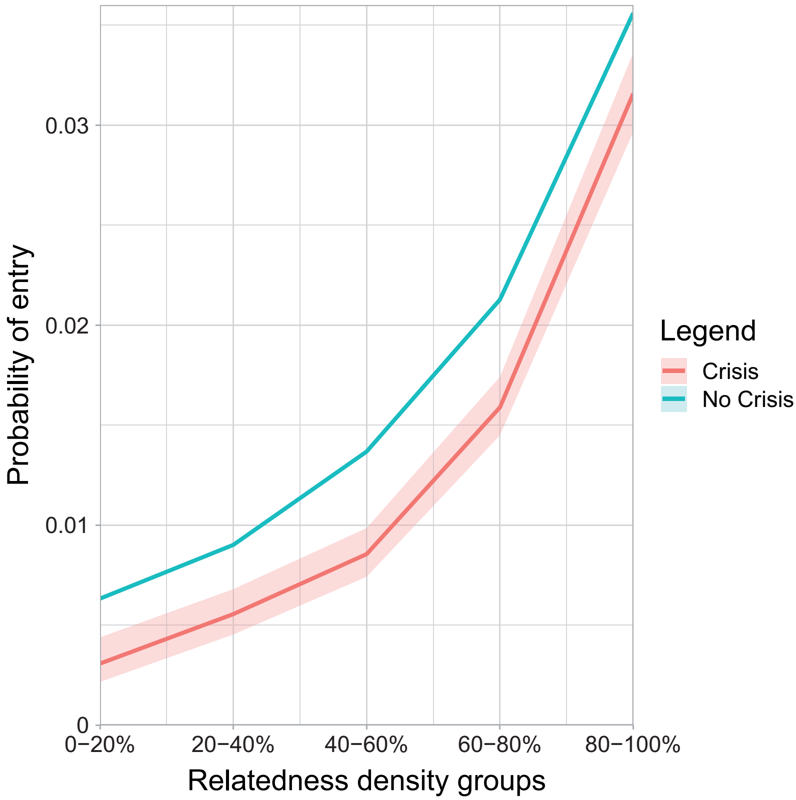

Figure A3. Probability of entry according to crisis status.

economic downturns. The downside of this method is that differences between these periods and those where most of the non-crisis periods are not fully captured by our time fixed effects and may therefore influence our results. Therefore, we reproduce the main results in Figure A6, in which we take all downturns in patenting activity of at least 35% into account.

The results confirm those in the main analysis. However, more interesting is that the confidence intervals are much smaller. This indicates that these crises behave in a very similar way as those in larger economic crises and that therefore statistical efficiency increases by adding these other crisis periods.

This also suggests that the two concerns expressed in Section 2 do not seem to matter that much. First, the number of patents per region seem a reasonable proxy for the economic activity of a region as these results show that also outside the large economic crises when we only have patent data to detect a local downturn diversification behaviour reacts exactly the same as during the large economic crises. This is also seen in the results of Appendix 3.2 when lowering the threshold of crisis depth from 35% to 25% loss of the number of patents per year regions in crisis diversify more similarly as regions that are not in crisis. Suggesting that less patent activity loss also leads to less changes in behaviour, which is exactly in line with that less patent activity loss also means less economic activity loss. This is in line with a larger literature acknowledging the link between patenting activity and economic activity (Duijn, 1983; Glaeser and Ponzetto, 2007; Perez, 2009; Rothwell et al., 2013; Petralia et al., 2017; Rigby et al., 2022). Second, one would expect that periods of strong technological

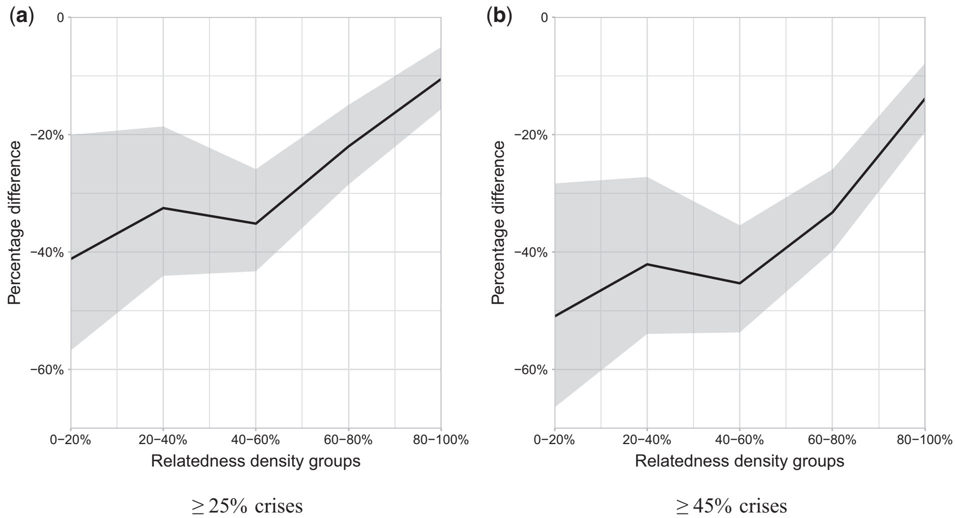

Figure A4. Difference in probability of entry during crises (≥25% and ≥45% crises). (a) ≥25% crises. (b) ≥45% crises.

change, such as in the three large crises considered here, would call for a stronger need to maintain or even increase diversification. Nonetheless, we find here that diversification behaviour during smaller local crises outside of periods of large technological change are similar.

A.3.5. Diversification during crises at the county level

Another data choice in this study was to look at the MSA level. However, MSAs are based on counties that are socially and economically integrated according to recent Census Bureau definitions. These levels of integration likely much less existed in history when infrastructure was less well developed and agglomerations not as large. Agents in an area were, therefore, more likely to interact and redistribute resources during crises within a smaller area. The finest spatial level at which data on patents and control variables is available is the county level. We reproduce the main results using county-level data in Figure A7.

Although the results are not statistically significantly different from the main results and show a similar pattern the underlying data is much more problematic than that for the main results, as the much larger confidence intervals already suggest. It is much more difficult at the county level to meet thresholds for the number of patents in total and per class. As a result, the number of observations is much lower here than in the main results 202,112 versus 724,752. Furthermore, not every county and time period, and not every entering technology, knows both crises and non-crises periods, which means that the marginal effect of crisis is based on comparing different instead of the same counties, time periods and classes, which is not the case in the main results.[12] Although it is reassuring about the main results to see that there is a similar pattern we advise not to highly value these results.

