OECD SME and Entrepreneurship Papers

Leapfrogging and Plunging in Regional Entrepreneurship Performance in the United States, with European Comparisons

Jonathan Potter, Haifeng Qian, Michael Fritsch, David Storey, Georgios Fotopoulos

This paper analyses persistence and change in the regional league table of entrepreneurship performance in the United States in comparison with England and Wales and West Germany. It examines whether regional rankings in start-up and self-employment rates in the United States are as sticky over time as in these European countries over approximately century, half-century and 30-year periods, or whether the United States is different. It identifies the types of regions that improve markedly ("leapfroggers") or decline sharply ("plungers") in their league table positions and the reasons for these changes and compares the countries on these issues. The paper draws out policy implications on regional levelling-up of entrepreneurship activity. It also sets out an agenda for further research.

JEL codes: L26 L53 R11 R58
Keywords: Entrepreneurship, Start-Ups, Self-Employment, Regional Development

OECD

ABOUT THE OECD

The OECD is a multi-disciplinary inter-governmental organisation of 38 member countries which engages in its work an increasing number of non-members from all regions of the world. The Organisation's core mission today is to help governments work together towards a stronger, cleaner, fairer global economy. Through its network of 250 specialised committees and working groups, the OECD provides a setting where governments compare policy experiences, seek answers to common problems, identify good practice, and co-ordinate domestic and international policies. More information available: www.oecd.org.

ABOUT THE SME AND ENTREPRENEURSHIP PAPERS

The series provides comparative evidence and analysis on SME and entrepreneurship performance and trends and on a broad range of policy areas, including SME financing, innovation, productivity, skills, internationalisation, and others.

This paper was approved for publication by the Committee for SMEs and Entrepreneurship on 30 November 2022 [CFE/SME(2022)21].

This paper was authorised for publication by Lamia Kamal-Chaoui, Director, Centre for Entrepreneurship, SMEs, Regions and Cities, OECD.

This publication was produced with the financial support of the Marion Ewing Kauffman Foundation. Its contents are the sole responsibility of the OECD and do not necessarily reflect the views of the Marion Ewing Kauffman Foundation.

Acknowledgements

This paper is an output of the Centre for Entrepreneurship, SMEs, Regions and Cities (CFE) of the Organisation for Economic Co-operation and Development (OECD), led by Lamia Kamal-Chaoui, Director. Funding was provided by the Marion Ewing Kauffman Foundation. It contributes to the programme of work of the OECD Committee for SMEs and Entrepreneurship (CSMEE) on developing ecosystems and policies for start-ups. It was approved for publication by the CSMEE in November 2022 under written procedure (CFE/SME(2022)21).

The paper is based on expert papers by Dr. Haifeng Qian, School of Planning and Public Affairs, University of Iowa; Professor Michael Fritsch, Friedrich Schiller University Jena, Germany; Professor David Storey, University of Sussex, United Kingdom; and Professor Georgios Fotopoulos, University of Peloponnese, Greece. The project was led by Dr. Jonathan Potter, Head of the Entrepreneurship Policy and Analysis Unit, CFE, OECD.

The opinions expressed and arguments employed herein do not necessarily reflect the official views of the OECD member countries or the Marion Ewing Kauffman Foundation.

Table of contents

FIGURES

TABLES

Executive summary

Study overview

This paper provides new insights into regional variations in entrepreneurship activity and their implications for entrepreneurship policies, pointing to the importance of levelling-up of entrepreneurship activity across regions. It examines the degree of persistence or stickiness of regional entrepreneurship league table rankings over periods of approximately a century, half-century and 30 years in the United States at the scale of commuting zones and metropolitan areas and for self-employment and business start-up metrics. It also identifies the types of regions where performance changes markedly relative to others and the explanations for the changes. It compares the US patterns with pre-existing evidence on persistence and change in the regional entrepreneurship league table positions for labour market regions in West Germany and administrative counties and local authority districts in England and Wales. Comparability is achieved by undertaking the US analysis in a way that corresponds as closely as possible to the analytical approach of the earlier European work. The paper draws policy lessons from the US evidence and international comparisons and sets out a forward research agenda.

Context

In some of the earliest work in the field, an OECD paper (Reynolds and Storey, 1993) showed that, even within the same country, there were wide regional variations in entrepreneurship performance in OECD countries. Most countries had business birth rates that were up to four times higher in some regions than others. These variations were potentially a matter of interest to policy makers since they correlated positively with measures of regional prosperity.

Subsequent research focused on identifying the factors associated with variations in regional business birth rates, on the grounds that, if these could be increased or improved, this would lead ultimately to an increase in regional prosperity. This research identified the role of "hard" factors such as education levels, access to finance and sectoral composition of regions, but also "soft" factors such as attitudes to risk, which differed between regions with high and low business birth rates. The combination of factors relevant for regional new business formation became referred to as the entrepreneurial ecosystem and the challenge for policy makers was to create regional ecosystems that promoted start-ups and their growth.

More recently, however, a second key finding has emerged from studies of business birth rates in several European countries, including West Germany and England and Wales. It is that the regional differences are not only considerable but are also strongly persistent over very long periods of time. In simple terms, the regions of a country which currently have low business birth rates are likely to be those which had low rates ten, thirty and even ninety years ago. The reverse is also the case, implying that there is little change in the regional "league table of entrepreneurship" over time, and it is said to be "persistent" or "sticky". Although the reasons for this persistence are still under discussion, there is widespread agreement that high regional levels of entrepreneurship are associated with regional entrepreneurial ecosystem characteristics, such as a regional culture of entrepreneurship, that, once established, change only slowly over time.

This persistence over long time periods implies that levels of entrepreneurship activity in a region have historical roots, i.e., important sources of regional development may lie in the past. Entrepreneurial ecosystems research has typically involved cross-sectional analysis, i.e., at a given point in time. It tends to observe the range of current characteristics in successful regions and draw the implication that less successful regions should seek to develop these characteristics. However, current strengths in the regional conditions conducive to entrepreneurship in high birth rate regions are not necessarily the original cause of the high birth rates; they may be the consequence of them. For example, a correlation between current ease of access to finance or a risk-taking mentality and high business birth rates in a region could reflect prior success.

A necessary condition for any attempt to identify the link between entrepreneurial ecosystem conditions and entrepreneurship rates at a regional level requires changes in conditions in an earlier period to be statistically associated with ***changes*** in entrepreneurship rates in a later period. The cross-sectional analyses typical in the current literature are able to point to a current correlation but not necessarily to causation. The latter requires longitudinal data analysis. Since the available evidence, from selected European countries, suggests that regional entrepreneurship league tables within countries change slowly, even over decades, this analysis requires long-run data analysis.

In this context, this paper seeks to address two central questions:

- First, is there similar evidence of long-run stickiness in regional entrepreneurship rate rankings in the United States as in England and Wales and West Germany? The United States is particularly interesting, since it is an economy widely seen as highly flexible and entrepreneurial by international standards. If stickiness in regional entrepreneurship rates were also high in the United States this may be pointing to a more general pattern with important implications for policy.
- Second, are the changes that do occur in the US regional entrepreneurship league tables occurring in the same types of regions, and with the same types of explanatory factors, as in the European countries?

Study approach

The US findings are derived from two long-run data sources, one on self-employment and the other on start-ups. These data are analysed for two types of geographic units, metropolitan statistical areas and commuting zones. The latter provide full geographical coverage of the United States. This is important because economic activity and entrepreneurship in the United States are more heavily concentrated in metropolitan areas than in European countries and there may be significant differences in regional entrepreneurship trends in rural areas which can only be picked up by the commuting zones analysis.

The US findings are then compared with previously published results for England and Wales and West Germany. The England and Wales evidence relates to long-run and medium-run trends in regional self-employment rankings. The West German evidence relates to long-run and medium-run trends in self-employment and business start-ups rankings. In addition, new analyses are undertaken on medium-run changes in regional business start-up rates in England and Wales and Scotland and contrasted with the US and German findings.

Key findings

International comparisons

The analysis finds three key similarities between the United States and England and Wales and West Germany:

- Confirmation is provided of earlier results (Reynolds and Storey, 1993) showing that the United States exhibits a broadly comparable level of regional variation in self-employment and business birth rates as in the European countries.
- A second, but novel, finding is that the high degree of persistence of the regional rankings of entrepreneurship rates of periods of up to one hundred years in the United States is broadly comparable to that of West Germany and England and Wales.
- Third, some of the factors explaining changes in regional levels of entrepreneurship activity, such as initial self-employment levels, establishment size and share of the population with higher education, were consistently significant in West Germany, England and Wales and the United States.

United States findings

- Although the overall picture is one of persistence over time, some US regions exhibit considerable change. The terms “leapfroggers” and “plungers” are coined to capture regions moving sharply up and down, respectively, the regional entrepreneurship league table.
- The main variable found to be significantly related to a change in a region’s position in the entrepreneurship league table in the United States was share of the population with higher education. Other influences were population density, age structure of the local population and the regional level of home ownership.
- The most successful US leapfrogging regions, for the commuting zones and the self-employment metrics, between 1980 and 2015-19 are a diverse group. They include the large cities of New Orleans, Miami, Atlanta, and New York. However, the top three in the group were all small towns: Jordan town and Scobey city in Montana and Soda Springs city in Idaho.
- The biggest plunging commuting zones in recent years do not include any large cities, tourist destinations, or innovation hubs. Instead, plungers are disproportionately concentrated in adjacent states around the American heartland: Kansas, Missouri, Illinois, Kentucky, Arkansas, and Oklahoma.
- The positioning of individual regions in the league tables of US regions varies somewhat between the two types of geographic units and the two entrepreneurship metrics used in this study. For example, using metropolitan areas, there were 13 regions in the top 25 regions for start-ups in both 1978-82 and 2015-9. These were mostly medium-sized metropolitan areas with high natural amenities dispersed generally across the country, but with no representation from the Midwest. However, these 13 regions have almost no overlap with those at the top of the regional start-ups table for commuting zones. This group is comprised of many small cities outside the metropolitan areas.
- Nevertheless, the overall pattern of persistence, and the evidence of leapfrogging and plunging of specific regions within this overall pattern, is common across the different geographic units and entrepreneurship metrics.

Implications

For policy

The finding that entrepreneurship rates vary considerably across regions of the United States and that these differences are strongly persistent over time – as in England and Wales and West Germany – is of great relevance for policy. This potentially opens the way to increasing overall entrepreneurship activity in these countries – and hence increasing prosperity – by "levelling up" the performance of the weaker regions. Although there is strong persistence over time of the performance of individual regions overall, lessons for levelling up can be drawn from identifying the causes of the changes in the leapfrogger and plunger regions and the regionally sensitive entrepreneurship policy levers they point to.

For research

The next step for research is to explore leapfrogging and plunging regions in more detail. This should focus on the relationships between changes in their internal and external economic environments in earlier periods and changes in their subsequent regional entrepreneurship league table positions. The aim is to identify policy levers to improve regional entrepreneurship performance where possible.

We propose two very different approaches for this task.

- The first is to conduct carefully selected regional case studies in the United States and other countries. These would focus on the leapfroggers and the plungers. The case studies would seek to identify explanations for the changes in the performance of these regions, which we expect to include both factors external to the regions and internal to them. The research could identify and analyse those regions with the greatest differences between their expected and observed end-period league table positions, as predicted by regression analysis. An alternative is to use Fuzzy-set Qualitative Comparative Analysis (FsQCA) to analyse different combinations of conditions accounting for high positive and high negative rank mobility, both to select regional cases for analysis and to provide more sophisticated analyses of the findings.
- The second approach is to undertake further quantitative research at national level. The evidence in this report points to the entrepreneurship league table of regions within a country changing only slowly, even over decades. This presents a problem for policy makers and elected politicians who seek policies that will make a difference in shorter periods of time. There is therefore a case for shorter term national-level quantitative studies, in the United States and other countries. The work would replicate the analysis in this paper over two decades, but then observe links over successive five-year periods. This would enable account to be taken of the impact of factors over which politicians and policy makers exercise more influence, such as state taxes, major construction projects and regulations affecting entrepreneurship.

In parallel, the research on patterns of persistence and change in regional entrepreneurship rankings should be extended to further countries.

1 What are the issues and why are they important?

Aims and scope of the paper

Entrepreneurship as measured by self-employment and new business formation is argued to have a number of positive effects on economic welfare.[1] These include intensified competition, the acceleration of structural change, amplified innovation, greater variety of products and problem solution, knowledge spillovers, the generation of new employment and economic growth (Fritsch, 2013). Moreover, studies suggest that self-employed people tend to experience higher levels of job and life satisfaction (Shir, 2016; Fritsch, Sorgner and Wyrwich, 2019). Reynolds and Storey 1993, in their early work for OECD, showed that the levels, as well as the effects, of entrepreneurship tend to vary considerably between the regions of a country and that these differences may well contribute to explaining divergent patterns of growth and welfare.

This paper examines the medium- and long-term development of entrepreneurship across regions of the United States. It then compares these patterns with previously published work on England and Wales and West Germany. Its purpose is to address the following questions:

- How pronounced is persistence and change in regional entrepreneurship rankings in the United States over long periods of time? How do the US patterns compare with the prior studies in the European countries?
- Even within an overall context of stability, why, over time, do some regions show a pronounced increase in their levels of entrepreneurship (leapfrogging) while others fall, often considerably, (plunging)? What are the factors behind such changes? Are there common factors that may be generalised, and do these differ between the United States and West Germany and England and Wales?
- What policy conclusions can be drawn from the evidence of long-term regional trajectories? Does the policy framework differ between leapfrogging and plunging regions in the United States?
- What avenues for further research can be identified? Would in-depth case studies of selected leapfroggers and plungers be helpful? How might such cases be selected?

Current evidence on this topic shows that, although national rates of entrepreneurship may change substantially over time, the regional “league table” of entrepreneurship exhibits striking “stickiness within countries for which evidence is available.”[2] Low enterprise regions therefore tend to remain at the bottom of a league table and high enterprise regions remain at the top, over time periods ranging from ten years to almost a century.

[1] Fritsch (2013) provides an overview of empirical studies. For more recent analyses see Fritsch and Wyrwich (2017) and Fritsch and Wyrwich (2023).

[2] Fotopoulos and Storey (2017), Fritsch and Kublina (2019), Fritsch and Wyrwich (2023).

This section makes the case that these regional variations in entrepreneurship rates – and also their "stickiness" over time – matter. This means they merit attention from researchers and policy makers. The section sets out our state of knowledge before this work on the United States began. This can be summarised as showing that, in both West Germany and in England and Wales, there was evidence of regional entrepreneurship stickiness in the short, medium and even longer term. The central question to be addressed in this work is whether the regions of the United States – commonly viewed as a highly entrepreneurial country – also exhibited regional entrepreneurial stickiness.[3]

This issue is addressed in Section 2, which presents analyses of both short and long-run persistence and changes of regional entrepreneurship rates in the United States. The comparisons with the European studies, particularly the analyses of England and Wales (Fotopoulos and Storey, 2017) and West Germany (Fritsch and Kublina, 2019) are made in section 3. The implications for policy are set out in section 4. A future research agenda is proposed in section 5.

Why are regional variations in entrepreneurship important?

Within OECD countries, there are wide regional variations amongst almost all social and economic indicators. These range from employment, firm dynamics and productivity to earnings and life satisfaction, and there is evidence that many of the geographical areas performing poorly on one metric also perform poorly on others.[4] There are three key arguments why regional variations are important and require addressing by policy makers concerned with entrepreneurship policies.

- The first reason is that, if the entrepreneurship performance of the under-performing areas could be raised, even to that of the currently average areas, then this would make a considerable contribution to national output or well-being. This argument can be considered as the "foregone potential" argument.
- A second reason why major regional variations in entrepreneurship should be of concern to policy makers is that they are reflected in a lower quality of life for individuals. This is referred to as the "social welfare" argument. Entrepreneurship offers individuals a job, which will normally offer a quality of life improvement over unemployment. The impact may be enhanced further if the enterprise created is successful and creates jobs for other people.
- Thirdly, and highly relevant in this context, there is evidence that these regional variations are persistent over long periods of time. The significance of long-run persistence means that equilibrating forces such as resources moving from high- to low-cost areas tend to be rather weak and insufficient. This makes such persistent regional differences an *a priori* case for policy intervention, referred to as the "policy" argument.

In short, all three are powerful reasons why public policy makers need to be concerned with regional imbalances in entrepreneurship.

What did we know before we started?

The uneven distribution of economic welfare across regions, with some regions being considerably more prosperous across a range of dimensions than others, has encouraged researchers to investigate the

[3] For example, the 2021/2022 Global Entrepreneurship Monitor (GEM) reports the United States as one of the countries with the highest level of Total early-stage Entrepreneurial Activity among OECD countries, considerably ahead of Germany and the UK.

[4] See Eurostat (2021), OECD (2020), UK Government (2022).

causes of this unevenness and to identify whether there are factors that can explain these differences. If so, this might enable policy-makers to take actions that would enable the less prosperous regions to improve.

The evidence of a positive statistical link between regional entrepreneurship and prosperity has motivated a number of national and regional governments to implement programmes seeking to raise regional entrepreneurship in the expectation that this will ultimately enhance prosperity.[5] However, evidence points to regional levels of entrepreneurship tending to be persistent, so making effective policy intervention difficult.

Unfortunately, our knowledge about the determinants of the levels of regional entrepreneurship is highly imperfect. Regional entrepreneurship is embedded in 'ecosystems' and little is known about how the complex interactions between actors and institutions that form this ecosystem shape the emergence and success of firms (Stam and van de Ven, 2021; Wurth et al., 2022). We know little about the factors leading to sustainable changes in between-regions entrepreneurial activity i.e., in the national ranking of regions in which the most enterprising areas are at the top and the least enterprising at the bottom.

The countries in which such league tables have been produced – West Germany and England and Wales – have demonstrated strong persistence over time. Although slightly different national metrics of enterprise and slightly different methods have been used, the striking finding is that the regions at the top of the table at the start of often very lengthy time-periods tend to be those that remain at the top at the end of the period in both countries. Equally, those at the bottom of the table at the start of the period tend to be those at the bottom at the end of the period. This is referred to as stickiness or persistence and measured as Regional Entrepreneurship Persistence.

The case for league tables

The core purpose of preparing regional entrepreneurship league tables is to validly compare changes in the entrepreneurship performance of one geographical area (region) within a country with another in the same country over an (extended) period of time. Their relevance is that it is not only absolute rates that are of interest to policy makers but whether "their" region is performing better than adjacent regions. So, even if all regions are becoming more – or less – entrepreneurial over a period of time then each is still likely to be concerned with their relative position against those against which they benchmark themselves. Changes in league table position provide that evidence.

A more analytical benefit of regional entrepreneurship league tables is that, by definition, they hold constant a range of potentially powerful influences on entrepreneurship that are set primarily or exclusively at a national level.[6] Alternatively expressed, changes in regional entrepreneurship league table position reflect regional – and not national – influences. This means that changes in the league table position of an individual region cannot easily be attributed to influences at the national level. Hence, it is valid, when explaining regional change in entrepreneurial activity, to focus on factors that are region-specific. This is an advantage when making comparisons over time in the sense that much is held

[5] In the UK these policy initiatives include the Scottish Business Birth Rate Programme and the Wales Entrepreneurship Action Plan, reviewed by Fotopoulos and Storey (2019).