A.3.6. RID values based on uniform time periods

12 As a result, one cannot use fixed effects in this regression. We tried to alleviate this effect by discerning four RID groups instead of five as in the main results. This increases the chance that counties, time periods and entering technologies are present both in crisis and non-crisis for each RID group.

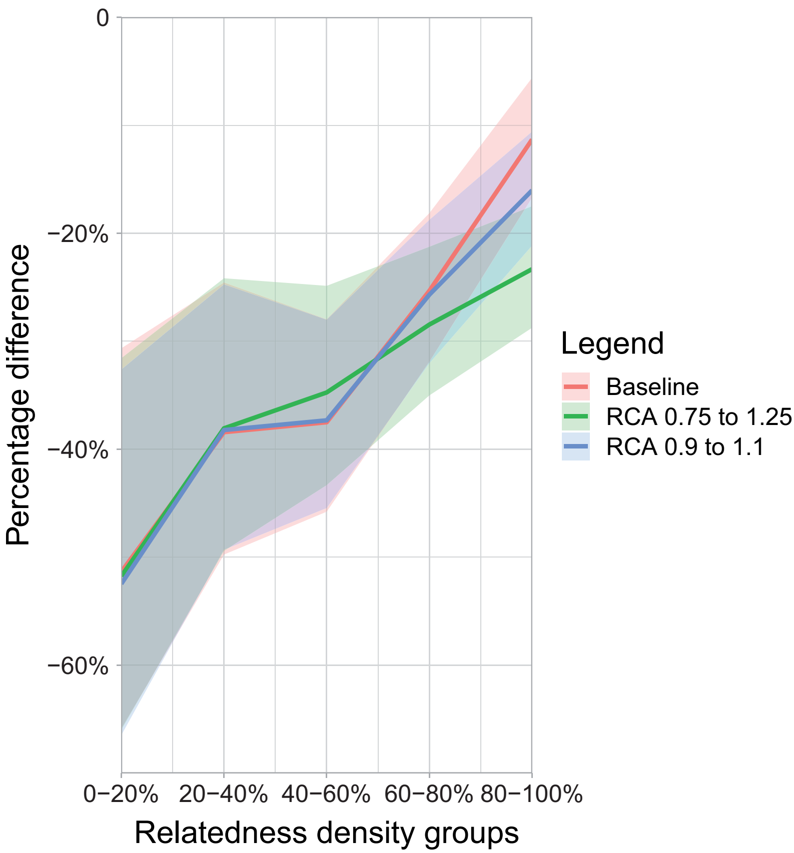

Figure A5. Percentage difference in probability of entry between crisis and no crisis (Entry RCA thresholds).

In the main results, we define time periods based on the boom–bust cycle algorithm of Harding and Pagan (2002). As a result, some time periods last for the minimum of 2 years, while the longest time period is 30 years with the median being 5 years. As we calculate RlD values based on the previous time period this also means that the technologies in the portfolios of cities and the relatedness between technologies are calculated at different distances. To make sure that these definitions do not influence results we calculate RlD values using the 0–5 years before the start of a time period for all time periods and reproduce the main results in Figure A8.

This confirms the main results but also shows that using this definition even leads to a stronger reduction of diversification in the least related technologies during crises and smaller confidence intervals compared to the main results. We also experimented with calculating RlD values in even earlier time periods but found that these results were not reliable.[13]

13 Over time technological portfolios of regions change. This means that entering technologies are related to technologies present in the region 5 years ago but not so much to those 20 or 30 years ago. The longer ago RlD values are calculated the lower RlD values to entering technologies are and the less predictive this variable is on entry, that is, the lines in Figure A3 become flatter and flatter. We found that this effect is purely driven by the technological portfolio of regions in earlier time periods because large regions, which have fewer large changes

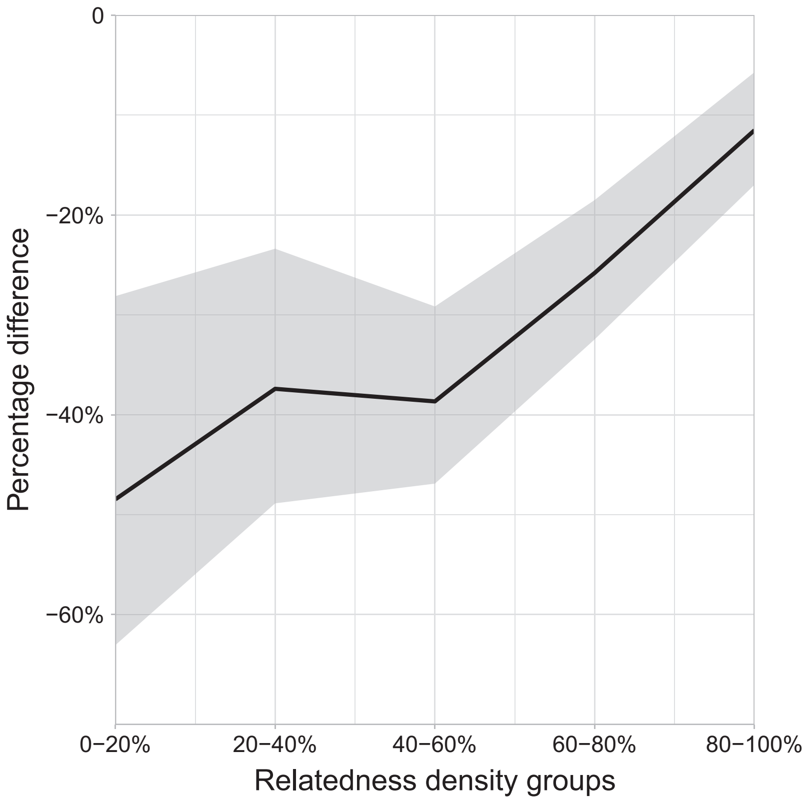

Figure A6. Difference in probability of entry during crises (all crises).

A.3.7. Quasi differences-in-differences approach

In the previous section, we used the same time period to calculate RID values for all MSA-time periods instead of the time periods based on the boom–bust cycle algorithm of Harding and Pagan (2002) in the main results. In this section, we take the approach one step further by setting all time periods equal and only using observations from the great historical crises. This means that not only the entering technologies are compared to the technological portfolio of a region at the same number of years earlier, like in the previous section, but also the time length in which these technologies can enter. Furthermore, by dropping observations outside of the great historical crises. Diversification in times of growth and crisis is compared at the exact same time period. Through this approach, we compare the diversification patterns of regions that enter a crisis to those that do not while controlling for observables, that is, diversity, population, degree centrality and RID, plus for unobservable at the MSA, technology or time level. Through this approach, we come closer to a difference-in-difference approach, as first experimented by Card and Krueger (1994). Although we have much less data to observe the extent to which non-crisis

in their technological portfolio over time, experience this effect to a much lesser extent. Also, when calculating relatedness based on patents from longer ago but keeping technological portfolios as in the main analysis leads to the same results.

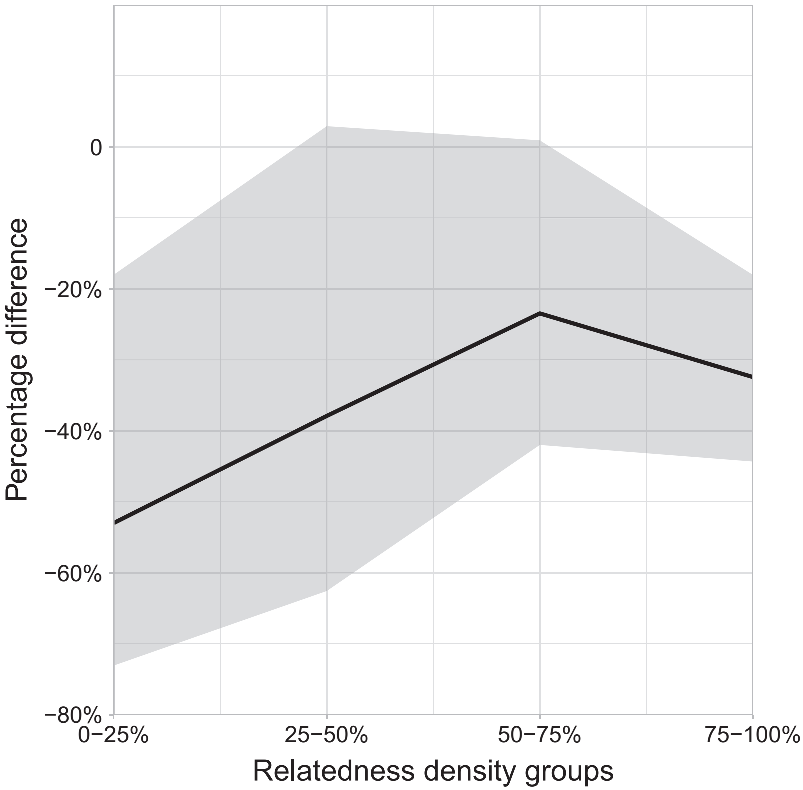

Figure A7. Difference in probability of entry during crises (county level).

and crisis counties are similar except for the mentioned observable characteristics and unobservable characteristics that are fixed at the regional, technological or time level.

For the Long Depression, we identify entering technologies between 1876 and 1879 in comparison to the technological portfolios of these areas and RID between 1873 and 1876. To be considered a successful entry, technologies still have to be present in the area between 1879 and 1882. For the Great Depression, these years are, respectively, 1932–1938, 1926–1938 and 1938–1944. For the 1970s recession, these years are, respectively, 1972–1976, 1968–1972 and 1976–1980. The time span is chosen to mirror the length of each of the crises.[14] We define a region as being in crisis if it is experiencing or entering a local crisis in the first year of these crisis periods.

Figure A9 shows that when one of the great historical crises hit regions that enter a crisis diversify less, in particular in unrelated technologies, than regions that are unaffected in the same time periods. This pattern is not statistically significantly different and similar to the main results. Nevertheless, the confidence intervals are much larger, in particular for the unrelated technologies. This is likely because there are notably fewer observations, in particular

14 Note that in differences-in-differences approaches it is also custom to take the period before the event, in this case, crises into account. In this way, crisis counties are not only compared to non-crisis counties in the same time period but also to themselves before the crisis. As these latter observations are very strongly present in the main results, where most non-crisis periods occur outside the great historical crises, we decided not to add these here to ascertain that the main results also hold for the comparison within the same time period.

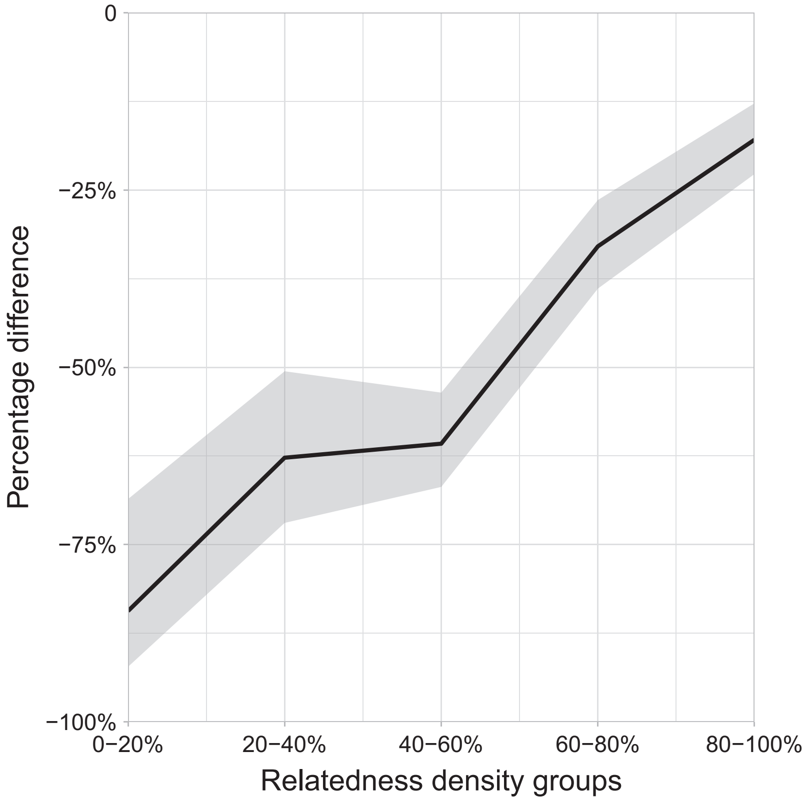

Figure A8. Difference in probability of entry during crises (Adj. RlD).

of non-crisis periods, as only few regions are not affected by the great historical crises, and of unrelated technologies, as these know relatively less entry than more related technologies.

That this approach confirms the main results suggest more strongly that there may be a causal link between entering a crisis and diversification patterns. Although it remains impossible to fully isolate the effect of crises on diversification patterns in this historical setting, like a natural experiment would.