[6] There are many examples of factors that, because they are set nationally, would not be expected to influence the position of a region in an entrepreneurship league table. The first is the interest rate set by a Central Bank and which then influences borrowing rates for all firms including new start-ups. A second group of factors is the role of monetary policy which Hamano and Zanetti (2022) show can significantly affect the entry of new firms. A third key influence on new firm creation that is set primarily at the national level is the business regulatory framework, although it may be enforced sub-nationally.

constant.[7] It is a key property of league tables that, for the areas that rise, there must also be complementary falls.

Persistence versus change in the league table

A range of theories have been proposed to explain regional levels of entrepreneurship.[8] The theory of occupational choice explains why in some regions more individuals choose business ownership than other forms of economic activity, such as being an employee, unemployment or economic inactivity. It assumes this is an informed, although not necessarily a fully-informed, choice in which, all else equal, the individual chooses the economic form that maximises their utility, frequently captured by earnings. On those grounds, the regions where earnings are relatively high will have lower rates of business ownership because individuals will shift to becoming an employee. Although this theory does not seek to predict or forecast which individuals will shift between the above four groups, it provides the framework for such considerations developed by Ghatak et al. (2007).

Further approaches to explain regional levels of entrepreneurship have emphasised aspects of the regional entrepreneurial ecosystem, including the sectoral and size structure of employment units, the age and gender structure of the working population, its educational attainment and skill level, innovation activities and the regional knowledge base, availability of resources such as capital for investments as well as advantages and disadvantages of location such as population density (agglomeration effects) as well as access to capital. Since such factors tend to change slowly, a region's league table position is also likely to change little, often over long periods of time (Fotopoulos 2014). In short, they are persistent.

Another favoured explanation for persistence in regional entrepreneurship rates is culture. This can be regarded as informal institutions[9] that differ between regions but change only slowly over time (North, 1994; Williamson, 2000). In their review of several empirical studies across different countries, Fritsch and Wyrwich (2023) conclude there is strong evidence of long-run spatial persistence, which is attributed to cultural factors. However, the challenge for cultural-based explanations is that some regions do change position. Some move up the league, often substantially, ("leapfroggers") and some move markedly down ("plungers"). It is an important task to explain these significant changes of regional entrepreneurship position in the national league table. Such explanations are currently rare within the entrepreneurial ecosystems and entrepreneurial culture frameworks.

We now return to the occupational choice framework and the role of economic shocks as proposed by Ghatak et al. (2007). Their model, applicable to leapfroggers, assumes that wages in region X rise sharply over an extended period, compared with other regions. This first round economic shock leads to a fall in the number of business owners because low productivity entrepreneurs shift to become employees where earnings are higher. The second round effect is that the exit of low productivity firms means that the average quality of those remaining rises. Those institutions providing financial capital recognise this improvement in quality and, in round three, they become more prepared to provide finance to new and small firms in the region. The outcome of this improved access to finance is that, in round four, firms in the region expand further seeking labour that cannot be supplied from within the region. Round five sees this labour being supplied by in-migration from outside the region further supplementing

[7] Another advantage is that due to their ordinal character, rankings are robust to extreme cases ('outliers'), which could bias the results if continuous metrics are used.

[8] For an overview see Parker (2018).

[9] The informal institutions are the unwritten rules, such as codes of conduct as well as social norms and values, which include religion. For the relationship between religion and entrepreneurship, see Parker (2018).

the profitability of the firms and their owners who, in turn, are able to acquire a range of consumer services provided by self-employed workers.[10]

Along similar lines, the incidence of plungers can also reflect negative economic shocks. Highly entrepreneurial regions with, at one point in time, a heavy concentration in specific trades or occupations undertaken by the self-employed or small business owners, may experience a long-run decline in demand leading to many closing their business and many fewer entering.[11]

Two studies have investigated regional changes in entrepreneurship levels in a league table framework.

Fotopoulos and Storey (2017) analysed the development of self-employment in regions of England and Wales over the period 1921 to 2011. They found that upward rank mobility is associated with improved qualifications of the regional workforce, high immigration, a rising share of service employment and an increasing rate of home ownership. Although the results are strongly shaped by a rise of the London region, many less densely populated and rural regions are among those at the top of the league table.

Fritsch and Kublina (2019) investigated the persistence and change of new business formation in the entrepreneurship league table of West Germany in the 1976/77 - 2006/07 period. They found that the regions rising up the league table were characterised by a high level of research and development activities, a high employment share in small businesses, high shares of manufacturing employment and high population density. Moreover, the regional wage level in regions that moved up the league table was relatively low. In West Germany, most regions at the top of the league table are located outside larger agglomerations, with some large cities such as Stuttgart being at the bottom.

What to expect

We expect the United States to be different from European countries in two respects. First, the US economy has tended to be more entrepreneurial, flexible and dynamic than the national economies in European countries in recent decades (Frydman et al., 2011). For this reason, we may expect less persistence of regional entrepreneurship levels and more pronounced changes in the league table.

A second clear difference between the United States and Europe is the geographic structure of its economic activity. Human settlement and economic activities are more concentrated in large metropolitan areas in the USA than in some European countries, including Germany and the United Kingdom (Fritsch and Wyrwich, 2021a). For example, metropolitan areas in the United States provided 96% of total employment, 95% of total establishments, and 96% of total new establishments in 2019. In terms of innovation, 82.7% of the inventors of US patents filed in 2015 had their residence in large metropolitan areas, while this share was only 35.9% in Germany and 32.3% in the UK (Fritsch and

[10] This model accurately captures the changes experienced by the region of London in the last forty years. The initial shock was the rise of the City of London, driven by the financial liberalisation of the “Big Bang’, and the wealth it generated amongst City-based individuals who were then able to purchase services supplied by new businesses and the self-employed. However, the regions immediately surrounding the City were soon unable to supply these services and so drew upon suppliers from a wider geographical area and also from immigrants from both outside the area and outside the country. This took place in the 1990s and 2010s with business ownership rates rising in the 2010s in regions that were more distant from the City of London. The shock effect of the City was to ripple out from its epicentre, implying that, in contrast with the expected economic model, it was the regions where wages rose fastest that experienced the largest increase in self-employment.

[11] An example, noted in Fotopoulos and Storey (2017), is the seaside tourism sector. Here the dominant employers in the 1950s were small hotels and the towns were some of the most prosperous in England and Wales. Over the subsequent 50 years, alternative holiday locations became more popular, visitor numbers fell considerably and today these former seaside towns are amongst the most deprived in the country with some of the lowest business birth rates.

Wyrwich, 2021a). In contrast, European regions outside the large agglomerations make important contributions to innovation and competitiveness (Fritsch and Wyrwich, 2021b).

There may therefore be differences in persistence and change in regional entrepreneurship patterns compared with the European cases.

Conclusion

This section has provided a brief summary of our state of knowledge of variations in regional rates of entrepreneurship and how regional rankings of entrepreneurship rates change over time. It provides the basis for our central test, which is whether a highly entrepreneurial country such as the United States exhibits the same regional patterns observed in the two European countries for which previous analyses have been undertaken – namely a long-run stickiness or persistence in regional entrepreneurship rankings. It also provides the background for our assessment of which types of regions show considerable movements up (leapfroggers) and down (plungers) a league table over a lengthy period of time.

A second main aim of our study is to learn more about the factors that are responsible for changes of regional positions in the entrepreneurship league table. What are the common factors that shape such changes in the European countries reviewed and the United States that may be generalised? What are the differences? Responses to such questions are intended to point to those elements of the regional entrepreneurial ecosystem that are of key importance for policies trying to make regions more entrepreneurial in order to stimulate prosperity.

2 Dynamics of regional entrepreneurship in the United States

Introduction

This section provides a detailed picture of the scale, nature and change in regional entrepreneurship metrics in the United States over several decades. Its core purpose is to judge whether the United States exhibits regional entrepreneurial stability over time. Perfect stability occurs when the entrepreneurship rank-order of the regions is unchanged over time but, in practice, this is very unlikely. Our second purpose is therefore to document the scale of any such movement by creating a national entrepreneurship "league table" for base and final years. This is then used to identify the extreme movers: the big risers – leapfroggers – and those falling sharply – the plungers.

Two groups of time-based comparisons are made of the regional entrepreneurship rankings for two different measures of entrepreneurship: 1920 to 2015-19 and 1980 to 2015-19 for self-employment rates; and 1978-82 to 2015-19 for business start-up rates.

In addition to providing a comprehensive picture of regional entrepreneurship metrics in the US, the analysis was undertaken so as to offer close comparability with two European studies that addressed the same issue: by Fotopoulos and Storey (2017) for England and Wales and by Fritsch and Kublina (2019) for West Germany.

This section sets out the US results, with section 4 focusing on the international comparisons.

The challenges

Three challenges had to be addressed to undertake this analysis:

- The first was to identify data sources that are currently representative of the United States in terms of their spatial and enterprise coverage.
- The second was to ensure that data coverage was consistent over several decades.
- The third was to prepare the US data to enable valid comparisons to be made with the two existing European studies.

Below we set out how these issues are addressed.

Spatial units

Two geographic categories are used in the analysis: commuting zones (CZs) and metropolitan statistical areas (MSAs). Their core characteristics are set out below.

- *Commuting zones (CZs)*: These "are intended for use as measures of local labour markets when researchers are not concerned with minimum population thresholds" (Tolbert and Sizer, 1996, p. 1). CZs cover all US counties or land and each includes one or more contiguous counties that are delineated by commuting ties. The 1990 definition of CZs (Tolbert and Sizer, 1996) is used. All 722 CZs in the 48 contiguous US States and District of Columbia are considered, with Alaska and Hawaii being excluded on the grounds that they have economies and geographies that are vastly different from the rest of the US states. Finally, an important key advantage of CZs is that their absence of minimum population thresholds makes them consistent with the European studies of Fotopoulos and Storey (2017) and Fritsch and Kublina (2019) that both find a considerable quantity of entrepreneurship outside the larger agglomerations.
- *Metropolitan statistical areas (MSAs)*. These are a second commonly-used geographic unit for regional economic analysis in the US. MSAs are also defined by a county or a group of adjacent counties with commuting ties like CZs, but represent labour markets above a minimum population threshold (at least 50 000 population in their urban cores) and do not cover remote counties without close commuting ties with these urban cores. MSAs are officially defined by the US Federal Government (OMB, 2013). Although they include less than two-fifths of US counties by area, MSAs provided 96% of total employment, 95% of total establishments, and 96% of total new establishments in the United States in 2019, based on the U.S. Census Bureau's Business Dynamics Statistics data. Innovative activity, based on either patents or small business innovation, is also heavily concentrated in MSAs (Haynes et al., 2012; Fritsch and Wyrwich, 2021a). The current study considers all 377 MSAs by the OMB 2013 definition in the 48 US contiguous states and the District of Columbia. The MSAs in Alaska and Hawaii are again excluded.

It should be kept in mind that the current regional definitions used may be less appropriate for earlier periods. Commuting patterns in the 1920s or the 1980s are different from those of today and metropolitan areas were geographically smaller or did not exist. Nevertheless, a meaningful inter-temporal comparison does require retaining a consistent spatial framework.

Entrepreneurship metrics

Two metrics were used to capture entrepreneurship. These are self-employment and business start-up rates. Each is described below.

- *Self-employment*: In the United States this includes self-employed workers in incorporated businesses, as well as self-employed workers in unincorporated businesses and their unpaid family workers. Workers in agriculture, fishery, forestry, and mining are excluded. Self-employment rates are normalised as non-agricultural self-employment per 1 000 members of the labour force. The definition is identical to that used in England and Wales. The labour force data used the Decennial Census or the American Community Survey (ACS). The ACS was introduced after the year 2000 to replace the sample survey in the Decennial Census, with employment questions asked.
- *Start-up activity*: The measure of start-ups used in this study is new business establishments per 1 000 labour force population. New business establishments are those with a positive number of paid employees on March 12 of the current year but zero paid employees on March 12 of the previous year. The Business Dynamics Statistics (BDS) from the US Census Bureau provide these establishment entry data by year between 1978 and 2019 and by county. The labour force data are taken from the Decennial Census and the ACS.

Timescales

Two principal timescales are used for the analysis, although others were tested and explored.

- *Long-run analysis*. Long-run analysis is possible for the self-employment measure. This is undertaken using time periods comparable with those of the England and Wales study. The long-run self-employment analysis for the United States compares 1920 and 2015-2019. This is very similar to the years 1921 and 2011 used for England and Wales. However, more recent data for the United States (2015-19) is used for the end-period, making the US study more up to date.
- *Medium-run analysis*. The medium-run self-employment analysis for the United States uses 1980 as the mid-point period. In comparison, the England and Wales study of self-employment trends used 1971 as the mid-point. The choice of 1980 (instead of 1970) as the middle point for the United States is motivated by the fact that the US new business establishment data are available only after 1978. The start-up data are analysed from 1978-82 to 2015-19. Hence the use of 1980 as the mid-point for the self-employment data allows for a better comparison between the self-employment and start-up trends within the United States.

Detailed data sources

More details are provided below on the data used for the analyses over the different time periods for the different entrepreneurship metrics and geographical units.

Long-run self-employment analysis for CZs: The US data source for 1920 self-employment is the 1920 Decennial Census. The full-count micro data are available from the Integrated Public Use Microdata Series, or IPUMS (Ruggles et al., 2021). To match the county information in the 1920 micro data with the 1990 definition of CZs, the methods and data from Eckert et al. (2020) are adopted.[12]

Medium-run self-employment analysis for CZs: The data source for 1980 self-employment is the 1980 Decennial Census. The county-level data are made available by the IPUMS National Historical Geographic Information System (Manson et al., 2021). The county-level self-employment and labour force data are aggregated into the CZ level in this study. The data source for 2015-2019 self-employment is the 2015-19 five-year estimates of the ACS.[13]

Medium-run business start-up analysis for CZs: For the CZ-level analysis, the county-level new business establishments and labour force data are aggregated into the CZ level. The beginning-period start-up rate for the CZs is measured by the 1978-82 five-year average of new business establishments per 1 000 labour force (the labour force data are only available for the Decennial Census year 1980 during this period). The five-year average is used to account for the yearly volatility of business entries. Similarly, the end-period start-up rate is measured by the 2015-19 five-year average of new business establishments per 1 000 labour force (using the 2015-19 five-year labour force estimates from the ACS). The data cover all counties in the United States.

[12] Note that the matching is neither perfect nor official. County boundaries were changing over time, and the current Federal Information Processing Standard (FIPS) for counties was introduced only around 1970 and not used for the 1920 Census. Following a recommendation by Eckert et al. (2020), when a 1920 county is split among different CZs, self-employed workers and labour force in this county are assigned to these CZs proportional to the areas falling into each CZ. This should be kept in mind when comparing 1920 patterns with 1980 and 2015-19 patterns, even though only a small number of 1920 counties have large shares of land in multiple 1990 CZs.

[13] It should be noted that the 1920 Census does not identify unpaid family workers, while the 1980 and 2015-19 aggregate data (Manson et al., 2021) explicitly include this group as part of self-employment. This calls for another layer of caution when comparing self-employment in 1920 with 1980 or 2015-19.

Long-run and medium-run self-employment analysis for MSAs: For the MSA-level analysis, the 1920 and 1980 self-employment and labour force data are processed in the same way as with the CZ analysis. The key difference is that county-level data are aggregated into the MSA level rather than the CZ level. The 2015-19 ACS provides MSA-level tabulations, which are directly used to calculate non-agricultural self-employment per 1 000 labour force population at the metropolitan level.

Medium-run business start-up analysis for MSAs: For start-up activity, the BDS directly provides MSA-level data on new establishments and total employment. The beginning-period MSA start-up rate is measured by the 1978-82 five-year average of new business establishments per 1 000 employees (based on yearly average employment for the same five-year period). The end-period MSA start-up rate is calculated in the same way for the 2015-19 period. Employment is used as the denominator, rather than the labour force, which was used in the CZ analysis. This is partly in order to follow Fritsch and Kublina (2019), and hence to increase comparability with the results for West Germany. However, it is also because the employment measure is more accurate than the labour force measure, because it is based on a real count for employment rather than sampled data for the labour force, it covers more years (1978, 1979, 1981 and 1982 in addition to 1980), and it avoids any mismatch between different data sources (since the entry and employment data both come from the BDS).

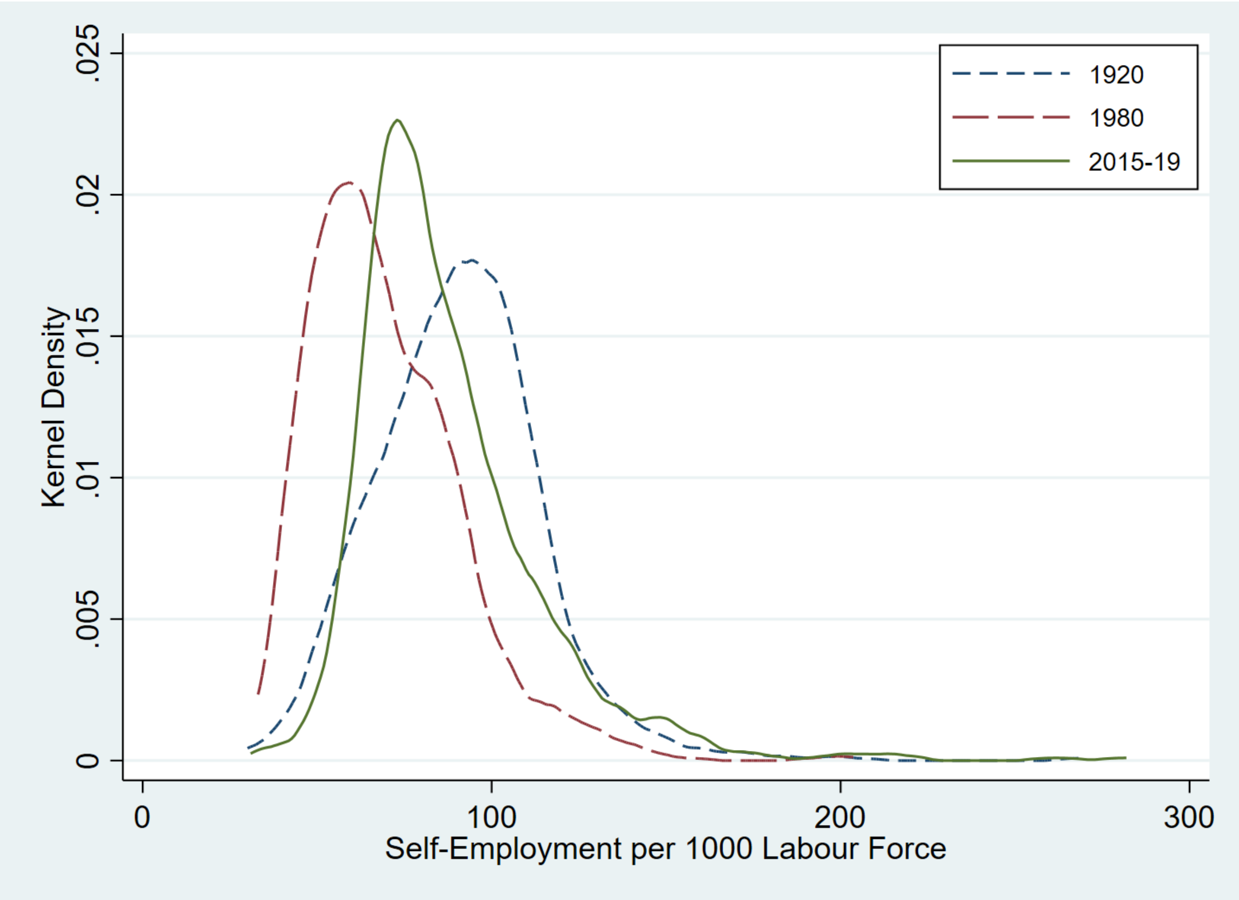
Commuting zones analysis

Self-employment

Description of regional self-employment stability in the United States

Figure 2.1 shows the density distributions of CZ self-employment rates over time. The average rate clearly decreased between 1920 and 1980. This likely reflects the corporatisation of the U.S. economy, particularly during the post-World War II period. The self-employment rates then rebounded between 1980 and 2015-19. Debbage and Bowen (2018, p. 147) note that recent self-employment growth in the United States may be a result of “the deindustrialization of the national economy and the shrinking workforce in manufacturing, the increased popularity of part-time self-employment, the decline in the number of farm proprietorships and the disruptive impact of scalable information technologies”. It is remarkable that current self-employment rates across CZs have both a lower spread and a lower median than in 1920.

Figure 2.1: Kernel density estimates of self-employment rates, 1920, 1980, 2015-19, US commuting zones



Note: Kernel density is a smoothed form of histogram. Instead of directly using the observed value in the histogram, it builds a kernel function for each data point to smooth the overall density function. In this paper, the Epanechnikov kernel function (quadratic form) is used.
Source: OECD analysis of US Decennial Census and American Community Survey from the US Census Bureau.

Self-employment rates in CZs exhibit temporal persistence between 1980 and 2015-19 (Spearman rank coefficient: 0.603), but much less so between 1920 and 1980 (Spearman rank coefficient: 0.169). Additionally, the 1920 self-employment rates are more strongly correlated with those of the 2015-19 period (Spearman rank coefficient: 0.241) than with the self-employment rates of 1980. This comparison has, however, to account for lower data quality in 1920.

Distinguishing CZs with high, medium and low population density (upper, middle, and lower third), the low-density regions have on average the highest self-employment rate in the 2015-19 period (99.94 per 1 000 labour force) followed by the regions with medium density (83.57) and the high-density regions (79.62).

Ranking and ranking changes

This sub-section moves beyond a description of the CZ population and offers insights into individual CZs that reflect key trends such as stability over time but also extreme growth and decline in regions – the leapfroggers and plungers. It creates three regional league tables, in which all CZs are ranked according to their self-employment rate in 1920, 1980 and 2015-19. Leapfroggers are defined as those that increase their league table position considerably over the periods 1920 to 2015-19 or 1980 to 2015-19, whereas plungers decline considerably. In addition, there are two other types of regions – those that were persistently strong performers and those that were persistently weak performers. More information is given below on the regions and types of regions fitting into these different categories.

Leapfroggers

The biggest self-employment leapfroggers between 1980 and 2015-19 were a diverse group including the large cities of New Orleans, Miami, Atlanta, and New York as well as small towns. The top three leapfroggers were all small towns: Jordan town and Scobey city in Montana and Soda Springs city in Idaho. Nevertheless, upward movement appears strongly linked to city size, with the top one-third CZs in terms of the 1980 population density, on average, moving up by 87 spots in the national league table. This suggests that urbanisation economies are a potential source of self-employment growth. Meanwhile, small tourist destinations are also well represented amongst leapfroggers and disproportionately concentrated in the Atlantic coastal and mountain west states.

Plungers

Plungers are disproportionately concentrated in states adjacent to the American heartland: Kansas, Missouri, Illinois, Kentucky, Arkansas, and Oklahoma. Figures 2.2 and 2.3 illustrate these spatial patterns. In contrast, plungers are rarely large cities, tourist destinations, or innovation hubs.

Distinguishing between CZs of high, medium and low density, the average number of rank changes is positive (+87) for the high-density regions and negative for the medium-density (-65) and the low-density (-22) group.

Persistent strong performers

An examination of individual CZs shows that only two small ocean-island CZs in Massachusetts near the Atlantic coast, Vineyard Haven and Nantucket, are consistently ranked among the top 25 CZs (and even among top 5) in the period 1920 to 2015-19. The economy in these CZs depends heavily on tourism. A further nine CZs that are ranked among the top 25 both in 1980 and in 2015-19 are all small CZs west of the Mississippi River, the largest of which had a population of 53 508 in 1990 (Kerrville city, Texas). They also tend to be tourist destinations.

Persistent weak performers

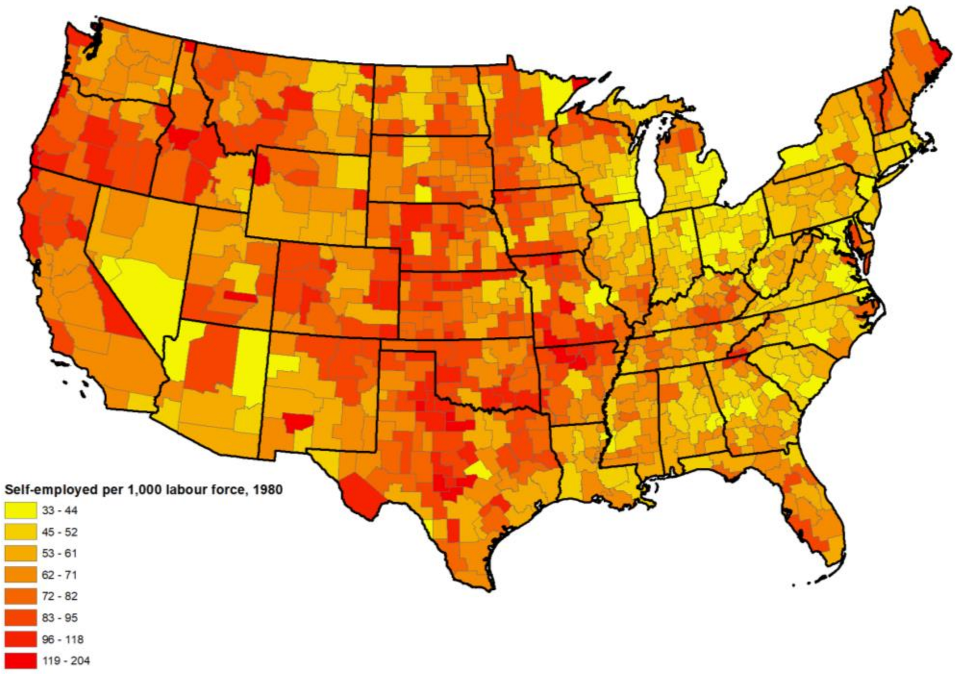
The other extreme form of spatial stability is where the CZ is in the bottom 25 in 1920, 1980 and in 2015-19. The only case was Welch city in West Virginia. It is relatively small, with a 1990 population of 64 223 and an economy that historically was dependent on the mining sector. Steubenville city in Ohio and Rosebud CDP in South Dakota are two sparsely populated regions that are in the bottom 25 CZs in 1980 and 2015-19 but not in 1920.[14]

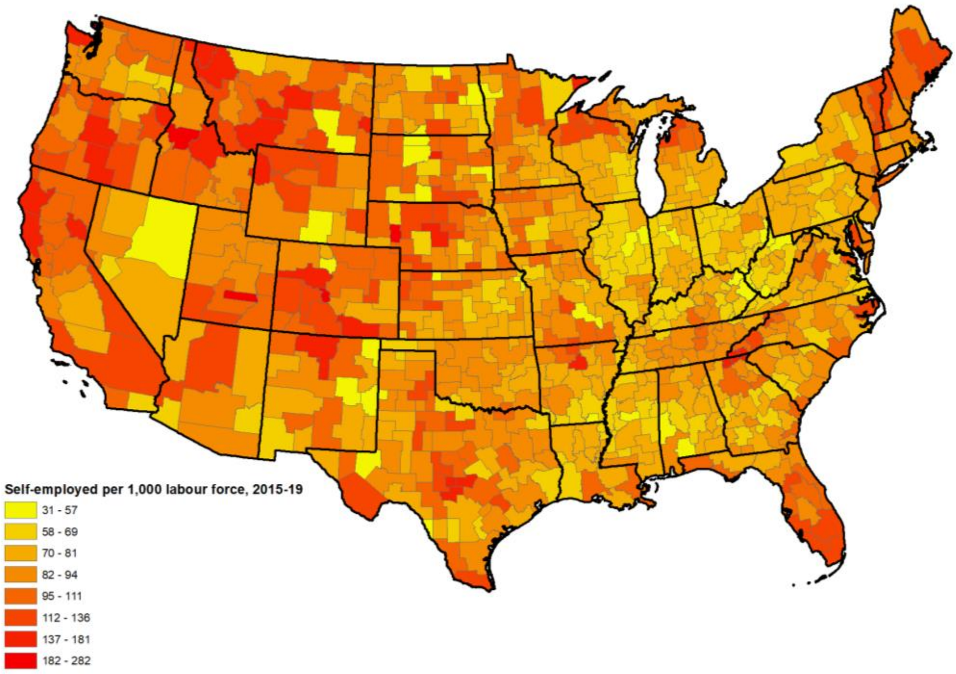
Spatial patterns of changes in self-employment rates

Figure 2.2 shows self-employment rates in US CZs in 1980 and 2015-19. Figure 2.3 shows the changes in rankings of CZs during this period.

[14] While Steubenville is a traditional mining and manufacturing region, Rosebud is an Indian reservation.

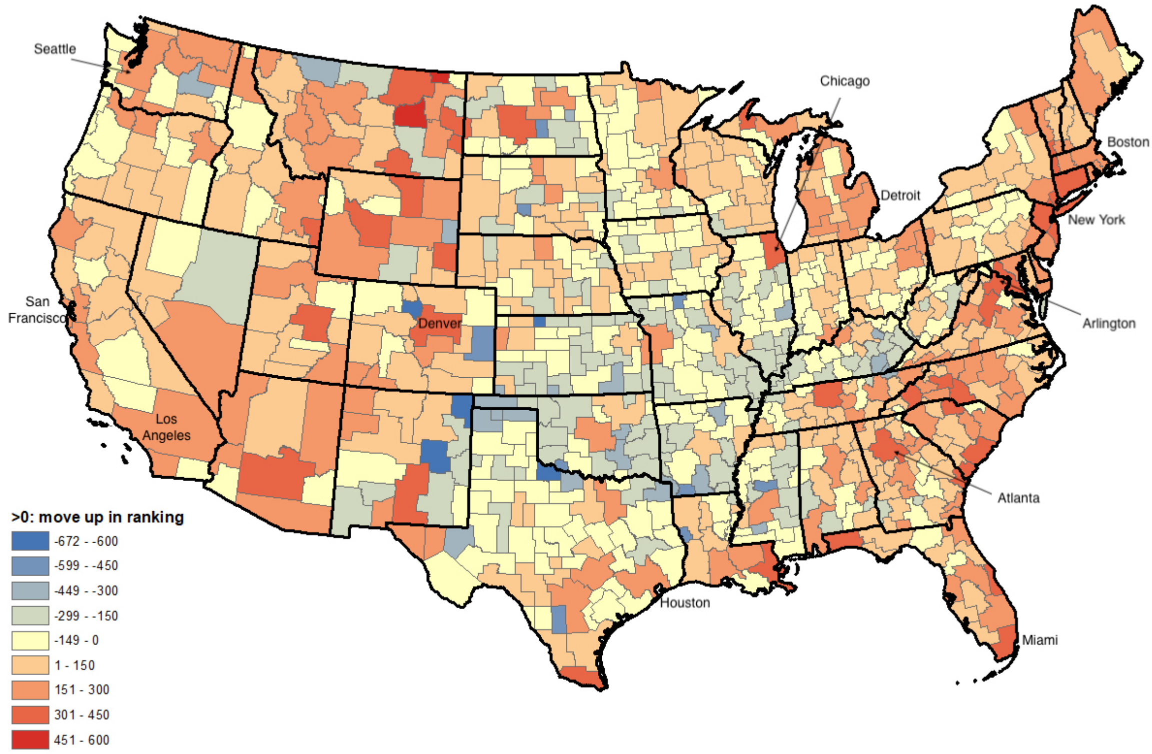
Figure 2.2: Self-employment rates in US commuting zones, 1980 and 2015-19





Source: OECD analysis of US Decennial Census and American Community Survey from the US Census Bureau.

Figure 2.3: Self-employment rank changes between 1980 and 2015-19, US commuting zones



Source: OECD analysis of US Decennial Census and American Community Survey from the US Census Bureau.

Factors predicting regional dynamics – regression analysis

Regression analysis aims to more formally explain the leapfrogging/plunging patterns in the United States over the period 1980 and 2015-19. This period is chosen to match, as closely as possible, that of Fotopoulos and Storey (2017) for England and Wales.

The analysis also adopts the novel Rank Mobility Index (RMI) created by Fotopoulos and Storey (2017), which, in this context, has a number of advantages over using a continuous measure. First, it captures the aim of regional politicians to be "above" their neighbour, even if this is by only a modest amount. Second, from an analytical viewpoint, it deflates the role of extremes, which can distort interpretations.

Formally, the CZ rank change is standardised by the highest possible rank change (i.e., N-1, where N is the total number of CZs being considered, or 722), with a value between -1 to 1. The value 1 represents the scenario when the CZ ranked the lowest in the initial year moves to the highest spot in the end year, while -1 represents the reverse move. The core purpose of the index is to provide symmetry, in the sense that an equal number of places in terms of either increase or decrease results in the same, in absolute value terms, value of the index.

For comparative purposes, the selection of independent variables also follows the self-employment model of Fotopoulos and Storey (2017).[15] OLS and unconditional quantile regression results based on robust standard errors are reported.[16]

[15] Since the core purpose is to examine long-run change, the independent variables selected for inclusion are those expected to have a long, rather than a short-run impact. They are also restricted to those where data are available over long periods of time. This means that some variables which, despite their mixed evidence, are occasionally

The dependent variable is self-employment RMI. The independent variables are listed in Table 2.1. Although Fotopoulos and Storey (2017) used the *changes* of factors during the study period as explanatory variables, we use the *initial-year levels* of these factors to mitigate any issues of endogeneity. Table 2.1 also describes the measures and data sources of these variables.

Table 2.1. Independent variables for the commuting zones self-employment model

Independent variable	Variable description
1980 self-employment	Self-employment rate, 1980
1980 population (logged)	Population (logged), 1980
1980 human capital	Share of BA degree among population 25+, 1980
1980 foreign born	Share of immigrant population, 1980
1980 55-64 years old	Share of population group 55-64, 1980
1980 establishment size	Average establishment size (employees per establishment), 1980
1980 home ownership	Share of homeowners among occupied homes, 1980
1980 service share	Share of service employment, 1980
1980 self-employment	Share of self-employed in the labour force, 1980

Notes: Data sources: 1980 County Business Pattern for establishment size; 1980 Census for all other variables

Table 2.2 presents the regression results. One of the key findings is that CZs with higher self-employment rates in 1980 (i.e. with higher ranks) performed worse in moving up in the national league table between 1980 and 2015-19. This result is consistent at the different quantiles and is larger at the 50th, 70th, and 90th quantiles. This finding may not be surprising. Structurally, already highly-ranked CZs have less room to improve their ranking.

Initial population size is positively and significantly associated with self-employment RMI both in OLS and in quantile regressions at the 10th and 70th quantiles. This further supports the large-city advantage notion observed in descriptive analysis earlier.

Human capital in terms of the share of bachelor's degree holders in 1980 adult population also has a positive and significant association with upward rank mobility. This finding is consistent with the knowledge spillover theory of entrepreneurship, which states that knowledge and skills in the local labour market facilitate entrepreneurial activity (Qian and Acs, 2013).

Another two consistently significant factors are the share of foreign-born workers and the share of workers in the 55-64 age group. Both are positively associated with self-employment RMI. Foreign born could be taken to indicate the diversity and openness of the region, which may stimulate entrepreneurial activity (Qian, 2013).

---

used in the literature to explain entrepreneurship metrics are also excluded, such as unemployment (Parker, 2018) or state taxes (Bruce and Deskins, 2012).

[16] The unconditioned quantile regressions result shows the impact of a change in an independent variable on the self-employment rank change for the CZs at the 10th, 30th, 50th, 70th, and 90th quantiles based on the RMI. CZs at the high quantiles (e.g., 90th) may be considered as leapfrogging regions, while those at the low quantiles (e.g., 10th) may be considered as plunging regions. Quantile regression results, therefore, can demonstrate potentially differentiated effects of the same regional factors on the performance of leapfrogging regions *versus* plunging regions *versus* other regions in the middle.

Additionally, a higher home ownership rate in 1980 is related to higher self-employment upward mobility between 1980 and 2015-19, perhaps reflecting easier access to capital or stronger market demand. Lastly, the initial share of service employment change is negatively and significantly associated with rank mobility based on the OLS results, though this is statistically significant (at the 0.05 level) only at the 30th quantile in the quantile regressions.