A.3.8. Diversification per crisis

In the main results, all three great historical crises are lumped together in a single analysis even though there are likely differences between them. First, we reproduce the quasi diff-in-diff approach of the previous section per crisis in Figure A10. The results show that compared to the regions that do not enter a crisis during nation-wide shocks the regions that do enter a crisis diversify less often and in particular less often in less related technologies. This confirms that the diversification pattern found in the main results holds for every crisis. Note that the confidence bands are much larger in this setting because there are far less observations per crisis, particularly, during the earlier time periods. The confidence intervals are also larger for the less related technologies where less cases of entry exist.

A.3.9. Entry and employment dynamics

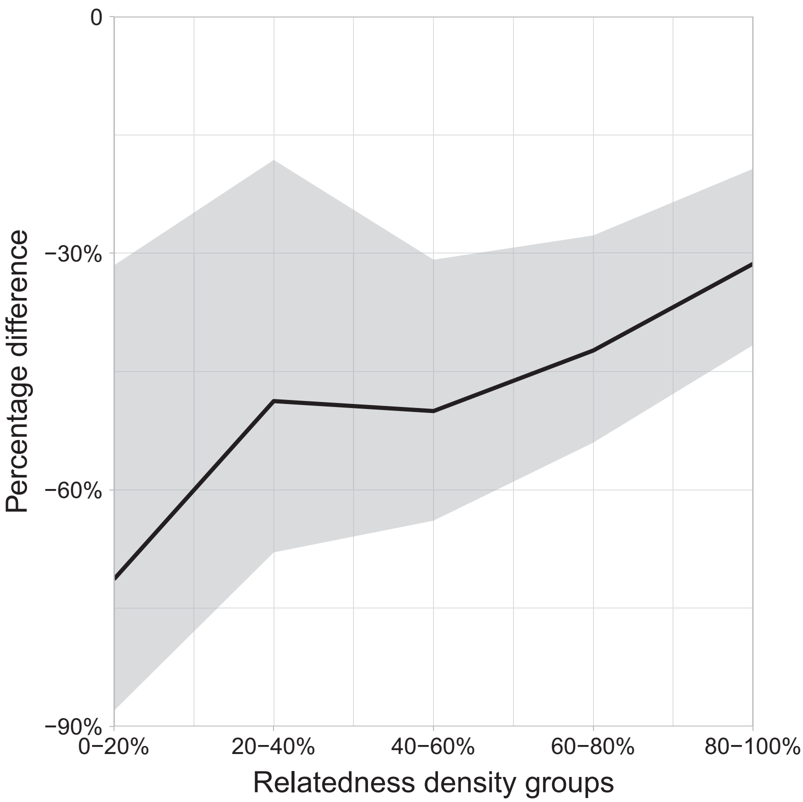

Figure A9. Difference in probability of entry during crises (quasi diff-in-diff).

In this section, we evaluate the impact of technological diversification during crises on employment growth. The focus is on the 1970s recession for which employment data o was kindly provided by Duranton et al. (2014). We use here only the data on manufacturing industries where technologies are generally applied. Associating employment in industries to employment using technologies was made using a concordance table by Kerr (2008), who builds on a time period between 1990 and 1993 in which the Canadian patent office registered both the inventing industry and the assigned industry where the patented inventions are put to work. This allows to estimate the number of employees working with a certain technology class per MSA in 1970, 1975, 1978 and 1989, which corresponds to, respectively, before, near the end, 3 and 14 years after the 1970s recession (1973–1975).

We specify Equation (A.1) to estimate the impact of the entry of a technology on the associated employment working with that technology. It is highly similar to the main Equation (5), ΔEMP is the dependent variable and is equal to the growth rate of employment that work with technology i in city c between two time periods. We will show results using different years at our disposition.[15] Using the growth rate of employment is in line with the

15 Some regions may have no workers working with a technology in the first period, which means that growth rates are subject to a divide by zero error. For this reason, we add 10 employees to the first year for each technology when calculating growth rates.

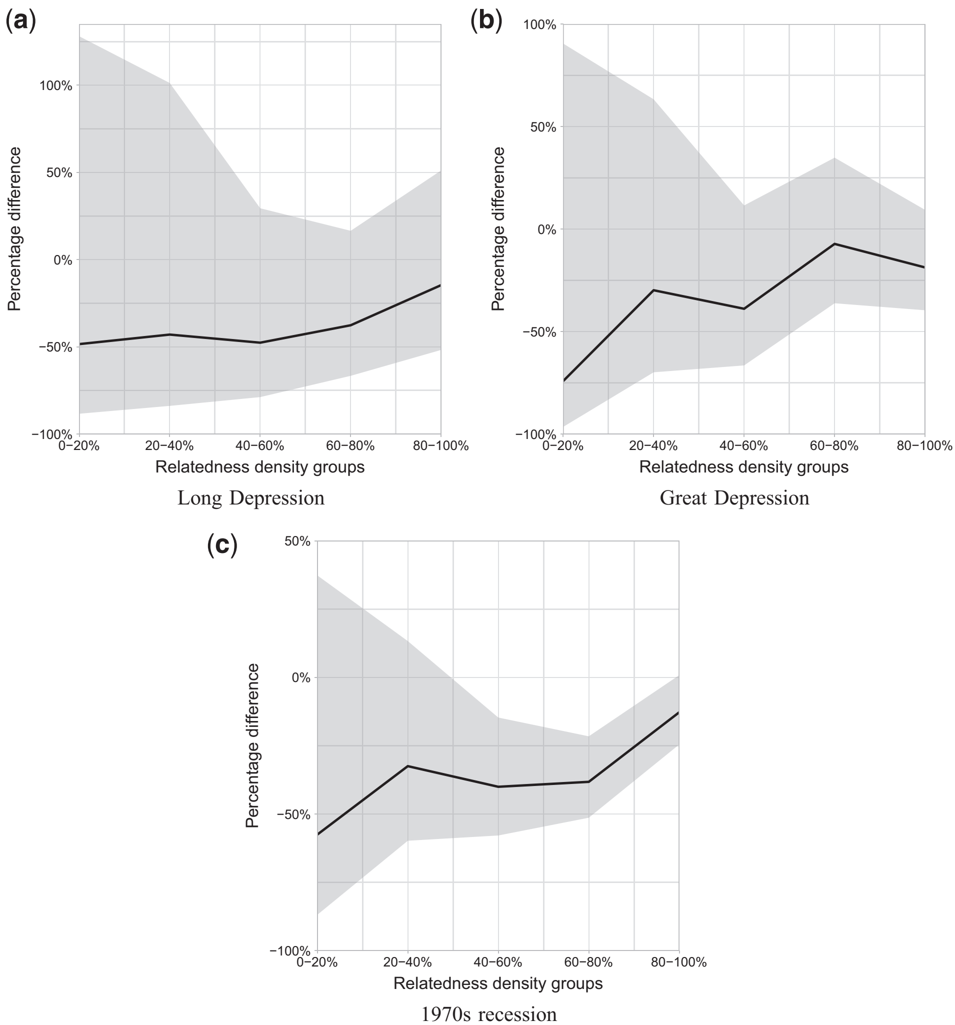

Figure A10. Difference in probability of entry per crisis (quasi diff-in-diff). (a) Long Depression. (b) Great Depression. (c) 1970s recession.

exercise in Rigby et al. (2022). We will also do a robustness check using the growth in log employment, following Glaeser et al. (1992).