Table 2.1: Regression results for the commuting zones self-employment model

	Dependent variable: self-employment rank mobility index (1980 to 2015-19)					
	OLS	Unconditional quantile regressions				
Independent variable		Q 10	Q 30	Q 50	Q 70	Q 90
1980 self-employment	-0.005***	-0.003**	-0.004***	-0.005***	-0.005***	-0.006***
1980 population (logged)	0.029**	0.062**	0.012	-0.002	0.027**	0.033
1980 human capital	2.641***	2.284***	2.860***	2.619***	2.704***	2.547***
1980 foreign born	1.452***	0.734*	1.443***	1.040**	1.357**	2.207**
1980 55-64 years old	2.901***	2.479**	2.942***	3.112***	2.248**	3.269*
1980 establishment size	-0.007	-0.008	-0.001	0.005	-0.005	-0.007
1980 home ownership	0.619***	0.531	0.583**	0.530*	0.712**	0.769*
1980 service share	-0.548***	-0.626	-0.597**	-0.293	-0.426*	-0.484
Constant	-0.665***	-1.301***	-0.708***	-0.537*	-0.617**	-0.504
R2 adjusted	0.294	0.063	0.145	0.213	0.194	0.122
Number of observations	722	722	722	722	722	722

Notes: *** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at the 10% level

Start-ups

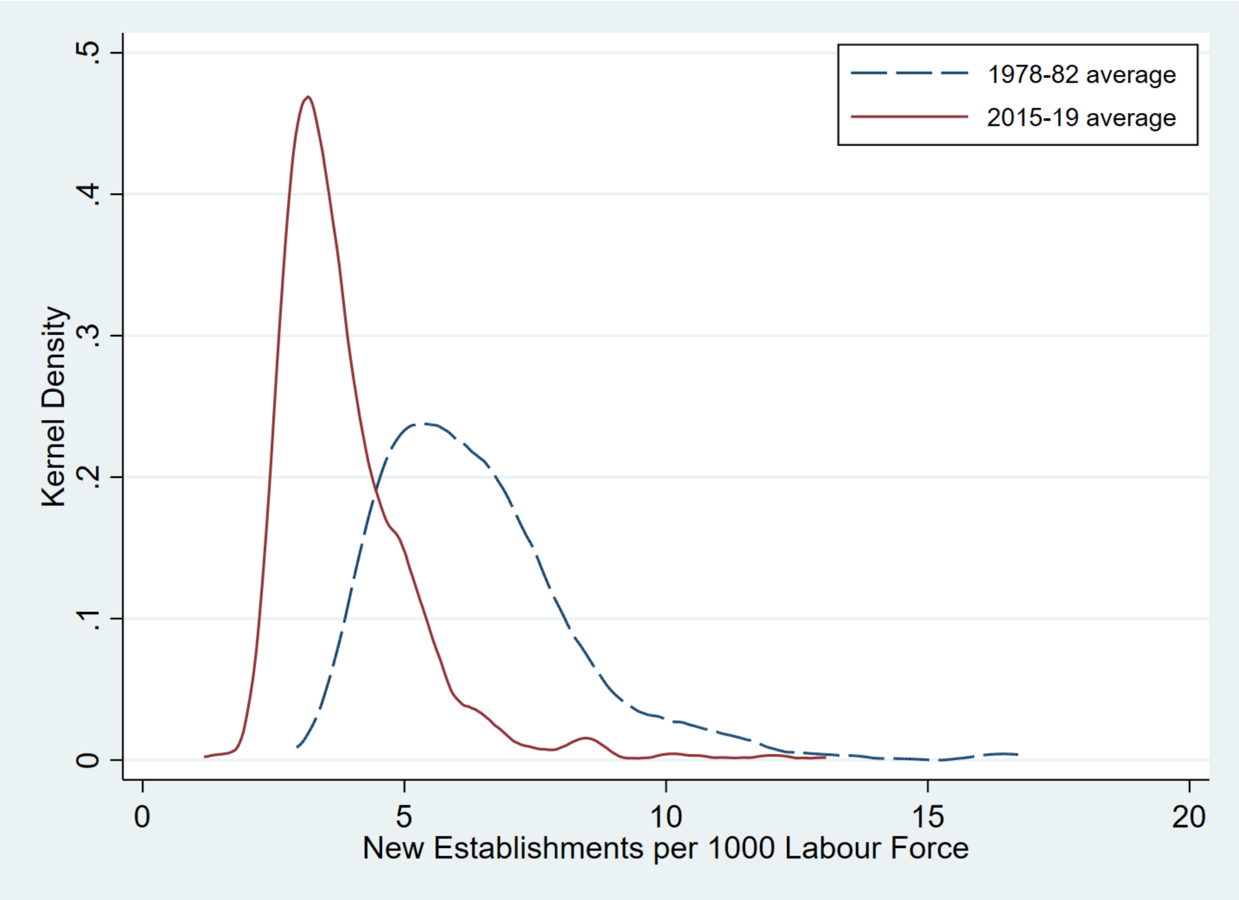
Description of regional start-up stability in the United States

The density distributions of CZ start-up rates in 1978-82 and 2015-19 are shown in Figure 2.4. In the 1978-82 period, median rates were lower and showed lower variance than in the later period. Amongst CZs, between 1978-82 and 2015-19, US start-up activity shows greater temporal persistence (Spearman rank coefficient: 0.729) than was the case for self-employment.

Distinguishing regions according to population density in 1980, the average start-up rate in the 2015-19 period is highest in the one third of regions with the lowest population density (4.72).[17] The average start-up rates in the high-density (3.49) and the medium-density regions (3.47) are in broadly the same range.

[17] This finding calls into question the view that start-up rates tend to be lower in rural areas than urban areas [see for example OECD (2022)]. A key consideration for such a comparison is whether an ecological measure or a labour market measure of the start-up rate is used. An ecological measure [as used in OECD (2022)] measures business start-ups as a share of all businesses, whereas a labour market measure (more commonly used in this field) measures business start-ups as a share of the workforce [for details see Audretsch and Fritsch (1994)]. There are likely to be significant differences between the findings of the two approaches. The labour market measure could be considered generally preferable because it shows the number of entrepreneurs as a share of potential entrepreneurs (i.e. members of the workforce).

Figure 2.4: Kernel density estimates of start-up rates 1978-82 and 2015-19, US commuting zones



Source: OECD analysis of Business Dynamics Statistics (BDS), US Decennial Census and American Community Survey from the US Census Bureau.

Ranking and ranking changes

Leapfroggers

The pattern of large city gains observed above in the self-employment rankings also applies to changes in the start-up rankings between 1978-82 and 2015-19. Measured by ranking changes in the start-up national league table, large cities such as St. Louis, Chicago, Newark (in New Jersey, next to New York), New York, Boston, Detroit, Charlotte, Arlington (in Virginia, next to Washington DC), and Baltimore are among the top 25 leapfrogging CZs.

The link with population density is confirmed, with the top one-third of CZs in terms of the 1980 population density, on average, gaining 43 places in the national start-up league table. This is consistent with the theory that urbanisation is a source of agglomeration economies, so facilitating start-up leapfrogging.

Plungers

The top 25 plunging CZs are typically small cities having a workforce with relatively low qualifications.

Persistent strong performers

An examination of the top and bottom 25 CZs by start-up rates in 1978-82 and 2015-19 shows that 12 appear in the top 25 CZs in both periods, and are classified as persistent, including four from Colorado, two each from Massachusetts and Oregon, and one from each of another four states (Wyoming, Washington, North Dakota, and Idaho). All are small CZs with less than 35 000 population in 1990 except for Bend city in Oregon (102 745 population) and Glenwood Springs city in Colorado (83 451 population). All these regions generally have high natural amenities.

Persistent weak performers

In contrast, Rosebud, an Indian reservation in South Dakota, had the lowest start-up rate in both time periods. Five other small or medium-sized, manufacturing-based CZs are also consistently ranked among the bottom 25.

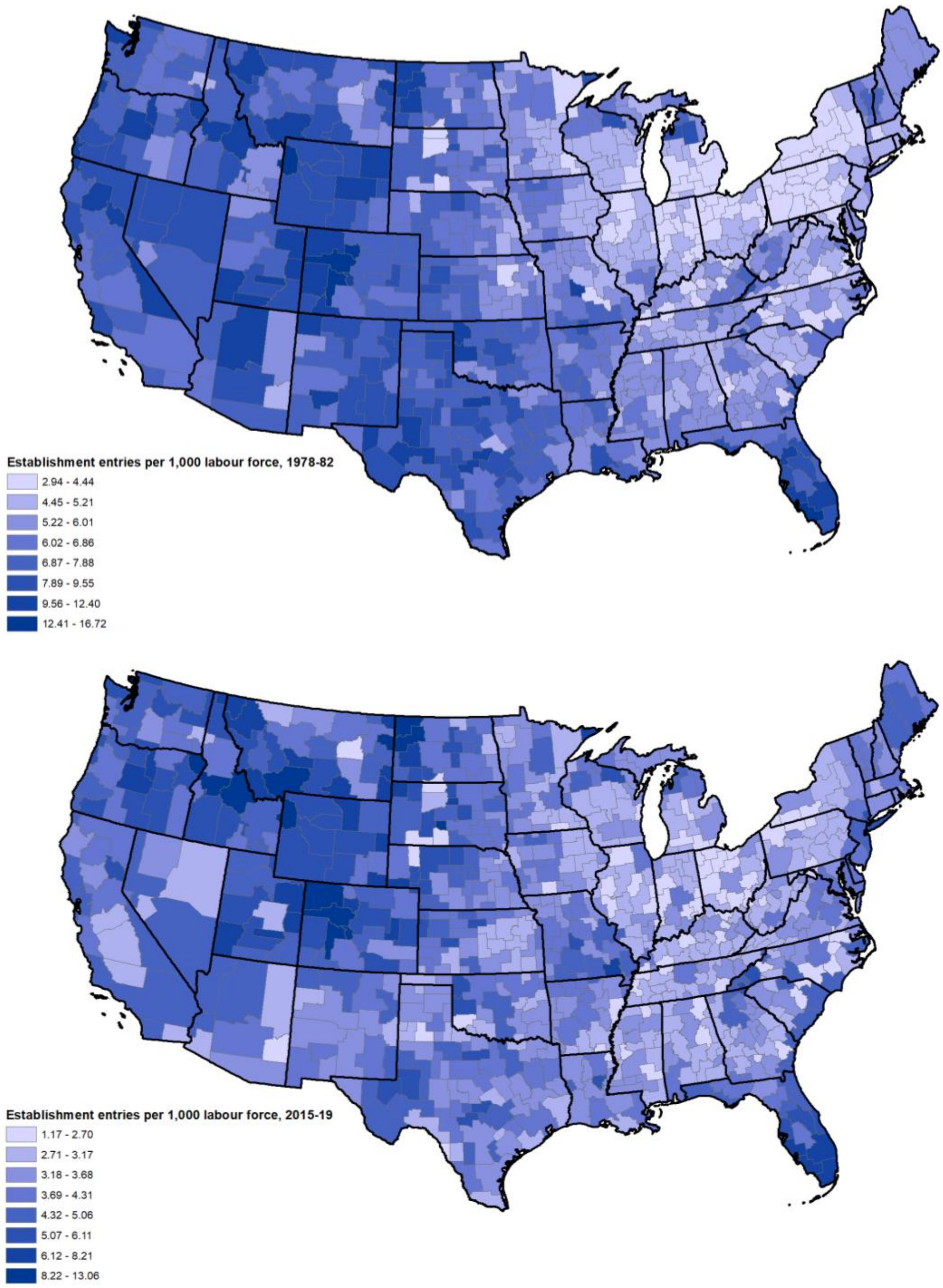
Spatial patterns of changes in start-up rates

Figure 2.5 shows start-up rates in US CZs in 1978-82 and 2015-19. Figure 2.6 shows the changes in rankings of CZs during this period.

Spatially, the leapfrogging CZs are disproportionately found in the Atlantic coastal states and the Midwestern states.

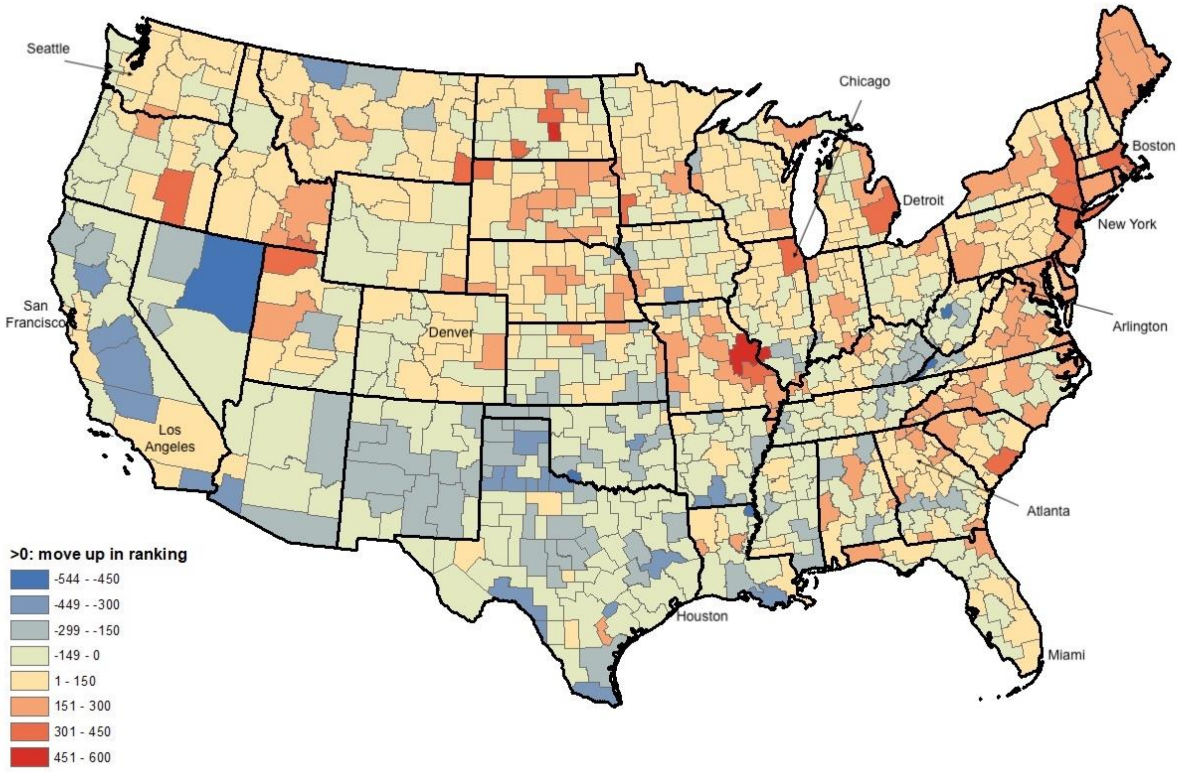
The plunging CZs, by the same measure, are disproportionately found in the Southern states and Texas in particular. See Figures 2.5 and 2.6 for these patterns.

Figure 2.5: Start-up rates in US commuting zones, 1978-82 and 2015-19



Source: OECD analysis of Business Dynamics Statistics (BDS), US Decennial Census and American Community Survey from the US Census Bureau.

Figure 2.6: Start-up rate rank changes between 1978-82 and 2015-19, US commuting zones



Source: OECD analysis of Business Dynamics Statistics (BDS), US Decennial Census and American Community Survey from the US Census Bureau.

Factors predicting regional dynamics – regression analysis

As with the self-employment analysis, regression is again undertaken to more formally explain the start-up leapfrogging/plunging patterns in the United States over the period 1978-82 to 2015-19. The dependent variable in this regression is start-up RMI. The independent variables and their measures are set out in Table 2.3. These closely follow those of Fritsch and Kublina (2019) to enable a valid comparison to be made with the findings for West Germany. For instance, Fritsch and Kublina used the manufacturing share as an explanatory variable, instead of the service share used for self-employment analysis earlier.

Table 2.2: Independent variables for the commuting zones start-up model

Independent variable	Variable description
1980 human capital	Share of BA degree among population aged 25+, 1980
1980 establishment size	Average establishment size (employees per establishment), 1980
1980 industry diversity	Employment industry diversity, 1980*
1980 average wage	Average wage per employee, 1980
1980 manufacturing share	Share of manufacturing employment, 1980
1980 population density	Population density, 1980

Notes: Data sources: 1980 County Business Patterns for 1980 establishment size and average wage; 1980 census for all other variables.
* Industry diversity is measured by (1-HHI), where HHI is the Herfindahl-Hirschman Index. To calculate HHI, the total local employment is divided into five sectors in this study: agriculture, construction, manufacturing, service, and public administration.

Table 2.4 shows the regression results. Human capital, the manufacturing share, and population density in 1980 are positively and significantly associated with start-up RMI; the average wage in 1980 exhibits a negative and significant relationship. These relationships vary at different quantiles in the quantile regression results. Human capital particularly benefits those CZs at the lower quantiles of upward mobility, so does the manufacturing share. By contrast, the negative relationship between initial average wage and start-up upward mobility, which is consistent with the entrepreneurial career choice model (Acs and Armington, 2006), is significant at the 0.05 level only at the 70th quantile.

Table 2.3: Regression results for the commuting zones start-up model

	Dependent variable: start-up rank mobility index (1978-2019)					
	OLS	Unconditional quantile regressions				
Independent variable		Q 10	Q 30	Q 50	Q 70	Q 90
1980 human capital	0.814***	2.167***	1.270***	0.646**	0.263	0.271
1980 establishment size	0.005	-0.007	-0.003	0.005	0.014***	0.008
1980 industry diversity	-0.027	-0.273	-0.072	0.160	0.015	0.222
1980 average wage	-0.000**	0.000	-0.000*	-0.000*	-0.000***	-0.000*
1980 manufacturing share	0.265**	1.161***	0.529***	0.175	-0.117	-0.049
1980 population density	0.000***	0.000	0.000	0.000	0.000	0.001
Constant	-0.078	-0.446	-0.163	-0.171	0.083	0.137
R2 adjusted	0.116	0.044	0.061	0.049	0.058	0.087
Number of observations	722	722	722	722	722	722

Notes: *** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at the 10% level

Metropolitan areas analysis

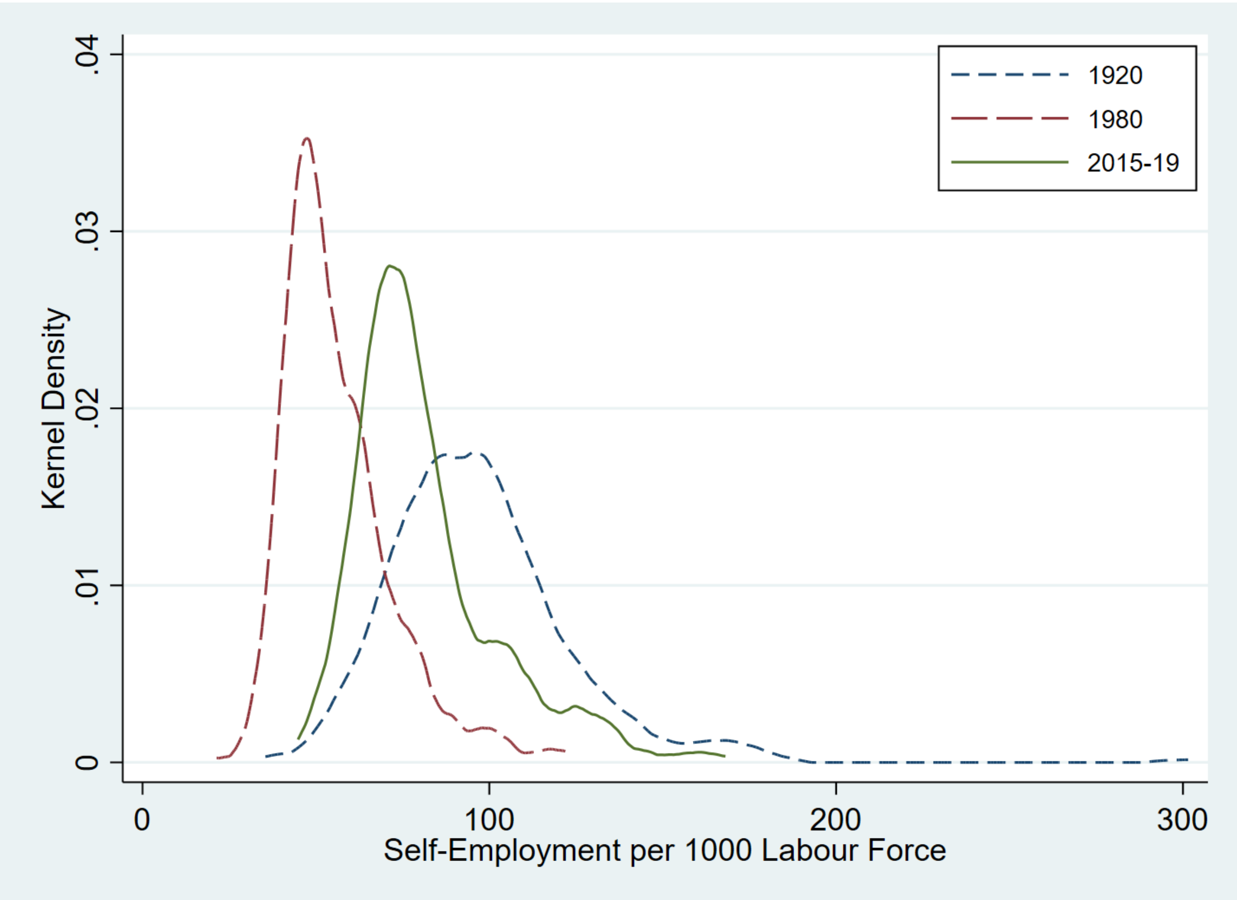
The same descriptive and regression methods are used for the medium-term MSA-level analysis as with the earlier CZ-level analysis. The only difference is that the selection of independent variables follows the broad literature on regional studies of entrepreneurship in the US context, which goes beyond Fotopoulos and Storey (2017) and Fritsch and Kublina (2019) by, for instance, integrating race, social capital, and natural amenities factors. In addition, the persistence of metropolitan start-up activity is investigated by sector. As with the analysis of CZs, our findings for MSAs begin with self-employment data and then turn to start-up data.

Self-employment

Description of regional self-employment stability in the United States

In line with the CZ pattern, there was a decrease of the self-employment rates among MSAs between 1920 and 1980 followed by a rebound between 1980 and 2015-19 (Figure 2.7). Again, there is a quite remarkable persistence of the levels of self-employment between the time periods. The Spearman rank correlation coefficient for self-employment rates in 1920 and 1980 is 0.440 and it is 0.673 between 1980 and 2015-19. Comparing self-employment rates over the longest available period 1920 to 2015-19 results in a Spearman correlation coefficient of 0.386. The correlation coefficients capturing persistence are higher among MSAs than CZs, suggesting the selection of geographic units matters.

Figure 2.7: Kernel density estimates of self-employment rates, 1920, 1980, 2015-19, US metropolitan areas



Source: OECD analysis of Decennial Census and American Community Survey from the US Census Bureau.

Ranking and ranking changes

Leapfroggers

The top 20 leapfrogging MSAs by self-employment rank changes between 1980 and 2015-19 include large metropolitan areas such as New Orleans, Chicago, Las Vegas, Washington DC, Charlotte, New York, Atlanta, Baltimore, and Detroit. As with the CZ analysis, this again demonstrates the advantage of large cities in entrepreneurship upward mobility. The denser MSAs moved up in the national league table, while less dense ones moved down. Noticeably, a good number of old industrial cities from the Midwest region, such as Youngstown, Detroit, and Akron, are among the top leapfrogging MSAs.

Plungers

The top 25 plummeting regions are small or medium-sized MSAs typically with low skill levels and population growth.

Persistent strong performers

Evidence of the higher persistence of regional self-employment rates in MSAs compared with CZs is reflected in the finding that there were four MSAs[18] in the top 25 group in each of 1920, 1980 and 2015-19 as compared to only two CZs. There were 17 MSAs among the top 25 performing regions in both 1980 and the 2015-19 period, exceeding the 11 found in CZs.

The MSAs that were among the top 25 performing regions on multiple instances are primarily medium-sized cities in three states: California, Florida, and Oregon. It is worth noting that the small CZs consistently identified as top self-employment performers earlier are mostly outside metropolitan areas, thus having limited overlap with the MSA results.

Persistent weak performers

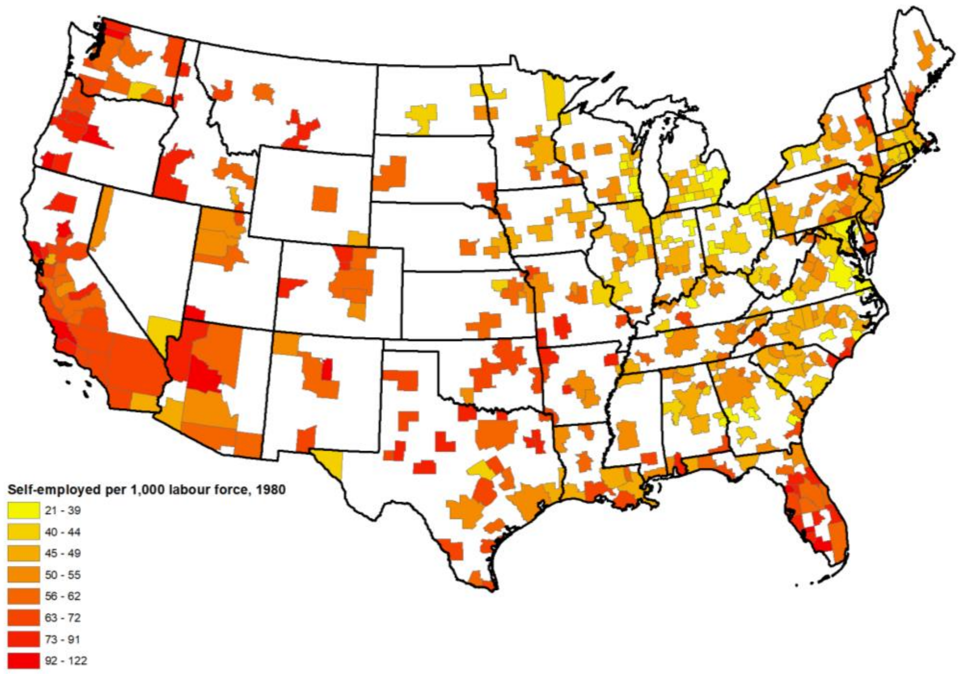
Three MSAs – namely Hinesville (GA), Jacksonville (NC) and Elizabethtown-Fort Knox (KY) – were consistently among the bottom 25 group in all three periods and another three were in this group in 1980 and 2015-19 only. All the MSAs consistently at the bottom are small or medium-sized, manufacturing-based cities.

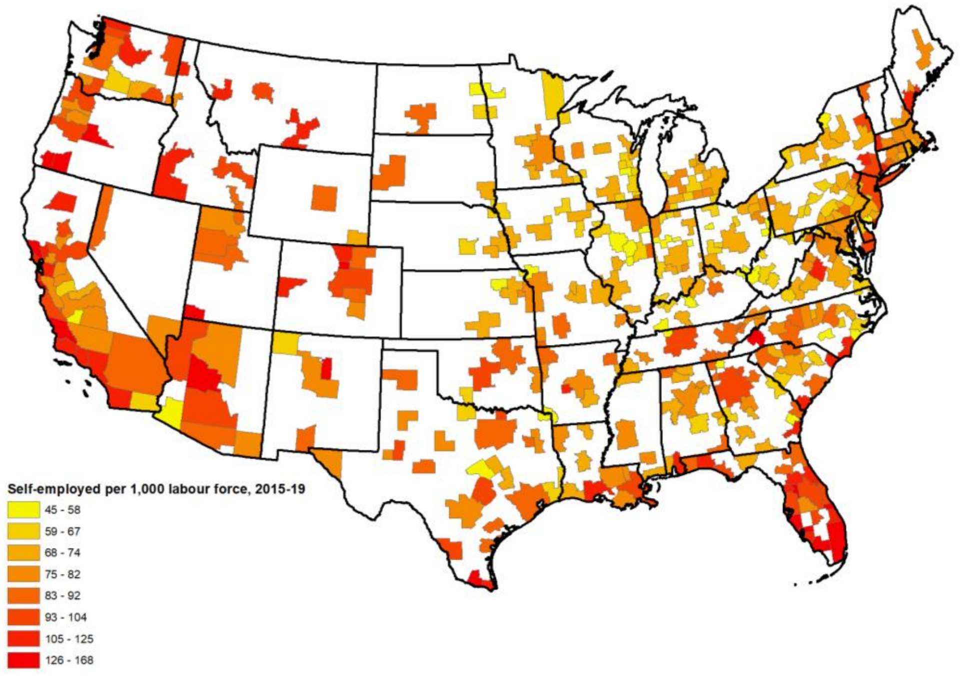
Spatial patterns of changes in self-employment rates

The spatial patterns of self-employment rank changes described in the CZ analysis also apply to the MSA analysis here (see Figures 2.8 and 2.9).

[18] These four MSAs are Naples-Marco Island (FL), Barnstable Town (MA), Santa Cruz-Watsonville (CA) and Medford (OR).

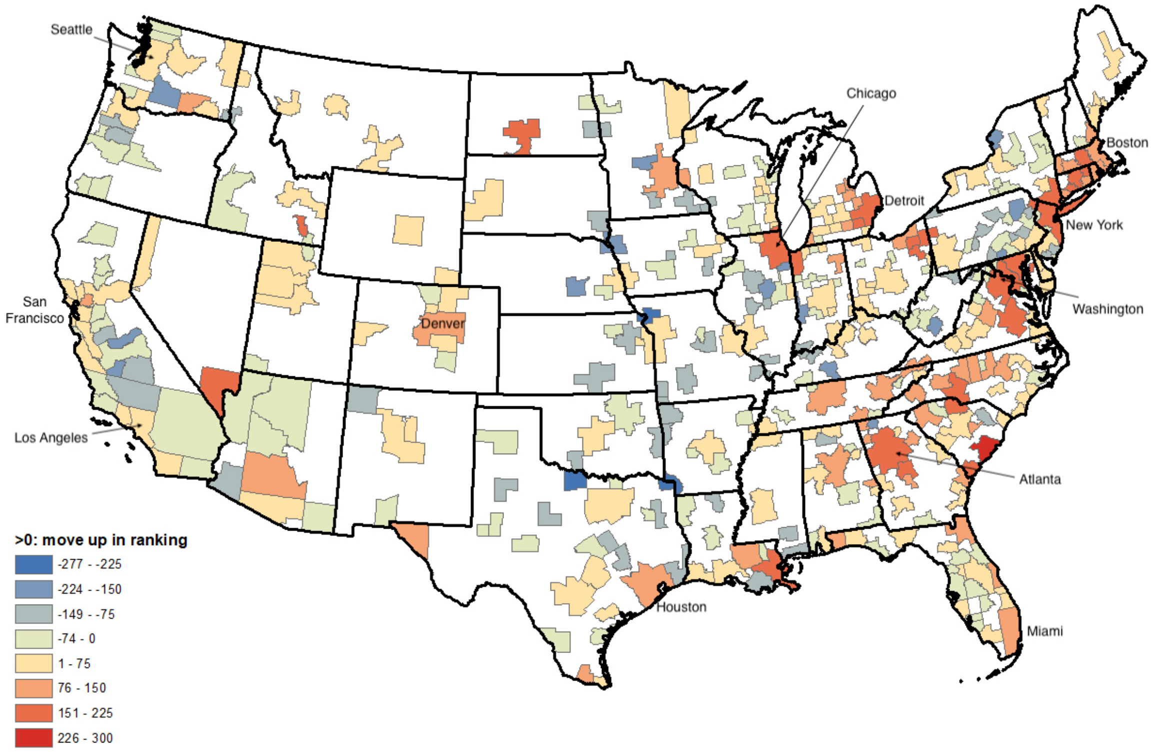
Figure 2.8: Self-employment rates in US metropolitan areas, 1980 and 2015-19





Source: OECD analysis of US Decennial Census and American Community Survey from the US Census Bureau.

Figure 2.9: Self-employment rank changes between 1980 and 2015-19, US metropolitan areas



Source: OECD analysis of US Decennial Census and American Community Survey from the US Census Bureau.

Factors predicting regional dynamics – regression analysis

In the regression analysis on metropolitan dynamics of self-employment, the following independent variables are added to those in the CZ model; social capital, natural amenities, and the share of Black population. They are defined in Table 2.5.

Table 2.4: Independent variables for the metropolitan areas self-employment model

Independent variable	Variable description
1980 self-employment	Self-employment rate, 1980
1990 social capital	County-population weighted social capital index by Rupasingha et al. (2006), 1990 *
Natural amenities	County-average of natural amenities scale by McGranahan (1999) **
1980 population	Log of population size, 1980
1980 human capital	Share of BA degree among population 25+, 1980
1980 foreign born	Share of immigration population, 1980
1980 Black population	Share of African American population, 1980
1980 55-64 years old	Share of population group 55-64, 1980
1980 establishment size	Average establishment size (employees per establishment), 1980
1980 home ownership	Share of homeowners among occupied homes, 1980
1980 service share	Share of service employment, 1980

Data sources: 1980 County Business Pattern for establishment size; Rupasingha et al. (2006) for 1990 social capital; McGranahan (1999) for natural amenities; 1980 Census for all other variables.
Notes: * The social capital index of US counties was created by Rupasingha et al. (2006) using principal component analysis (PCA) on four variables: the 1990 number of membership associations per 10 000 people, the 1990 number of non-profit organisations per 10 000 people, the Census mail response rate for 1990, and the 1988 presidential election voting rate. The first principal component, accounting for 46% of the total variation, was used as the social capital index by Rupasingha et al. (2006). In this study, the county-level index is converted to the MSA level using the population-weighted county average. ** McGranahan (1999) built the county-level natural amenity index based on six factors: average January temperature, average January days of sun, low winter-summer temperature gap, low average July humidity, topography scale, and the proportion of the water area in the county. They are combined based on standardised scores (i.e., z-scores). In this study, this county-level index is converted to the metropolitan level using the county average.

Table 2.6 shows the regression results. As with the CZ results, the 1980 self-employment level is a negative and significant predictor of self-employment RMI in MSAs overall and across different quantiles. Among other variables, cities with higher natural amenities, larger population, greater human capital, higher shares of Black population, higher shares of 55-64 years old, larger establishment size and greater home ownership in 1980 rose up the national self-employment league table in the following four decades, although the impact does vary between the quantiles. 1990 social capital, 1980 foreign born, and the 1980 service industry share are not significantly associated with rank changes.

Table 2.5: Regression results for the metropolitan areas self-employment model

	Dependent variable: self-employment rank mobility index (1980 to 2015-2019)					
	OLS	Unconditional quantile regressions				
Independent variable		**Q 10**	**Q 30**	**Q 50**	**Q 70**	**Q 90**
1980 self-employment	-0.006***	-0.006***	-0.005**	-0.007***	-0.005***	-0.006**
1990 social capital	-0.020	-0.018	-0.034	-0.019	-0.035	-0.019
Natural amenities	0.023***	0.040***	0.036***	0.022***	0.003	0.005
1980 population	0.032***	-0.004	0.045**	0.056***	0.055***	0.019
1980 human capital	1.608***	2.365***	1.869***	1.624***	1.272***	1.347
1980 foreign born	0.435	0.911	-0.085	0.149	0.679	1.477
1980 Black population	0.536***	0.817**	0.388	0.408**	0.321	0.927***
1980 55-64 years old	1.563**	1.848	0.837	0.108	1.131	2.337
1980 establishment size	0.013**	0.014	0.015**	0.000	0.011	0.025*
1980 home ownership	1.041***	1.725***	1.546***	1.127***	0.818*	1.056
1980 service share	0.243	0.327	0.318	-0.182	0.048	0.567
Constant	-1.616***	-2.178***	-2.311***	-1.290***	-1.405***	-1.589***
R2 adjusted	0.328	0.113	0.171	0.251	0.229	0.154
Number of observations	377	377	377	377	377	377

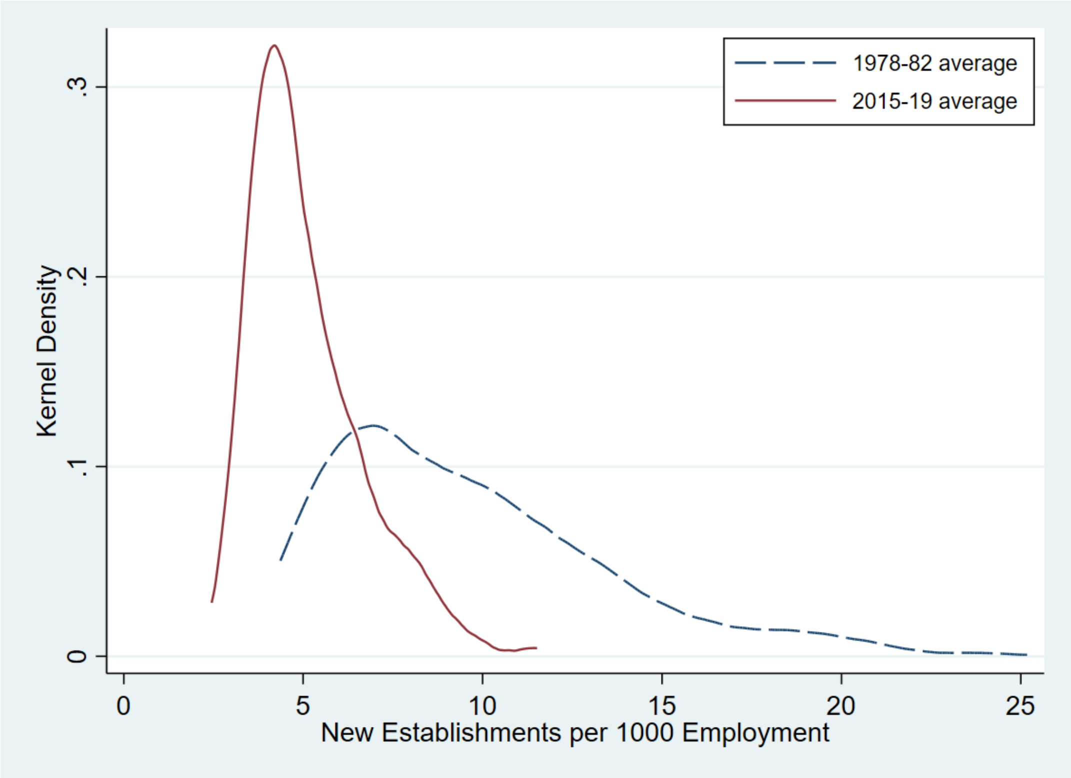
Notes: *** statistically significant at the 1% level; ** statistically significant at the 5% level; * statistically significant at the 10% level

Start-ups

Description of regional start-up stability in the United States

Between 1978-82 and 2015-19, metropolitan start-up activity has significantly declined on average. Less well documented is that the variance in start-up rates also declined across MSAs (see Figure 2.10). As with self-employment, the regional persistence of start-up activity during this period is greater among MSAs (Spearman rank coefficient: 0.817) than among CZs.

Figure 2.10: Kernel density estimates of start-up rates 1978-82 and 2015-19, US metropolitan areas



Source: OECD analysis of Business Dynamics Statistics (BDS) from the US Census Bureau.

Ranking and ranking changes

Leapfroggers

Charlotte, St. Louis, Chicago, New York, and Los Angeles are notable large cities among the top 10 leapfrogging MSAs in these four decades. This once again points to possible agglomeration economies effects, supported by the finding that the top one-third MSAs in terms of their 1980 population density, on average, gained 31 places in the national start-up league table. As an example, the most prominent leapfrogging MSA on the start-up metric is the manufacturing-based Midland in Michigan where Dow Chemical is headquartered. It moved up 245 places from 1978-82 to 2015-19.

Plungers

The top 25 plunging MSAs are mostly small or medium-sized metropolitan areas, but with diverse characteristics. They are a mixture of less-skilled cities, but also highly-skilled college towns such as Tuscaloosa (home to University of Alabama), Iowa City (home to University of Iowa) and Morgantown (home to West Virginia University).[19]

Persistent strong performers

An examination of start-up rates in 1978-82 and 2015-19 finds that 13 (mostly medium-sized) metropolitan areas appear in the top 25 in both groups of years. Once again, these locations have almost no overlap with those consistently included in the two CZ groups. Instead, they tend to have high natural amenities, are dispersed across the country, but with notably no representation from the Midwest.

[19] Motoyama and Mayer (2017) showed that U.S. research universities do not necessarily enhance regional entrepreneurship.