Our main independent variables of interest are if a technology has entered during the crisis, *entry*, the RlD of the technology if it enters, entryRlD, if a city is in crisis during the 1970s recession Crisis, and the interactions between these variables. We also added the same city-level control variables as before in Equation (5) plus the log employment level in the starting year. Note that there is no *t*-subscript indicating time periods as there is only one time period because we only consider the 1970s recession and have used the equally sized time periods and crisis definitions as in Appendix 3.7. For this reason there are also only technology fixed effects θ_i and no city or time fixed effects.

Table A3. Descriptive statistics—employment dynamics

Statistic	*N*	Mean	St. Dev.	Min	Max
Δemployment$_{1975–1989}$	57,847	0.238	0.561	−0.676	2.913
Entry	57,847	0.033	0.179	0	1
RlD of entry	57,847	0.006	0.035	0.000	0.276
Crisis	57,847	0.245	0.430	0	1
Log employment in start year	57,847	3.314	1.594	−5.485	10.171
Population	57,847	504,753.200	1,250,302.000	61,815	16,756,851
Present × **W**	57,847	0.00004	0.00003	0.00000	0.0003
Diversity	35,457	1.015	0.268	0.355	1.634
Degree centrality	35,457	108.587	311.921	5.600	3510.333

$$\begin{aligned}\Delta \mathrm{EMP}_{ci} = {} & \mathrm{Constant} + \beta_1 \mathrm{entry}_{ci} + \beta_2 \mathrm{entryRlD}_{ci} + \beta_3 \mathrm{Crisis}_c + \beta_4 \mathrm{entry} \times \mathrm{Crisis}_c \\ & + \beta_5 \mathrm{entryRlD}_{ci} \times \mathrm{Crisis}_c + \delta City_c + \eta \mathrm{Pr}_i \times \mathbf{W} + \theta_i + \epsilon_{ci},\end{aligned} \tag{A.1}$$

Descriptive statistics are given in Table A3.

Results are given in Table 3, the coefficient on entry in column (1) tells us that the entry of a technology during the 1970s recession, that is, between 1972 and 1976, is associated with an increase in the growth rate of employment using that technology by 8.5% between 1975 and 1989.[16] The second coefficient gives that when an entering technology is a standard deviation more related the increase in employment growth rate is even 1.4% higher. This suggests that regions that are not in crisis, the reference category, benefit of technological diversification and even more when this technology is related to their current portfolio. This is in line with the literature that suggests that diversification is more likely to be successful when related to other activities in the region (Neffke et al., 2011).

The coefficient on crisis suggests that if a region is in crisis than on average the growth rate of employment is 14.3% lower, which is to be expected. Interestingly, the interaction between entry is strong and highly statistically significant. It suggests that the entry of a technology during a crisis is associated with a 16.2% stronger growth rate compared with entry outside of crises. On the other hand, the interaction between the RlD of entering technologies with crisis shows a negative effect of 5.3%, while it was smaller and positive, that is, 1.4%, outside the crisis. These two results suggest that diversifying during a crisis is extra beneficial for employment growth but that in contrast with periods of growth there is more growth to be obtained in unrelated technologies. This is strongly in line with the suggestion that developing new activities is a beneficial activity to overcome crises (Pike et al., 2010; Boschma, 2015). The fact that it is unrelated activities that seem to be more beneficial is in line with the fact that regions in crisis may be faced with a technological lock-in in which the current industrial portfolio does not offer much opportunities for growth (Grabher, 1993; Boschma, 2015).

In Column (2), we add technology fixed effects, results stay very similar. The largest difference is in the crisis coefficient, which is statistically significantly smaller in this

16 This finding differs from the results of Rigby et al. (2022), who found no statistically significant effect on employment growth. However, they look at total employment growth instead of sectoral employment growth and for a more recent time period where services are more relevant than manufacturing (for which patenting is relevant) and where there is a larger likelihood that invention and production are taking place in more distant locations.

specification. This is likely because employees working with certain technologies are more strongly hit due to the crisis and these are likely to be concentrated in the areas that are in crisis and therefore also more strongly hit.

In Column (3), the dependent variable is the growth rate between 1970 and 1989 instead of 1975 as starting year. Results are very similar. Note that the additional positive effect of entry during a crisis is no longer statistically significant but also not statistically significantly different from the coefficients in the previous columns.

In Columns (4) and (5), we look at a relatively shorter time span with 1978 as end year and, respectively, 1970 and 1975 as starting year. The coefficients on the main variables of interest are not statistically significantly different between these two specifications. Nevertheless, the positive effects of unrelated technological diversification are statistically significantly smaller compared with the coefficients on the long-term dynamics in the first three specifications. This suggests that benefits of unrelated technological diversification during a crisis are experienced after a longer time period compared to technological diversification outside of crises.

Column (5) shows the results when using the change in log levels of employment instead of percentage growth rates. The interpretation of the coefficients is hence different. For example, the coefficient on entry now gives that the entry of a technology during the 1970s recession is associated with an increase of 7.9 in log employment, which is equal to about 2700 employees, between 1975 and 1989. Although the interpretation of the coefficients is different, the results are in line with those in Column (2).

The control variables also show some interesting findings. The coefficient on diversity and the presence of the technology in neighbouring cities are statistically significant and negative meaning that these aspects generally lead to less growth. Note that this is while controlling for the fact that both these aspects do lead to a large chance of technological diversification, as found in the main results in Table A2, and that entry is generally associated with growth. On the other hand, a larger degree centrality is associated with negative growth in employment and also with a smaller chance of entry according to the main results. While larger cities were not statistically significantly associated with entry but are here associated with positive employment growth.

The results support the point of view that changing local capabilities in face of crises is a beneficial strategy (Pike et al., 2010; Boschma, 2015). Note that nevertheless technological diversification may be a less performing proxy for more recent time periods where manufacturing, for which patenting is more prevalent than services, is a less important part of the economy and where patenting and production are increasingly taking place in different areas (Duranton and Puga, 2005). The advice for policy would be to focus on the ability to renew capabilities but not necessarily to literally focus on technological diversification. Also note that it takes careful thinking what type of new activities one wants to stimulate. Balland et al. (2019) may offer some suggestions in this respect.