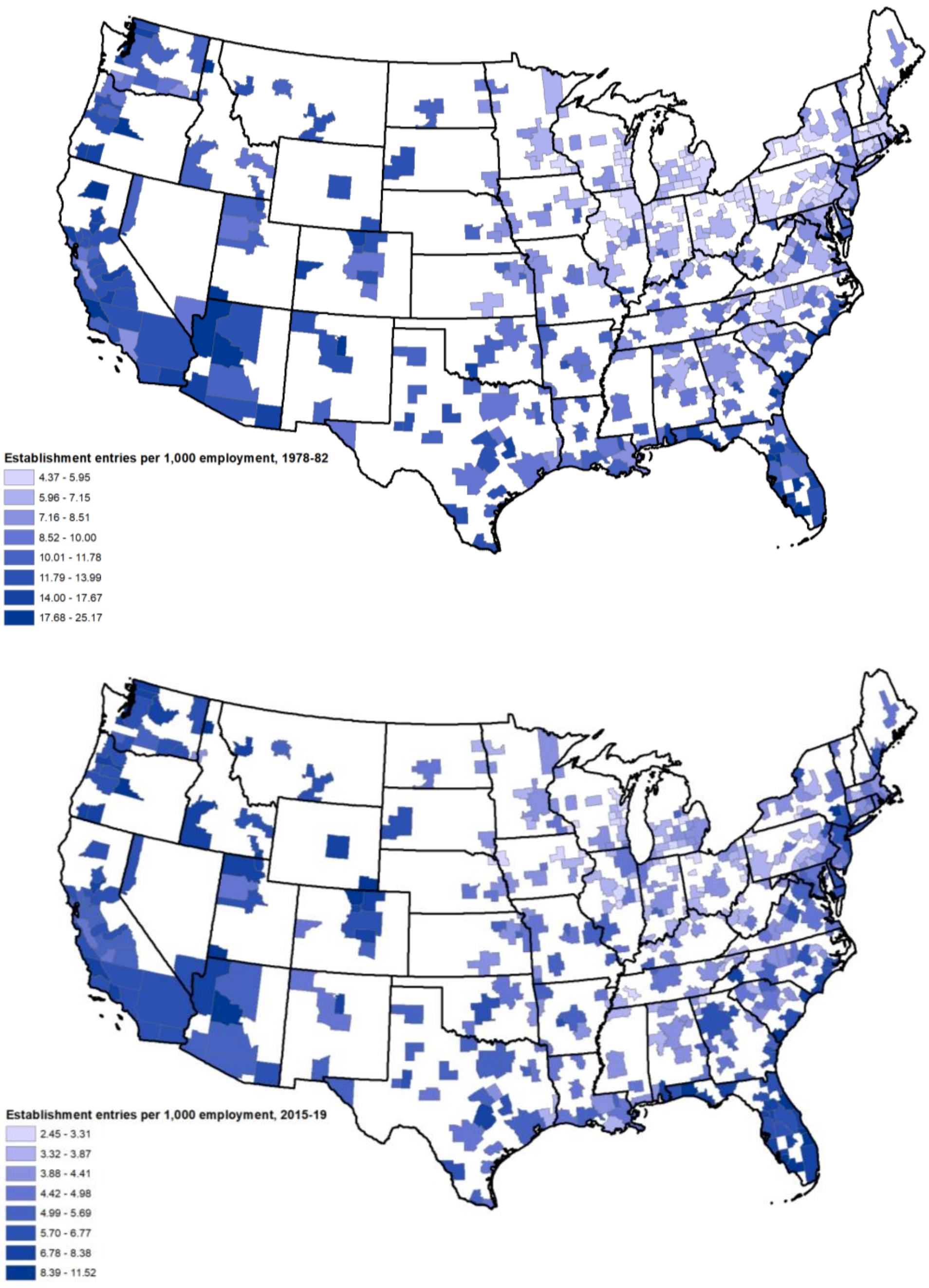
Persistent weak performers

Seven small or medium-sized, manufacturing-based MSAs from the Midwest are in the bottom 25 MSAs in both 1978-82 and 2015-19.

Spatial patterns of changes in start-up rates

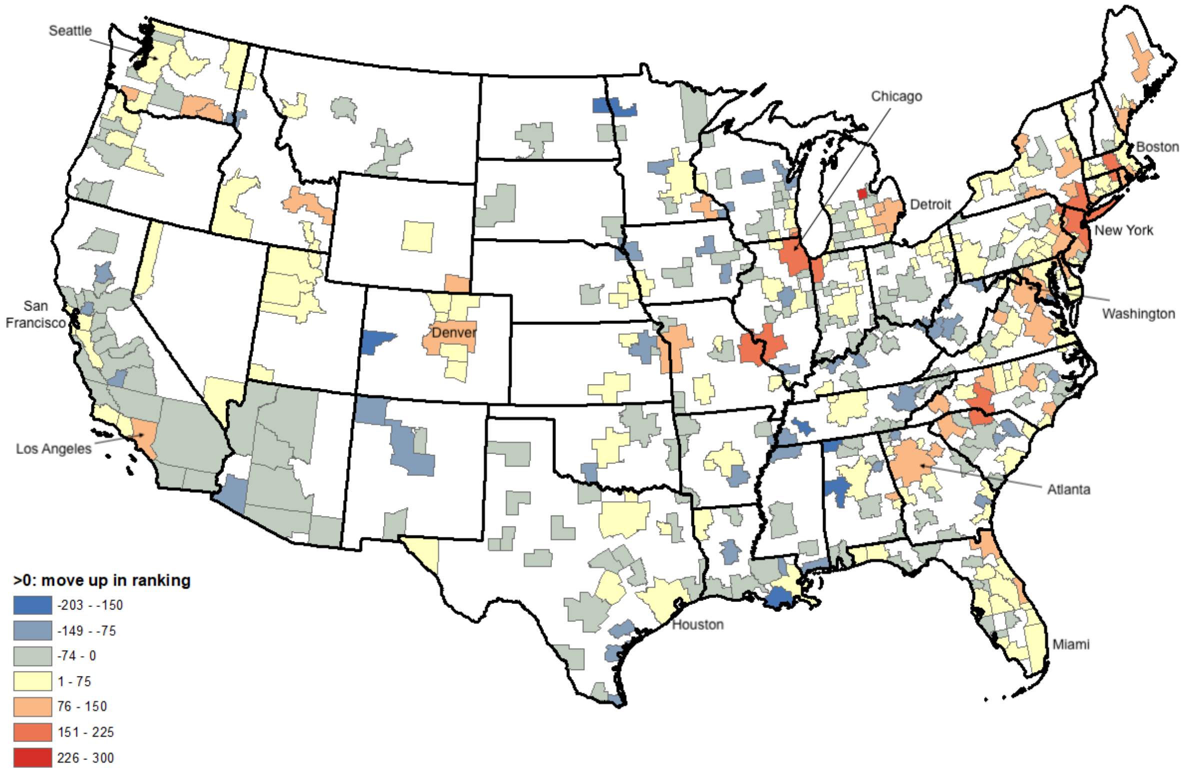
Figures 2.11 and 2.12 shows the spatial patterns of start-up rank changes among MSAs. They are similar to the spatial patterns discussed in the CZ analysis.

Figure 2.11: Start-up rates in US metropolitan areas, 1978-82 and 2015-19



Source: OECD analysis of Business Dynamics Statistics (BDS) from the US Census Bureau.

Figure 2.12: Start-up rate rank changes between 1978-82 and 2015-19, US metropolitan areas



Source: OECD analysis of Business Dynamics Statistics (BDS) from the US Census Bureau.

Factors predicting regional dynamics – regression analysis

Table 2.7 shows the independent variables used to explain the RMI of MSAs on start-up rates. The regression models again build on Fritsch and Kublina (2019) and then include additional demographic variables, as well as social capital and natural amenities.

Table 2.6: Independent variables for the metropolitan areas start-up model

Independent variable	Variable description
1980 social capital	County-population-weighted social capital index by Rupasingha et al. (2006), 1990
Natural amenities	County-average of natural amenities scale by McGranahan (1999)
1980 population density	Population density, 1980
1980 human capital	Share of BA degree among population 25+, 1980
1980 foreign born	Share of immigration population, 1980
1980 Black population	Share of African American population, 1980
1980 55-64 years old	Share of population group 55-64, 1980
1980 establishment size	Average establishment size (employees per establishment), 1980
1980 industry diversity	Employment industry diversity, 1980 ***
1980 average wage	Average wage per employee, 1980
1980 manufacturing share	Share of manufacturing employment, 1980

Data sources: 1980 County Business Patterns for 1980 establishment size and 1980 average wage; Rupasingha et al. (2006) for 1990 social capital; McGranahan (1999) for natural amenities; 1980 Census for all other variables.
Notes: *The social capital index of US counties was created by Rupasingha et al. (2006) using principal component analysis (PCA) on four variables: the 1990 number of membership associations per 10 000 people, the 1990 number of non-profit organisations per 10 000 people, the census mail response rate for 1990, and the 1988 presidential election voting rate. The first principal component, accounting for 46% of the total variation, was used as the social capital index by Rupasingha et al. (2006). In this study, the county-level index is converted to the MSA level using the population-weighted county average. ** McGranahan (1999) built the county-level natural amenity index based on six factors: average January temperature, average January days of sun, low winter-summer temperature gap, low average July humidity, topography scale, and the proportion of the water area in the county. They are combined based on standardised scores (i.e., z-scores). In this study, this county-level index is converted to the metropolitan level using the county average. *** Industry diversity is measured by (1-HHI), where HHI is the Herfindahl-Hirschman Index. To calculate HHI, the total local employment is divided into five sectors in this study: agriculture, construction, manufacturing, service, and public administration.

Table 2.8 presents the regression results. It shows that MSAs with denser populations, more human capital, higher shares of those aged between 55 and 64 years old, and a larger average establishment size in 1980, were significantly more likely to rise up the national league table in the following four decades. Natural amenities, which were a positive and significant predictor of MSA self-employment RMI, are not a significant predictor of MSA start-up RMI.

Table 2.7: Regression results for the metropolitan areas start-up model

	Dependent variable: start-up rank mobility index (1978-82 to 2015-2019)					
	OLS	Unconditional quantile regressions				
Independent variable		**Q 10**	**Q 30**	**Q 50**	**Q 70**	**Q 90**
1990 social capital	-0.024*	0.011	-0.005	-0.033**	-0.044***	-0.050*
Natural amenities	0.005	0.017**	0.008	0.009*	0.007	-0.008
1980 population density	0.000**	-0.000	-0.000	0.000**	0.000***	0.000*
1980 human capital	1.233***	1.271***	1.115***	1.276***	1.323***	1.513**
1980 foreign born	0.123	0.144	0.314	-0.533	-0.436	-0.000
1980 Black population	-0.028	-0.027	0.009	-0.062	-0.008	-0.036
1980 55-64 years old	2.454***	4.027***	2.834***	1.897***	2.092**	1.761*
1980 establishment size	0.011**	0.018**	0.002	0.008	0.024***	0.008
1980 industry diversity	0.037	-0.076	-0.246	-0.319	0.284	0.535
1980 average wage	0.000	-0.000	0.000	0.000	0.000	0.000
1980 manufacturing share	0.308*	0.374	0.506***	0.453**	0.007	0.131
Constant	-0.827***	-0.975***	-0.676***	-0.538***	-0.931***	-0.932**
R2 adjusted	0.278	0.101	0.149	0.181	0.207	0.104
Number of observations	377	377	377	377	377	377

Notes: *** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at the 10% level

The role of sector in regional start-up activity

Distinct from other parts of analysis in this section, this MSA start-up analysis has standardised start-ups by employment (instead of labour force). Unlike labour force, employment has a sectoral dimension. The Business Dynamics Statistics (BDS) dataset includes sectoral details for both start-ups and employment. To gain more insights into the persistence of regional start-up activity, sectoral patterns of regional start-up rates over time are now analysed at the metropolitan level. The 1978-82 and 2015-19 start-up rates are calculated separately for each sector, defined by the two-digit codes under the North American Industry Classification System (NAICS). This is motivated by the finding in Cosci et al. (2022) that there are sectoral variations in the persistence of regional start-up rates in the Italian case.

The correlation coefficients of sectoral start-up rates between the two time periods are shown in Table 2.9. Sectoral variations can be clearly observed. The manufacturing sector demonstrates the strongest temporal persistence in start-up activity at the metropolitan level (Spearman rank coefficient: 0.747). It is followed by the non-public administration service sector and the wholesale sector. At the other end of the scale, the management of companies and enterprises sector and the information sector show barely any temporal persistence.

Table 2.8: Spearman rank correlations of sectoral start-up rates between 1978-82 and 2015-19, metropolitan areas

NAICS code	Sector name	Spearman rank correlation	Number of observations
31-33	Manufacturing	0.747	376
81	Other Services (except Public Administration)	0.689	377
42	Wholesale Trade	0.677	377
23	Construction	0.673	377
52	Finance and Insurance	0.647	377
44-45	Retail Trade	0.628	377
54	Professional, Scientific, and Technical Services	0.601	377
62	Health Care and Social Assistance	0.544	377
53	Real Estate and Rental and Leasing	0.482	377
48-49	Transportation and Warehousing	0.463	376
56	Administrative and Support and Waste Management and Remediation Services	0.443	377
61	Educational Services	0.441	350
71	Arts, Entertainment, and Recreation	0.436	372
72	Accommodation and Food Services	0.401	377
55	Management of Companies and Enterprises	0.251	354
51	Information	0.233	371

Notes: The sectoral start-up rate is measured by the number of new business establishments per 1,000 employees in a sector. For some sectors, some MSA observations are missing due to data suppression in BDS. Four sectors are not considered: 11 – Agriculture, Forestry, Fishing and Hunting; 21 – Mining, Quarrying, and Oil and Gas Extraction; 22 – Utilities; 92 – Public Administration.

Regression analysis based on the OLS model in Table 2.10 is also conducted at the sectoral level. It shows the existence of sectoral variations in persistence of regional start-up rates in the United States. The dependent variable is start-up RMI for each of the 16 sectors considered. The independent variables are the same as those used in Table 2.7, except that the manufacturing share is replaced by the initial-year employment location quotient (LQ) of each sector using BDS data. This new variable examines whether initial specialisation in a sector is a significant predictor of start-up rank upward mobility in that sector in the following decades. The results are shown in Table 2.10.

The initial clustering of sectoral employment is a positive and significant predictor of start-up upward mobility in nearly all sectors. The results for other explanatory variables mostly vary by sector. For instance, initial human capital positively predicts start-up rank changes in sectors such as manufacturing, transportation, finance, administrative support, and accommodation services, while it negatively predicts a start-up rank change in the information sector.

Table 2.9: Regression results for the metropolitan areas start-up models by sector

Independent variable	Sector 23	Sector 31-33	Sector 42	Sector 44-45	Sector 48-49	Sector 51	Sector 52	Sector 53
1990 social capital	0.016	-0.008	0.021	-0.023	-0.011	-0.019	-0.029	0.034*
Natural amenities	-0.009	-0.005	-0.019***	0.000	-0.003	0.002	-0.007	0.016**
1980 population density	0.000***	0.000	0.000	0.000***	0.000	-0.000	-0.000	-0.000
1980 human capital	-0.137	0.915***	-0.217	0.380	0.765**	-2.203***	1.021***	0.185
1980 foreign born	0.901**	0.112	0.641	-0.240	1.455***	-1.020	0.941*	-0.689
1980 Black population	0.032	0.086	0.172	0.301*	0.279	0.103	0.160	0.249
1980 55-64 years old	1.690**	2.935***	1.470*	2.034**	2.483***	0.336	2.545***	0.135
1980 establishment size	0.024***	0.011**	-0.006	0.029***	-0.005	0.004	0.013**	0.040***
1980 industry diversity	-0.170	0.381	-0.077	-0.001	-0.019	0.550	0.682**	0.355
1980 average wage	-0.000***	0.000	-0.000***	0.000**	0.000*	0.000*	0.000	-0.000***
1978-82 sector LQ	0.164***	0.001	0.147***	0.192*	0.225***	0.216***	0.117**	0.370***
Constant	-0.374	-0.837***	0.228	-1.228***	-0.793***	-0.519	-1.134***	-0.803***
R2 adjusted	0.155	0.080	0.112	0.272	0.206	0.169	0.087	0.253
Number of observations	377	376	377	377	376	371	377	377
Independent variable	**Sector 54**	**Sector 55**	**Sector 56**	**Sector 61**	**Sector 62**	**Sector 71**	**Sector 72**	**Sector 81**
1990 social capital	-0.005	0.053*	0.056***	-0.004	0.043*	-0.044	0.035	0.013
Natural amenities	0.000	0.013	-0.014*	-0.005	0.014**	-0.008	-0.007	0.000
1980 population density	-0.000	0.000	0.000	0.000	0.000**	0.000	0.000	0.000**
1980 human capital	0.142	0.008	1.019**	0.318	-0.180	-0.113	2.036***	-0.024
1980 foreign born	0.034	0.412	0.200	-1.341*	-0.481	-0.431	2.087***	1.297***
1980 Black population	-0.234	0.303	0.207	-0.298	-0.007	-0.280	0.369*	0.025
1980 55-64 years old	2.391***	-0.375	2.009	-1.871	-0.528	0.019	3.208***	2.258***
1980 establishment size	0.012**	0.003	-0.001	-0.006	0.020***	0.011*	0.006	0.017***
1980 industry diversity	-0.838***	-0.012	0.623*	0.027	-0.460	0.151	0.054	0.353
1980 average wage	-0.000	-0.000	0.000	-0.000	0.000	0.000*	0.000***	-0.000
1978-82 sector LQ	0.157**	0.178***	0.148***	-0.011	0.230***	0.069***	0.115**	0.228***
Constant	-0.059	-0.153	-0.842***	0.342	-0.338	-0.530	-1.452***	-0.932***
R2 adjusted	0.154	0.106	0.169	0.022	0.216	0.059	0.310	0.158
Number of observations	377	354	377	350	377	372	377	377

Notes: *** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at the 10% level.
Sector codes: 23: Construction; 31-33: Manufacturing; 42: Wholesale Trade; 44-45: Retail Trade; 48-49: Transportation and Warehousing; 51: Information; 52: Finance and Insurance; 53: Real Estate and Rental and Leasing; 54: Professional, Scientific, and Technical Services; 55: Management of Companies and Enterprises; 56: Administrative and Support and Waste Management and Remediation Services; 61: Educational Services; 62: Health Care and Social Assistance; 71: Arts, Entertainment, and Recreation; 72: Accommodation and Food Services; 81: Other Services (except Public Administration).

Conclusion

The prime focus of this section has been to examine the degree and patterns of persistence and change in regional entrepreneurship rankings in the United States.

A first key finding is that of persistence in the US regional entrepreneurship rankings over the long-run and medium-run on two separate measures of entrepreneurship – self-employment and business start-ups – and two separate types of geographic units – commuting zones and metropolitan statistical areas. Over the long run, the analysis shows striking persistence in US regional self-employment rate rankings over the 1920 to 2015-19 period, i.e. nearly a century. There is also a high persistence in regional start-up rate rankings over the longest period for which regional start-up data are available, i.e. 1978-82 to 2015-19. The persistence in regional entrepreneurship rankings is also strong over the shorter time periods investigated. The start-up rankings were more persistent than the self-employment rankings over the most comparable time periods (1978-82 to 2015-19 period and 1980 to 2015-19). Rankings for start-ups and self-employment were both more persistent at the MSA level than at the CZ level.

This overall persistence means that the geographical areas with the highest entrepreneurship rates (i.e. those at the top of the regional entrepreneurship league table) in the base year were also likely to be at the top of the table many years later. Equally, those at the bottom tended to stay at the bottom.

This strong spatial stability in regional entrepreneurship rankings has occurred despite clear changes in rates of entrepreneurship at national level over time. For example, the median US self-employment rate clearly decreased between 1920 and 1980. This is likely to reflect the corporatisation of the US economy, particularly during the post-World War II period. It then rebounded between 1980 and 2015-19. Furthermore, recent self-employment rates across CZs have both a lower spread and a lower median than in 1920. Yet, despite the significant changes in the overall distribution of self-employment over time at national level, the spatial league table changes are more modest. This could be reflected in a region experiencing an increase in self-employment over time, yet not having any change in its league table position because of the overall increase.

A second key result, particularly for policy makers, is that despite an overall pattern of persistence, there are groups of CZ and MSA regions that do experience considerable change in their league table positions. Those that rise sharply are referred to as leapfroggers and those that drop sharply are referred to as plungers. The section identified these leapfroggers and plungers and conducted regression analyses to highlight their characteristics.

Different regions appear in different groupings depending on the entrepreneurship metric used – self-employment or start-ups – and the type of geographic areas – CZs or MSAs. As examples, the top 10 leapfrogging MSAs derived from start-up data include Charlotte, St. Louis, Chicago, New York, and Los Angeles which, as large cities, might suggest a possible role was played by agglomeration economies. This contrasts with leapfroggers derived from self-employment in CZs. This is a much more diverse group of regions so, although it continues to include large cities such as New Orleans, Miami, Atlanta, and New York, the top three in the group are, in fact, the small towns of Jordan town and Scobey city in Montana and Soda Springs city in Idaho. These small towns are located outside of metropolitan areas.

The above illustrates the importance of clarity over the chosen measures of entrepreneurship. Regions that perform well using self-employment as a measure of entrepreneurship are frequently different from those performing well using start-ups as the chosen metric. This emphasises the need for further work to refine data sources and to make informed decisions to select the most appropriate data sources.

With this in mind, for US commuting zones, the regression analyses report statistically significant associations between self-employment rank mobility and initial year share of self-employment, population size, human capital, foreign-born population, 55-64 age group population, home ownership and service sector share in the initial year. For start-ups, the regressions report statistically significant associations between rank mobility and initial-year human capital, wage level, manufacturing share, and population density.

The US MSA-level regression analyses show that MSAs with lower self-employment, higher natural amenities, larger population, greater human capital, higher shares of Black population, higher shares of 55-64 year olds, larger establishment size and greater home ownership in 1980 rose up the national self-employment league table in the following four decades. MSAs with denser populations, more human capital, higher shares of those aged between 55 and 64 years old and a larger average establishment size in 1980 were significantly more likely to rise up the national start-up league table in the following four decades.

The overall picture that emerges is therefore one of long-run overall regional persistence, combined with quite pronounced, but also persistent, diversity across US regions in terms of changes in performance. If national policy makers wish to identify levers that will level-up regional start-up performance, and policy makers at the level of individual regions wish to improve the league-table position of their own regions, then both groups need to better understand the causes of this regional diversity. Future research work needs to lead to an improved understanding why some regions change their rankings, and others do not, over time. This understanding can be developed from an examination of carefully-selected cases of leapfroggers and plungers as well as shorter-term quantitative analyses. Proposals for this work are set out in section 5.

3 International comparisons

This section takes the findings on entrepreneurship persistence in the regions of the United States, as reported in section 2, and compares them with the findings of long-period studies of regional self-employment rates and business start-up rates in West Germany and England and Wales, with regional additional coverage within the UK and Germany for a few measures. The comparisons cover broadly similar years, namely an initial year of 1920/21, an intermediate year of 1970 or 1980 and a recent year of 2015-9 for the United States and 2011 or 2020 for West Germany and England and Wales.

Making the comparisons

The extent to which regions are viewed as entrepreneurially "persistent" over time is likely to be affected by four factors discussed below.

The first are the specific circumstances of the period in history during which the persistence is measured. To address this, the comparisons in this section provide four tables for four different time periods. The first, referred to as the "long period", covers close to a century, beginning around 1920. The second is called the "early period" and covers the half-century ending in the early 1970s. The third is the "recent period" covering the latest half-century. Finally, the availability of much more extensive data[20] means it is possible to examine in somewhat more detail regional entrepreneurship persistence in the last three decades. This is called the "most recent period". To take account of the expected differences between the time periods, Tables 3.1 to 3.4 present the findings for each time period separately.

A second factor likely to influence the comparison is the number of years over which the comparison is made. It might be expected that change would be more modest over short periods of time. It is for this reason that comparisons were made over a century, over two broadly equal half-centuries and finally, with improved data quality, over a relatively short period of time. To address this Table 3.1 covers the full century, Tables 3.2 and 3.3 each cover half a century. Finally, Table 3.4 examines changes over only 30 years.

The third factor is the entrepreneurship metric chosen for the comparison. This study uses self-employment and the business start-up rate because these are metrics for which long-run data are available. Both have their advantages and disadvantages as measures of entrepreneurship for policy development purposes and their merits depend heavily on the qualities sought from entrepreneurs. Our view is that risk-taking is the core choice exercised by entrepreneurs, as articulated by Knight (1921), with the entrepreneurship choice being driven by the risk-adjusted comparative rewards available to the entrepreneur and the employee. Self-employment captures this entrepreneurship choice. However, it excludes what many view as other important dimensions of entrepreneurship such as innovation, management and growth. These dimensions are captured, although imperfectly, by the other long-run dataset available to us – on business start-ups. By using both metrics, we aim to provide more comprehensive comparisons of regional entrepreneurship persistence.

[20] For example, in the case of the UK, regional start-up data have become available for the most recent period, enabling analysis on a second entrepreneurship metric in addition to the census-based self-employment data.

The final factor is the spatial unit chosen for the comparison. In the case of the United States, different results were obtained if commuting zones were used, compared with metropolitan statistical areas. In the case of England and Wales, administrative counties were used for long-run studies, whereas (smaller) local authority districts (LADs) were used in more recent years (see Fotopoulos, 2022a). The German comparisons are at the level of labour market regions, which represent functional regions comparable to US commuting zones with regard to concept and geographic size.[21] The varying number of observations between the countries also needs to be acknowledged when interpreting the significance of the coefficients.

The measure of persistence which is used is simple correlation, with a correlation of unity seen to reflect perfect persistence, a correlation of minus one to reflect complete change of rank position and a statistically insignificant correlation coefficient to reflect an absence of association over time.

Long period correlations

Table 3.1 shows the rank correlations for the long period from the 1920s to the 2020s. Over approximately a century, there is clear evidence of statistical persistence in each of the United States, England and Wales and West Germany on the self-employment metric. The US and German findings can be considered the more robust since they are based on considerably more observations. The robustness of the US findings is further supported by the similar results for both CZs and MSAs.

Given the disruptions caused by World War II, it is a surprise that the correlation coefficient for the West German regions was broadly comparable to US CZs. The negative correlation coefficient for East Germany is assumed to be a result of German separation between 1945 and 1990, when East Germany was subject to a communist regime that implemented massive anti-entrepreneurial policies. Moreover, German reunification in 1990 caused further disruptions that affected regional levels of entrepreneurship (Fritsch et al., 2022). The highest correlation of self-employment rates over the full period is found for England and Wales.

Table 3.1: Correlation coefficients of regional self-employment rankings in the long period: United States, England and Wales and Germany

	United States		England and Wales	Germany		
	Commuting zones	Metropolitan Statistical Areas		All	West	East
Time period: Approximately 1921-2021	1920 to 2015/19 [n=722] 0.241	1920 to 2015/19 [n=377] 0.386	1921 to 2011 [n=59] 0.74	1925 to 2019 [n=253] 0.228	1925 to 2019 [n=200] 0.242	1925 to 2019 [n=53] -0.151

Notes: Spearman rank correlation coefficients; n = number of observations.

[21] The number of labour market regions varies between years for two reasons. First, the Saar region changed twice between French and German administration in the period following the First World War. Second, statistics for periods after German unification in 1990 do not distinguish between East and West Berlin. Hence, Berlin is omitted in all comparisons after 1990.

Early period correlations

The correlations for the early period, approximately 1920 to 1970, are shown in Table 3.2. Our expectation is that the longer the time-period the more likely it is that regions will change their league table position and hence the positive correlation coefficients will fall over time. However, this is not supported in all cases. For example, in the United States, using MSAs, the correlation coefficient is similar (0.407) in the first half century to that in the full century (0.386). In the case of England and Wales the change is as expected. The barely positive correlation coefficient for West Germany probably reflects the wartime experience and subsequent partition, so questioning its value as a comparator in this time period.

A second important comparison is between the MSA and CZ results in Tables 3.1 and Table 3.2 because these appear to move in different directions. The MSA correlation coefficient rises, compared with the full century, implying greater persistence, whereas the CZ coefficient falls. The counties of England and Wales exhibit very strong persistence in this half century.

Table 3.2: Correlation coefficients of regional self-employment rankings in the early period: United States, England and Wales and West Germany

	United States		England and Wales	Germany		
	Commuting zones	Metropolitan Statistical Areas		All	West	East
Time period: Approximately 1921-1971	1920 to 1970 [n=722] 0.132	1920 to 1970 [n=377] 0.407	1921 to 1971 [n=59] 0.802	n.a.	1925 to 1970 [n=200] 0.0743	n.a.

Notes: Spearman rank correlation coefficients; n = number of observations; n.a. = not available.

Recent period correlations

Correlations for recent periods are shown in Table 3.3. The first set of international comparisons is made using self-employment as the entrepreneurship measure. This enables a comparison to be made with both the previous half century and between countries. The second, more restrictive comparison is made using start-up data.

Table 3.3: Correlation coefficients of regional self-employment rankings and start-up rankings in recent time periods: United States, England and Wales, Great Britain and West Germany

		United States		England and Wales	Great Britain	Germany		
		Commuting zones	Metropolitan Statistical Areas			All	West	East
Time period: Approximately 1970-2020	Self-employment rate rankings	1970 to 2019 [n=722] 0.524	1970 to 2019 [n=377] 0.537	1971-2020 (NUTS3, n=145) 0.683 1971-2020 (NUTS2, n=35) 0.775	n.a.	n.a.	1970-2019 [n=204] 0.286	n.a.
	Start-up rate rankings	1978-2019 [n=722] 0.729	1978-2019 [n=377] 0.817	1981-2020 (NUTS2, n=35) 0.549 1981-2020 (NUTS3, n=145) 0.343	1981-2020 (NUTS2, n=40) 0.616 1981-2020 (NUTS3, n=167) 0.388	n.a.	1978-2020 [n=204] 0.493	n.a.

Notes: Spearman rank correlation coefficients; n = number of observations; n.a. = not available.

The self-employment comparison shows that, unlike in the first half-century, the US correlations reported for the CZ and MSA spatial units are very similar (0.524 and 0.537). This provides reassurance that the picture painted by each is consistent. While the correlation of self-employment rates in England and Wales is even higher than in the United States, it is based on many fewer observations. In contrast, the correlation for West Germany is considerably lower than the US and with considerably more observations than England and Wales.

When comparisons are made between the first and more recent half-centuries it appears, perhaps surprisingly, that spatial persistence in entrepreneurship has increased over the past fifty years in the United States. This is clearest for CZs, where the correlation coefficient rises from 0.132 to 0.524, but it is also found for MSAs. It implies that regional entrepreneurship persistence is more pronounced in more modern times.

The correlation coefficient for England and Wales on self-employment is 0.683 using the NUTS3 spatial measure and 0.775 for NUTS2 units. This is higher than for either of the US geographical units but slightly lower than the result for the previous half century. The findings for West Germany point to positive persistence, but lower than either the United States or England and Wales.

The lower half of Table 3.3 shows correlation coefficients using start-up data. The metric for start-up activity in the USA is from the Business Dynamics Statistics (BDS) from the US Census Bureau for establishment openings. It is identical to the start-up measure of Fritsch and Kublina (2019) which is used for the comparison with West Germany. The start-up data for England and Wales and Great Britain (Fotopoulos and Storey 2017; Fotopoulos 2022a) are, however, at the enterprise level.[22]

The most striking finding is that, for the United States, these are markedly higher for both CZs and MSAs (0.729 and 0.817 respectively) than they were for self-employment. It therefore confirms that the spatial persistence of entrepreneurship is an issue of importance in the United States. For regional start-up rankings both the CZ and MSA coefficients for the US are higher than the start-up coefficients for England and Wales, Great Britain and West Germany.

Most recent time period correlations

Correlations for the most recent time period (approximately 1990-2020) are shown in Table 3.4. For this period, we are able to draw upon the widest range of data sources. As with Table 3.3, the first comparison is made using self-employment and the second comparison is made using start-up data.

[22] One might suspect start-up data at establishment level to show higher degrees of regional persistence than start-up data at the enterprise level because new establishments include newly set up subsidiary plants that may be more likely to be closed down again than headquarters. If such a 'headquarter effect' should occur it is, however, extremely unlikely that it affects comparisons of regional persistence of start-up rates across the countries, because the share of multi-site enterprises is only very small.

Table 3.4: Correlation coefficients of regional self-employment rankings and start-up rankings in most recent time periods: United States, England and Wales, Great Britain and Germany

		United States		England and Wales	Great Britain	Germany		
		Commuting zones	Metropolitan Statistical Areas			All	West	East
Time period: Approximately 1990-2020	Self-employment rate rankings	1990 to 2019 [n=722] 0.658	1990 to 2019 [n=377] 0.721	1991 to 2011 [LADs, n=348] 0.573 1991-2020 (NUTS3, n=145) 0.756 1991 to 2020 (NUTS2, n=35) 0.869	n.a.	1991 to 2019 [n=258] 0.267	1991 to 2019 [n=204] 0.772	1991 to 2019 [n=53] 0.280
	Start-up rate rankings	1988/92 to 2015/19 [n=722] 0.806	1988/92 to 2015/19 [n=377] 0.863	1989 to 2020 (NUTS3, n=145) 0.609 1989 to 2020 (NUTS2, n=35) 0.732	1989 to 2020 (NUTS2, n=40) 0.743 1989 to 2020 (NUTS3, n=167) 0.623	1993 to 2020 [n=258] 0.393	1993 to 2020 [n=204] 0.642	1993 to 2020 [n=53] 0.106

Notes: Spearman rank correlation coefficients; n = number of observations; n.a. = not available.

The US findings on regional self-employment rate rankings are in line with the expectation that change is likely to be slow, implying that the shorter the period over which the change is measured, the smaller is the likely change. The table confirms this, showing positive and significant correlation coefficients which are higher than those for the half-century. It also confirms the earlier finding that the results differ little between CZs and MSAs. Overall, the US data provide clear evidence of regional persistence in entrepreneurship rates over time. England and Wales provide three comparisons based on three different types of spatial units. All show positive and significant correlation coefficients implying temporal persistence.

Although the US MSAs are generally considerably larger than the England and Wales local authority districts, there is some merit in comparing the two Table 3.4 shows an England and Wales coefficient of 0.573, which is below that of 0.721 for US MSAs, implying that over the past 30 years there was greater persistence of regional entrepreneurship rankings across the United States than in England and Wales.

The self-employment comparison with Germany is notable primarily for the striking difference between the West and the former East, which explains why, overall, Germany has a much lower correlation coefficient than either the United States or England and Wales. The correlation coefficients for West Germany are, however, comparable to England and Wales.

Turning now to start-ups, Table 3.4 shows that, in the most recent time period, the correlations are stronger for start-ups than for self-employment in the United States. This is also the case for Germany (all) but not so for England and Wales.

A comparison between Tables 3.3 and 3.4, using the start-up metric, confirms the earlier US results on self-employment with the correlations being stronger in the more recent period than for the half-century as a whole.

In summary, in this case the start-up and self-employment metrics paint a broadly similar picture for the United States. It is one in which there is strong evidence of persistence with, if anything, this increasing over time. It appears that in more recent times regional entrepreneurial stability is more in evidence in the US than in the European countries examined.

Do the same factors explain leapfroggers and plungers in the United States, England and Wales and West Germany?

Section 2 uses regression analysis to link the Rank Mobility Index (RMI) between 1980 and 2019 in the United States to a set of potential explanatory variables, chosen for their comparability with existing analyses for Germany (Fritsch and Kublina, 2019) and England and Wales (Fotopoulos and Storey, 2017). In addition, new analysis of regional start-up persistence for England and Wales and Great Britain (Fotopoulos, 2022a) was undertaken to expand the international comparisons possible in this paper.[23]

Several variables were significant in all studies. For example, there was a negative association with the initial self-employment rate and positive associations with initial human capital, home ownership and size of foreign-born population across several of the models in all the countries.

For England and Wales, population density is not a significant factor explaining changes in regional self-employment rankings, whereas regional industrial diversity is. This is the reverse of the USA.

Turning now to the German comparison, the significant associations in the United States of initial human capital (share of adults with tertiary education qualifications), manufacturing share, and population density and the insignificant association of initial industry diversity are all consistent with the analyses of Fritsch and Kublina (2019) for the case of West Germany.

Finally, any comparison between the United States and the European countries has to acknowledge that, in the United States, economic activity and entrepreneurship are heavily concentrated in metropolitan areas. This implies that the entrepreneurial ecosystems in non-metropolitan areas are characterised by low population density. The empirical analysis in section 2 at many points suggested that larger agglomerations in the United States have important advantages over other regions due to their density and size (see also Florida, Adler and Mellander, 2017). This is in contrast to many European countries, which provide numerous examples of rural regions that have well-functioning and productive entrepreneurial ecosystems (e.g., Bosma and Sternberg, 2014; Fritsch and Wyrwich, 2021b).

[23] In making the comparisons between the United States and England and Wales, it is important to recall that CZs in the United States represent much larger regional labour markets than local authority districts in England and Wales. The local authority districts are smaller and are more likely to belong to one larger regional labour market. For instance, there are 32 local authority districts in the Greater London area. The spatial dependency among neighbouring districts within the same labour market risks “inflating” the correlation coefficients that measure persistence.

Conclusion

Across a wide range of metrics, time-periods and statistical approaches the evidence points to a, perhaps surprising, degree of similarity in the persistence of regional entrepreneurship rankings between the United States, England and Wales and West Germany. Most notably, the regional league table of entrepreneurship is, if anything, even more persistent over time in the United States than in these European countries.

Despite this overall persistence, there are instances where individual regions have moved sharply up or down the league table. The main common variable that was found to be significantly related to an increase of a region's position in the entrepreneurship league table, in both the United States and the European countries reviewed, is greater initial human capital, measured by share of the adult population with tertiary education qualifications. Other influences are population density, age structure of the local population and the regional level of home ownership.

There are also effects that are strong primarily in individual countries. The evidence for West Germany points to a strong positive role for regional R&D activities. The effect of the local wage level was found to be negative for Germany. The studies for England and Wales and West Germany both found a positive effect of small firm presence on regional levels of self-employment, while in the United States the relationship with average establishment size is not a significant factor in the CZ-level analysis.

Policy makers concerned with strengthening entrepreneurial ecosystems and levelling-up regional entrepreneurship rates may be particularly interested in leapfrogging regions in the national entrepreneurship league table. However, the comparative story is less consistent on this measure given some ambiguity in the US findings. First, although US large cities are disproportionately likely to be leapfroggers, there are also many small towns in this category. Hence a story of success based around a growing importance of agglomeration economies is not sufficient to explain the US case. A further problem is that the US regions defined as leapfroggers using self-employment as the entrepreneurship metric differ considerably from those when start-ups are used as the entrepreneurship metric. The implications of these issues for policy-makers are explored further in section 4.

4 Policy implications

This paper highlights four key findings relating to regional entrepreneurship that merit consideration by public policy makers.