A.3.10. Crises, diversification and technological change

The great historical crises all occur during periods of great technological change. However, the type of technological change varies. The Long Depression and the 1970s recession fall in the time periods of, respectively, the second industrial revolution based on electricity and the third industrial revolution based on the semiconductor, also known as the computer revolution (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998). The Great

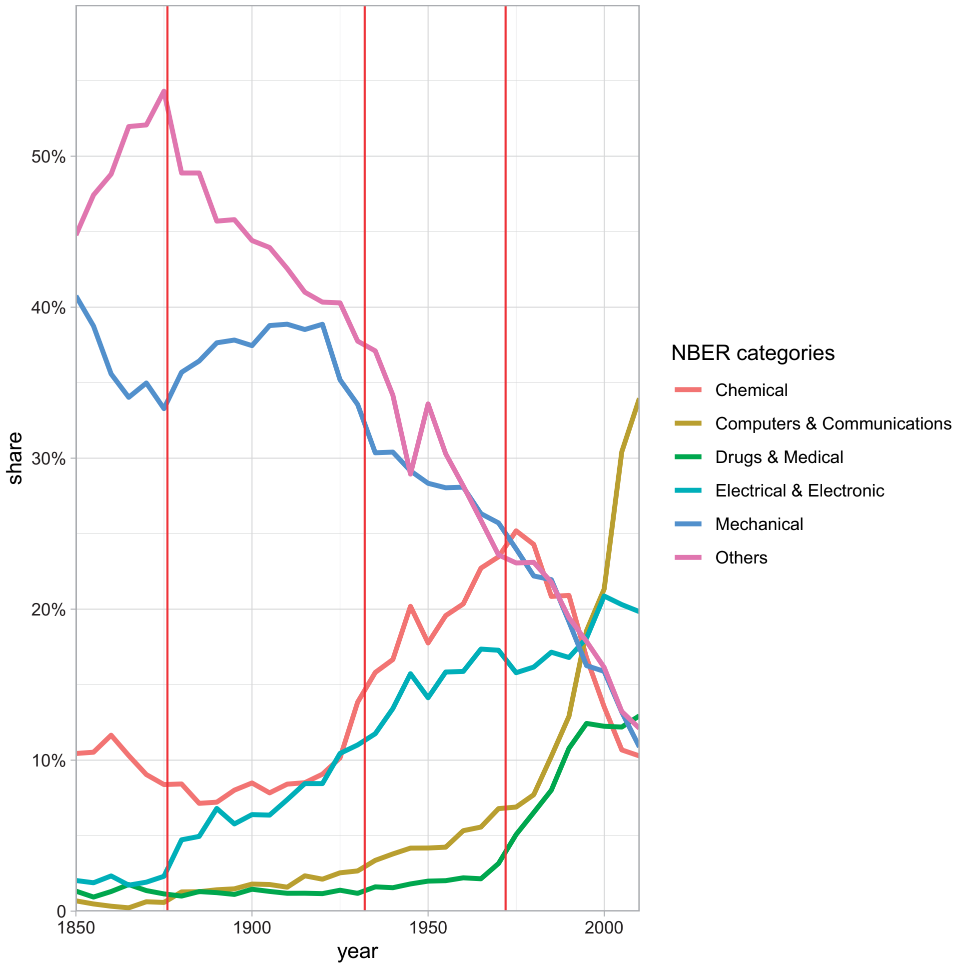

Figure A11. Share of patents per NBER category over time.

Depression lies outside of industrial revolutions. Perez (2009) explains this difference in nature by suggesting that the Long Depression and the 1970s recession occur when new major technologies come up and replace previous technologies while the Great Depression occurs after a great surge in the new major technology that leads to a bubble that bursts into a crisis but not to a change in the dominant technology. Relatedly, Boschma (1999) identifies the time periods of the Long Depression and the 1970s recession as industrial revolutions where radical product innovation takes place while during the time period of the Great Depression, the focus was on production innovation in which the radically new products are applied to invent radical new production methods. The radical nature of technological change likely implies that some technologies and cities show different diversification patterns than others as technologies are coming up while others become outdated. This section explores these differences.

Our patent data captures the coincidence of technological change and the great historical crises, as is illustrated in Figure A11, where the share of patents per NBER technological category is given over time with the red vertical lines indicating the start of each of the respective crises. Here one can clearly see that at the time of the Long Depression, which coincides with the electrical revolution, the upcoming technologies belong to the categories mechanical and electrical and electronic while those in others, textiles among others, become outdated. During the Great Depression, the chemical and electrical and electronic technologies are upcoming while those in others and mechanical are outdated. One can note that in line with this time period not being an industrial revolution there is less of a major change in trends of technology groups. During the 1970s recession, which coincides with the computer revolution, the previously upcoming technologies in chemical and electrical and electronic become outdated while computers and communication and drugs and medical come up.

Upcoming technologies may give rise to different diversification patterns. After all, when in crisis it may be worth the risk, that is, having less related capabilities, to invest in promising technologies. On the other hand, outdated technologies may be a less interesting option no matter how related.

Furthermore, cities that are specialised in outdated technologies may have a different diversification pattern than other cities. There is a strong risk of technological lock-in (Boschma and Lambooy, 1999; Hassink, 2005; Pike et al., 2010; Boschma, 2015). However, it is unknown if this shows in diversification patterns. In the main text, we showed that diverse regions have an advantage in diversifying compared to specialised regions, within and outside crises, here the question is to what extent this holds for cities specialised in outdated technologies.

To this end, we classify technologies per time period into upcoming, outdated or neither based on the observations from Figure A11, discussed above. We classify MSAs as upcoming, outdated or neither if they have an LQ in one of these categories.[17] Because of this classification technology fixed effects and MSA fixed effects are dropped from the analysis.

Table A4 shows the marginal effects of the baseline regression, as shown in Equation (5), with the addition of dummy variables indicating if technologies, respectively, MSAs, belong to, respectively, are specialised in, upcoming or outdated technologies. As well, as an interaction of these variables with the crisis dummy. Per column, we use data around each crisis and period of technological change: 1870–1919 for the Long Depression; 1920–1969 for the Great Depression; 1970–2000 for the 1970s recession. The final column groups together all three of these datasets.

The RlD variables behave in a similar fashion as before, as expected more RlD leads to a larger probability of entry. Although note that RlD seems to matter more during the time period since the Great Depression. The crisis variable is (close to) insignificant in the case of the Great Depression and the 1970s recession for the reference category, which in this case is not only the non-crisis periods of the 20% lowest RlD values but also technologies and cities that are neither upcoming nor outdated.

Interestingly, in the time period around the Great Depression and in particular around the 1970s recession upcoming technologies have a larger chance of entry, respectively, 0.04% and 0.16% to be exact, see Columns (1) and (3) in Table A4. This may seem small but the probability of entry for the reference category in these time periods is only 0.06% and 0.14%, which suggest almost a doubling of the probability of entry.[18] The fact that these

17 When a MSA has a LQ in two of these categories we choose the category with the largest LQ. It is technically impossible to have an LQ in all three.

18 Note that this relationship is not mechanical because of the definition of upcoming technologies as entry is based on the fact that a region obtains a *relative* specialisation in this technology and not an *absolute* specialisation.

Table A4. Regression results—technological change—marginal effects

Dependent variable: entry of technology class i in the technological portfolio of city c at time t				
	Long Depression (1)	Great Depression (2)	1970s recession (3)	All crises (4)
RlD (20–40%)	0.0078***	0.0062***	0.0038***	0.0042***
	(0.0054, 0.0106)	(0.0042, 0.0085)	(0.0020, 0.0062)	(0.0033, 0.0052)
RlD (40–60%)	0.0155***	0.0180***	0.0104***	0.0110***
	(0.0122, 0.0193)	(0.0149, 0.0214)	(0.0072, 0.0143)	(0.0096, 0.0125)
RlD (60–80%)	0.0272***	0.0403***	0.0226***	0.0237***
	(0.0224, 0.0326)	(0.0353, 0.0459)	(0.0170, 0.0296)	(0.0214, 0.0261)
RlD (80–100%)	0.0454***	0.0827***	0.0464***	0.0473***
	(0.0383, 0.0535)	(0.0739, 0.0922)	(0.0361, 0.0592)	(0.0433, 0.0515)
Crisis	−0.0034***	−0.0016	−0.0008*	−0.0015***
	(−0.0049, −0.0009)	(−0.0039, 0.0015)	(−0.0018, 0.0005)	(−0.0023, −0.0006)
Upcoming technologies	0.0004**	0.00001	0.0016***	0.0003***
	(−0.0001, 0.0010)	(−0.0006, 0.0007)	(0.0010, 0.0024)	(0.0001, 0.0006)
Outdated technologies	0.0005**	−0.0013***	−0.0004***	−0.0004***
	(−0.0001, 0.0011)	(−0.0018, −0.0008)	(−0.0007, −0.0001)	(−0.0007, −0.0002)
Upcoming MSAs	−0.0011***	0.0011***	0.0003*	−0.000002
	(−0.0015, −0.0006)	(0.0005, 0.0017)	(−0.0001, 0.0007)	(−0.0002, 0.0002)
Outdated MSAs	−0.0002	0.0020***	−0.0001	0.0006***
	(−0.0007, 0.0003)	(0.0010, 0.0031)	(−0.0006, 0.0005)	(0.0003, 0.0009)
Diversity	0.0035***	0.0045***	0.0023***	0.0024***
	(0.0033, 0.0037)	(0.0042, 0.0048)	(0.0021, 0.0025)	(0.0023, 0.0025)
Population	−0.0028***	0.0006***	0.00004	0.0001
	(−0.0035, −0.0022)	(0.0002, 0.0009)	(−0.0001, 0.0002)	(−0.0001, 0.0002)
Present × **W**	0.0036***	0.0054***	0.0019***	0.0028***
	(0.0035, 0.0038)	(0.0052, 0.0056)	(0.0018, 0.0019)	(0.0028, 0.0029)
Degree centrality	0.0010***	−0.0022***	−0.0008***	−0.0009***
	(0.0003, 0.0017)	(−0.0025, −0.0018)	(−0.0010, −0.0006)	(−0.0010, −0.0007)
Time fixed effects	Yes	Yes	Yes	Yes
Technology fixed effects	No	No	No	No
MSA fixed effects	No	No	No	No
Observations	200,348	338,464	172,912	711,724

Notes: The RlD groups, crisis and technology-related groups are dummy variables with as reference category, respectively, the 20% lowest RlD values, non-crisis time periods and technologies/MSAs that are neither upcoming or outdated.

***$p < 0.01$, **$p < 0.5$, *$p < 0.10$.

coefficients are statistically significant but not the one of the Great Depression is in line that this last crisis is not considered an industrial revolution (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998). The particularly high rate of entry in the 1970s recession may be because of the trade competition in that time period, notably from Japan, that already adopted computerised machinery (Storper and Scott, 1992), which increased pressure to diversify to upcoming technologies in computers and communications.

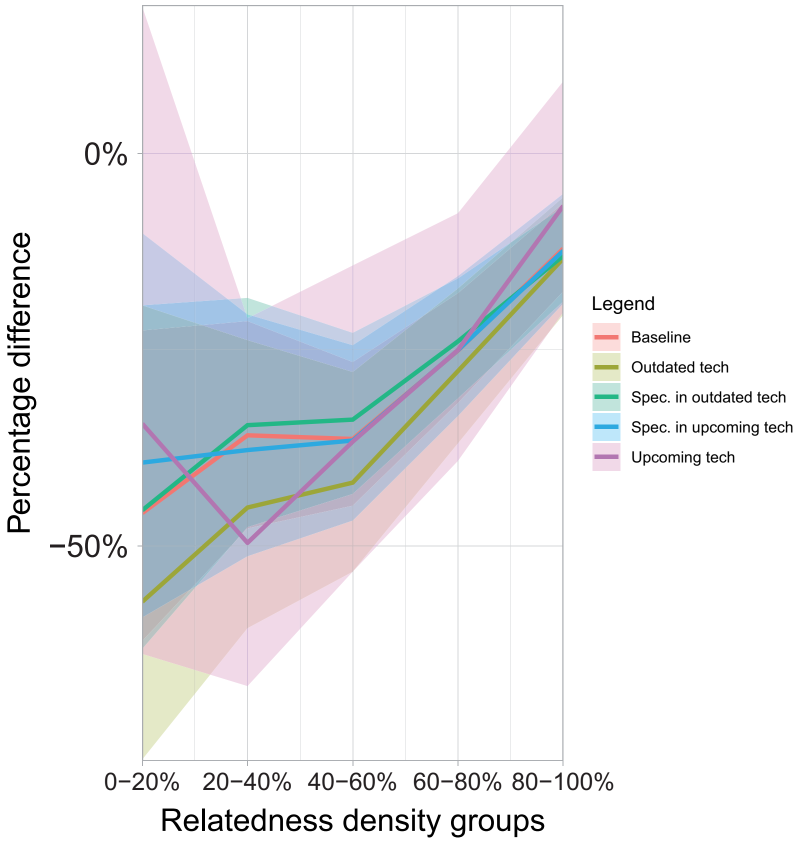

Figure A12. Percentage difference in probability of entry between crisis and no crisis (technological change).

Outdated technologies, on the other hand, have a smaller probability of entry, which is to be expected. The only exception being the Long Depression, which may be due to less competition and less circulation of new ideas in relation with the more limited connectivity between cities in that time period. In this line, Perlman (2015) show that patenting activity in the 19th century is strongly related to railroad access, which was not fully developed at the time of the Long Depression.

Cities specialised in upcoming technologies show mixed results in terms of diversification. Whereas those in outdated technologies show either virtually non-existent or positive marginal effects. All in all, the coefficient on diversity remains strongly positive and much larger across all specifications, which suggests that advantages at the city level are derived from this aspect rather than a specialisation in a certain category of technologies.

Table A4 gives differences in the probability of entry but not how diversification changes in a relative sense when entering a crisis. To show this latter aspect, we reproduce Figure 1 per type of technology and MSA in Figure A12.

The change in diversification patterns when entering a crisis is similar to the baseline results in red for most of these types. MSAs that are specialised in outdated technologies show virtually the same pattern as MSAs that are specialised in upcoming technologies and the baseline results. Outdated technologies show a stronger relative decrease in entry probability when entering a crisis, in particular, when unrelated to the technological portfolio of a region. This suggests that diversifying into these technologies is even less attractive when entering a crisis, plausibly to avoid technological lock-in. However, confidence intervals are too large to state that this pattern is significantly different from the baseline results.

Most interesting is the line of upcoming technologies. The effect of a crisis is not statistically different from a period of non-crisis for both the most related as well as the most unrelated technologies. This suggest that these technologies remain (close to) equally as attractive to diversify into even when in crisis. This is likely because these technologies contain the General Purpose Technologies of that industrial paradigm (Helpman and Trajtenberg, 1998).

When we reproduced Figure A12 per crisis, we found that it was during the 1970s recession that unrelated upcoming technologies, in particular, showed less decrease in entering probability. This gives more ground to the earlier claim that computer-based import competition motivated regions to diversify in the upcoming computer and communication technologies of that time period, even when these were not so related to the technologies that were previously patented in the area.

A.3.11. Diversity and diversification

In the main results of Table 2, we conclude that diverse regions have an advantage compared with their specialised counterparts to develop new activities outside and during crises. This brings up the question on how diverse regions change the focus of their diversification when entering a crisis compared to more specialised regions, as done in Figure 1. In other words: do diverse cities switch more strongly to less related technologies during crises than specialised cities? To this aim, we reproduce Figure 1 but by estimating the effect for different groups according to RDI. The resulting Figure A13 is shown below.

When entering a crisis, the 67–100% percentile of most diverse regions, lose over 67.9% of the diversification in the least related technologies. While the most specialised regions, in the 0–33% least diverse percentile, only lose 41.7%, and the intermediate group only lose about 6% during crises than outside of crises.

A possible explanation is that diverse regions are more likely to have unrelated variety between industrial sectors, see Frenken et al. (2007), meaning that some sectors are not affected by regional crises and that developing technologies related to these unaffected sectors is a secure and reasonable use of resources. On the other hand, more specialised regions when hit by a crisis are less likely to have unaffected industries to continue to develop and as such there's more incentive to focus on locally less common, and therefore, less related technologies. The fact that averagely diverse cities (33–67% diversity values) focus more strongly on unrelated technologies than their most specialised counterparts (0–33% diversity values) may be due to the latter being in a state of technological lock-in, see Grabher (1993) and Boschma (2015), in which the knowledge of actors and views in an area are focused on such a way on current core activities that it inhibits the development of new sectors and technologies.

However, the confidence intervals are so large that these differences are not statistically significant.[19] All in all, one cannot claim that there are significant differences in diversification patterns in relation to the diversity of a region.

19 Note that there are no formal testing methods available as each marginal effect has a different baseline (depicted in blue in Figure A3). Therefore, we have to rely solely on the confidence intervals.

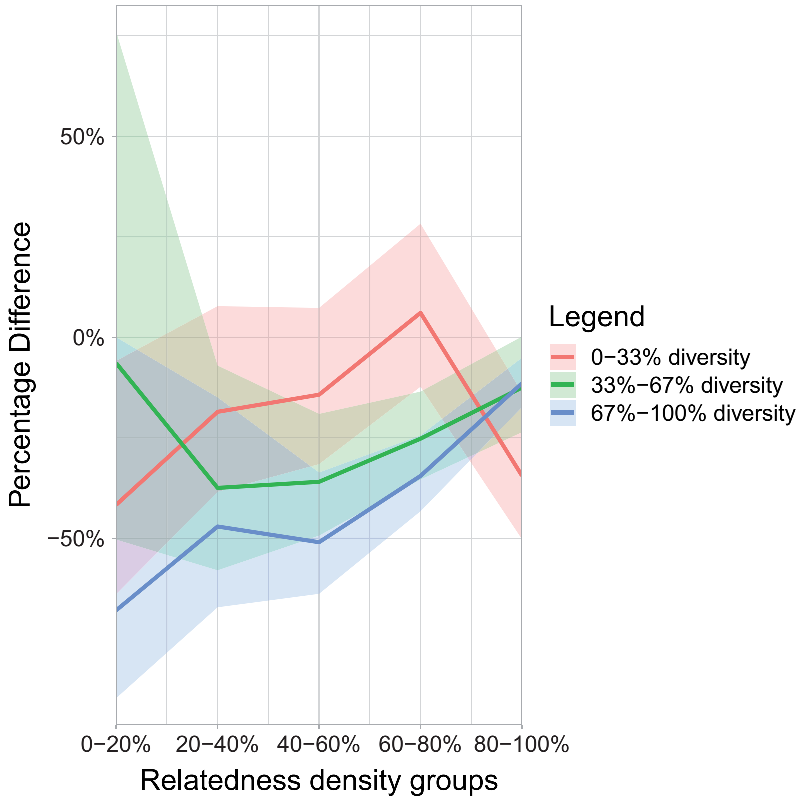

Figure A13. Percentage difference in probability of entry between crisis and no crisis across RDI groups.

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