1. The regions of the United States show long-term persistence in their levels of entrepreneurial activity, so confirming earlier findings for other countries.
2. Many regions are likely to remain in a broadly similar position in their national entrepreneurship "league table" for many decades. Some regions do, however, move up and down the national entrepreneurship league table over time.
3. The factors underpinning the entrepreneurship trajectories of different regions differ, and entrepreneurship policies need to take account of these differences.
4. The explanations for changes in regional entrepreneurial "league table position" in the United States differ in some respects from those identified in the European studies.

This Section discusses the policy implications of these findings, focusing on the policy messages for regions that are at the lower end of the regional entrepreneurship league table. This is critical to the challenge of "levelling up" entrepreneurship activities across regions.

Improving the performance of low entrepreneurship regions should be a policy target

Having a large number of regions with relatively low levels of entrepreneurship is undesirable because of the link between entrepreneurship activity and economic welfare. Policies that raise entrepreneurship rates in low enterprise regions can make a considerable contribution both to regional and national economic output and efficiency. This is characterised as the "foregone potential" argument for regional entrepreneurship policies.

A second rationale for entrepreneurship policy aimed at low enterprise regions is that low levels of economic activity reflect a lower quality of life for individuals. This is referred to as the "social welfare" argument. Its relevance for entrepreneurship is that, compared with being unemployed, having any job frequently improves the quality of life for an individual.

Both rationales represent necessary conditions for public intervention. The sufficient condition to justify public intervention here is the expectation that without explicit public policy measures the respective regional entrepreneurial ecosystems will not lead to the desirable quantity and quality of firms.

There are at least two reasons for this expectation. First, many important elements of a regional entrepreneurial ecosystem are the result of previous public policies, and initiating a change in these elements requires public decisions. Second, the finding that regional levels of entrepreneurial activity tend to be strongly persistent over long periods of time suggests that the forces that could lead to changes of the regional levels of entrepreneurial activities are relatively weak. Hence, without policy intervention the desirable changes would occur 'too slowly' and remain 'too incomplete'.

Entrepreneurship policy should take account of region-specific development trajectories

The substantial current diversity in rates of entrepreneurship activity across regions, particularly the fact that there are very different region-specific development trajectories, has important implications for the design of entrepreneurship policy interventions. The variance of the regional entrepreneurship rates across the United States and various European countries, combined with the presence of leapfroggers and plungers, demonstrates that a single 'one size fits all' policy framework to enhance entrepreneurship is unlikely to be ideal. If the objective of policy is to raise entrepreneurship activity nationally then entrepreneurship policies need to take these region-specific conditions into account. Hence, policy needs to identify the main constraining and enabling factors and relevant levers for policy action in different types of development trajectories. Because regional actors are usually more familiar with conditions in their own region than those from the central state, regional actors should be assigned a significant role in decision-making about the appropriate policy interventions.

Regional entrepreneurship policies need to be in it for the long term

The finding of strong persistence over time in regional entrepreneurship rate rankings within the United States as well as West Germany and England and Wales, implies that policies aimed at increasing the level of entrepreneurship in regions will often require considerable periods of time before significant improvements are observed. This is consistent with the recognition that, in general, informal institutions change only slowly and over long periods of time (North, 1994; Williamson, 2000). This may include many of the factors that promote and hinder entrepreneurship in a region, such as entrepreneurship culture. It points to a possible conflict between the electoral cycle, which incentivises politicians to promote policies that can offer observable impacts within a three- to five-year cycle, and the likely time period for entrepreneurship policy, which will be considerably longer. Policy makers need to make it clear to stakeholders that the policies being pursued are for long-term benefit.

The explanations for different regional development trajectories can reveal levers for entrepreneurship policy

Although this paper has confirmed that, within the United States, the dominant characteristic of regional entrepreneurship rankings over time is that of stability or persistence, it has also highlighted that there are regions which changed their league table position significantly. Those improving their league table position are called leapfroggers and those in decline are called plungers.

Although there is an understandable interest by those at the lower end of the league table in those regions consistently at the very top, the case made here is that there are even more valuable lessons to be learnt from those regions that considerably improved their position in the league table, i.e. the leapfroggers and, perhaps to a lesser extent, from the plungers. The analysis here has begun the process of identifying these regions. The next task is to better understand the combination of factors, including policy, that brought about such major changes in the entrepreneurship performance of certain regions.

Specifically, analysis needs to identify the reasons for significant changes and the extent to which they are influenced by actions taken by the regions. Was it the arrival of a new enterprise from outside the area; was it the establishment of a new college; was it the spectacular growth of a local start-up; was it a major change in the local tax regime; was it the dynamism of a local mayor; was it the discovery and exploitation of a natural resource? Further important issues, of course, are why do some regions rank persistently high in the national league table and others have so persistently low levels of entrepreneurial activity over long periods of time. All this would help to explain contexts in which policy intervention may be particularly propitious.

Moreover, it is important to identify the factors associated with the movements in the rankings of different types of regions. What difference does it make if a leapfrogging region starts from a position in the middle or at the bottom of the league table? Do the factors responsible for a decline in the league table position differ for regions that plunge from a top position as compared to those that start from a medium position? This will also provide information on the types of policy measures that could be employed to improve performance or arrest decline in these types of regions.

An example of the potential policy learning comes from findings linking upward moves in the regional entrepreneurship league table with increased human capital. This applies in the United States, England and Wales and West Germany and is in line with other research linking the regional knowledge base in entrepreneurship with innovative start-ups (Acs et al., 2009; Qian, 2017). Therefore, policies seeking to strengthen the regional knowledge base may be one of the key elements of policy positions aimed at developing leapfroggers.[24]

Some of the most relevant policy levers for the United States may be different to European countries

While many of the explanations for leapfrogging and plunging in the regional entrepreneurship league tables revealed by the regression analyses are common to the United States, England and Wales and West Germany, there are also some important differences in context and drivers between the United States and the European countries covered here. For example, there is a strong geographic concentration of entrepreneurial and broader economic activity in metropolitan areas in the United States, which is not characteristic of the European countries. The conditions for entrepreneurship in US rural areas may therefore differ from those in rural areas in European countries. Further research is needed to understand how different rural entrepreneurship policy should be between the United States and European countries.

Also, the role of agglomeration advantages for entrepreneurship in the United States is still unclear. Although high population density areas (commuting zones and metropolitan statistical areas) on average have been moving up in the national entrepreneurship league tables, their average start-up and self-employment rates are still lower than low population areas after four decades of catching up (otherwise we would not observe the high rank persistency of regional entrepreneurship). Nevertheless, there appears to be a trend of convergence in entrepreneurship rates across US regions. Our regression results also support this conclusion. They show that larger population size, or density, and greater concentration of large businesses, which historically signify disadvantages in entrepreneurship rates, are positively associated with upward rank moves. These empirical results are different from studies in the European countries. It is important to further examine why we observe this trend of convergence in the United States.

A further area of uncertainty is the role played by formal and informal institutions – an issue which can only be fully understood by the case-based approach we propose in section 5.

[24] While improving the regional knowledge base would probably be beneficial for all types of regions, it is unclear what else is required to create a leapfrogging region.

Clarity is needed on which type of entrepreneurship is being targeted by policy

OECD (2023), in its guidance on SME and entrepreneurship policy evaluation, emphasises the importance of being clear on specifying the objectives and targets of policy. It notes that policy in the entrepreneurship area to date has been characterised by either the absence of objectives or targets, hence making policy difficult to evaluate, or by the presence of multiple targets, where policy success is difficult to assess.

The evidence presented in section 2 on the United States and Section 3 on the international comparisons emphasises that policy-makers face a genuine dilemma over the key metrics on which entrepreneurship policy is to be formulated. Self-employment and business start-ups produce often very different regional league tables. They may also be associated with different economic and social results. Issues tend to become even more complicated when different sub-categories of entrepreneurship are used (e.g., innovative and knowledge-intensive start-ups, self-employed with employees, surviving start-ups) are distinguished. For this reason, it is vital for an informed discussion to take place on the merits of each metric to be set up as the objective and target of the policy and for this to be specified prior to any policy being implemented.

Conclusion

The most important finding of this research is that the regions of the United States show high levels of long-term and medium-term persistence of entrepreneurial activity, which are broadly comparable to the levels of persistence found for the European countries of England and Wales and West Germany, while at the same time there are important movements up and down the regional entrepreneurship league table for a minority of regions. This section has explored the policy implications of these findings.

The findings point to the importance of levelling up regional entrepreneurship performance within countries and particularly improving the performance of regions experiencing low performance over long periods of time. They point to the need for policy makers and the electorate to recognise that it may require considerable periods of time for policy to turn regional entrepreneurial performance around. They also point to the need for a set of regionally-specific entrepreneurship policy interventions that recognise that the drivers of improvements in regional entrepreneurship performance vary by country and region. This emphasises the importance of the inclusion of local knowledge and expertise in designing entrepreneurship policies, and finding inspiration from the experience of ‘ordinary’ regions that have made improvements in their relative entrepreneurship performance.

The final section sets out a research agenda for acquiring greater knowledge about enhancing entrepreneurial activity at a regional level.

5 Future research directions

This paper has shown that:

- Within the United States there are significant variations in regional entrepreneurship rates, with these differences being correlated with measures of economic welfare.[25]
- In line with England and Wales and West Germany, where this issue has also been examined, the US league table of regional entrepreneurship rates is broadly stable over long periods of time.
- However, within this overall pattern of stability, there are some regions that experience considerable changes in their rankings – the leapfroggers and the plungers.

Based on these findings, the paper makes the proposition that:

Future research should draw lessons from those regions that experience significant changes – positive and negative – in their rank positions on the entrepreneurship league table within their country over time.

The paper has argued that the potential policy levers that may drive improvements in regional entrepreneurship performance in lagging regions are clearer from an examination of the reasons for change in regions that have substantially improved or deteriorated in their entrepreneurship performance within their country than from an examination of the features of regions that are consistently at the top of the regional entrepreneurship performance rankings, which is the more typical approach in the entrepreneurial ecosystems literature.

We argue that the overall task then is to investigate what explains the performance of leapfroggers and plungers and to what extent these factors can be influenced by regionally-sensitive entrepreneurship policy levers. This can provide vital evidence for the design of policies aimed at levelling up regional entrepreneurship performance within countries and hence increasing the overall level of entrepreneurship.

Following up this agenda, this section seeks to identify the key unresolved questions in regional entrepreneurship and policy, where additional knowledge would be of the greatest value. It also proposes research methodologies to fill the knowledge gaps in the form of regional case studies, shorter period quantitative analyses, and extension of the analysis to further countries to increase confidence in the generalisability of the results.

The unresolved questions

What drives the long-run regional trajectories of entrepreneurship?

Policy makers often refer to the concept of entrepreneurial ecosystems when seeking to design policies to support entrepreneurship at regional level. The concept focuses on a multiple, inter-linked set of factors thought to support or hinder productive start-ups and scale-ups in a region, and which are seen to

[25] See Fritsch (2013); Glaeser, Kerr and Kerr (2015); Fritsch and Wyrwich (2017, 2022); and Fritsch, Sorgner and Wyrwich (2019).

vary spatially (OECD, 2019a; 2019b; 2019c; 2019d; 2021). However, an issue that needs to be better addressed in entrepreneurial ecosystems research is what drives improving regional performance.

A major weakness of entrepreneurial ecosystems research to date has been that it tends to set out a multiplicity of factors that are correlated with "successful" entrepreneurial ecosystems and to promote these factors as solutions for weaker regions. However, analysis vaunting the success factors of the most successful entrepreneurial ecosystems provides only limited guidance to policy makers concerned with developing entrepreneurship in lagging regions for three reasons:

1. The factors explaining the success of the most successful current performers (e.g. high-tech regions) are not necessarily the most relevant for weaker regions (e.g. former coal-mining areas).
2. Since policy is aiming to bring about change, the focus on high, or persistently high, levels of regional entrepreneurship performance risks being misleading. Instead, it is more relevant to focus on the factors explaining changes in the performance of the leapfrogger and plunger regions.
3. More guidance is needed from research about which of the entrepreneurial ecosystem elements merits the most attention by policy-makers to bring about change in specific regions or types of regions. This is more useful than the conclusion that policy needs to act on all elements of a successful entrepreneurial ecosystem simultaneously.

A research programme to address these three weaknesses of existing entrepreneurial ecosystem research would need to develop methods to:

- Demonstrate that an association between entrepreneurship ecosystem characteristics and entrepreneurship rates is clearly causative.
- Assess whether the factors explaining a positive change in regional entrepreneurship performance are linked to an available policy instrument.
- Assess whether these policy-amenable factors are associated with leapfroggers and plungers rather than the stable most successful performers.
- Take account of external economic shocks which have been shown to be at the root of change in many of the local cases identified in England and Wales and West Germany.

In order to throw light on these issues, and increase our understanding the diverse entrepreneurship development trajectories of regions, we propose that, based on our analysis, five distinct types of entrepreneurial regions are identified, each implying distinct policy regimes:

- The first three types exhibit only persistence. In other words, their position in the entrepreneurship league table changes little over time. Type A regions remain at a high level (i.e. at the top of the league table), Type B regions remain at a medium level (position in the middle of the ranking) and Type C regions at a low level (bottom of the ranking).
- The second two are regions that change over time, but where the change is different depending on initial starting level. Type D regions are leapfroggers that began in a middle or low rank position, and Type E regions are plungers that began in a high or mid-rank position.[26]

We therefore argue that the emphasis of entrepreneurial ecosystems research should be on understanding the reasons for changes in performance of regions over time, particularly those starting from weaker positions, rather than identifying the success factors of the stable, most successful regions.

[26] For simplicity we disregard the possibility that leapfroggers start in a high position or plungers start in a low position.

Understanding persistence

Regions of Type A, B and C, with constant positions in the regional entrepreneurship league table at different levels (high, medium and low), illustrate the considerable differences with regard to the underlying forces of persistence. Several authors (e.g. Fritsch and Wyrwich, 2023) hypothesise that a main explanation of persistence at high and medium levels of entrepreneurship is the prevalence of a positive entrepreneurial culture that is characterised by widespread entrepreneurial values and attitudes among the local population.

The reasons for a persistent low level of entrepreneurial activity may be very different. A common explanation for persistently low regional levels of entrepreneurship is that the dominance of large-scale industries has created a long-lasting non-entrepreneurial culture with norms that are out of line with core entrepreneurial values such as individualism, autonomy and self-realisation. Quite often these firms create well-paid jobs with good prospects of an internal career and requiring only a "9 to 5" commitment. As is the case with an entrepreneurial culture, the employment legacy of large firms and the norms it created tend to be long-lasting and often remain, even when the large enterprises no longer exist (Glaeser, Kerr and Kerr, 2015; Obschonka et al., 2018). The link between regional dominance of large-scale industries and entrepreneurship has begun to be investigated specifically for coal-mining areas in England and in the United States (Stuetzer et al., 2016; Gherhes et al., 2020; Beresford, 2013; Glaeser, Kerr and Kerr, 2015).[27] This work identifies both economic and cultural factors that explain the link.[28]

Understanding change

Studies of regions that show persistence of entrepreneurial activity at different levels of entrepreneurial activity provide helpful cases that capture legacy effects. There remain, however, clear gaps in our understanding of why changes of regional levels of entrepreneurship occur. While regional case studies provide 'anecdotal' evidence for these changes, a systematic analysis with a clear focus on leapfroggers and plungers is still missing. Such systematic analyses of significant changes of regional positions in the entrepreneurship league table may be particularly important for identifying appropriate policy strategies. Although studying the success stories of leapfroggers may suggest policies that worked well[29], cases where entrepreneurship performance did not work out well may also provide valuable learning opportunities. Generally, we know little about leapfroggers and our knowledge about plungers is even less.

[27] For an early study of this phenomenon see Checkland (1976) who analysed the effects of the shipbuilding industry in Glasgow and argued that the dominance of large firms had destructive effects upon the development of other industries in the region.

[28] One of the reasons for a negative relationship between regional dominance of large firms and entrepreneurship is that presence of large firms implies that there is only a relatively small number of self-employed persons in the local population. Hence, demonstration and role model or peer effects from existing entrepreneurs that might stimulate start-ups are less frequent. A second reason is that the working environment in large firms tends to be much less conducive to the acquisition of entrepreneurial skills, values and attitudes than working in small entrepreneurial businesses (Parker, 2009). In particular, work environments in large organisations often provide less opportunity to acquire a variety of skills ('balanced skills') that are conducive to successfully starting and running a business (Lazear, 2005). A third reason is that a large minimum efficient size of the dominating industry may result in relatively few opportunities for entry. Moreover, it is likely that local policy makers are 'captured' by the requirements and wishes of the large firms and industries that dominate the region. As a result, local policies may tend to neglect the small and new business sector. Finally, large scale industries often emphasise cultural factors focused on mutual collaboration rather than those emphasising the individual.

[29] It should also be recognised that such success is also embedded in certain social, political, economic and temporal conditions that should be accounted for.

Are there differences in what shapes the regional entrepreneurship league tables across countries?

Given the expected differences between the entrepreneurial characteristics of the United States and European countries and the expected levels of flexibility of these economies identified in the literature (Frydman et al., 2011; GEM, 2022), the level of similarity in the persistence of regional entrepreneurship rates identified in this paper is surprising. It is, of course, unwise to generalise the results based on England and Wales and West Germany to Europe as a whole, but the current findings make a powerful case for conducting such analyses in a wider range of countries in order to understand whether they can be generalised.

We consider a key strength of our current findings to be our efforts to ensure that, as far as possible, the datasets and analytical methods are comparable across countries. To achieve this requires a powerful central co-ordination role to ensure the data are comparable and that the analytical methods are both sophisticated and common across the studies.

What is the entrepreneurial potential of rural regions?

The heavy concentration of economic activity, including entrepreneurship, in the urban areas of the United States, poses the question of whether such areas have a, possibly permanent, agglomeration advantage that works to the disadvantage of the non-urban areas (Florida, Adler and Mellander, 2016). In contrast, Europe seems to provide a different picture. Not only is the geographic concentration of entrepreneurship much less pronounced than in the United States; there are also many examples of low-density regions with highly effective and economically successful entrepreneurial ecosystems (Fritsch and Wyrwich, 2014b).[30] This contrast merits further investigation, with a particularly interesting question being whether policy interventions to enhance the entrepreneurial performance of low-density rural areas in the United States could be an effective means of reducing regional inequality and increasing economic and social welfare there.

Promisingly, the empirical analysis of the United States in section 2 has demonstrated that there are a number of rural, remote, low-density areas that perform well in the US entrepreneurial league tables, both in terms of rank levels and improvements in rankings. Learning more about why these regions are so successful is therefore a research priority. For such an analysis, it would be desirable to have a variety of information about determinants of entrepreneurship in different types of regions. This includes measures of the regional economic structure, the regional knowledge base, and the accessibility of important resources as well as of different dimensions of proximity, such as markets, skills, and sources of finance (Boschma 2005). Categorising regions according to their population density into ‘rural’ and ‘urban’ is not sufficient. It would be particularly interesting to learn more about the historical roots of strong entrepreneurship performance in successful rural regions.

What type of entrepreneurship should policy target?

One of the issues that research has to address is the nature of the entrepreneurship to be targeted by policy. This study investigated two entrepreneurship metrics – namely self-employment rates and/or start-up rates. The choice of these two major entrepreneurship metrics for this analysis was based on long-term data availability, which is better for these two general measures than for more sophisticated measures. However, it is also relevant to construct measures of regional entrepreneurship persistence and change that involve economic impact considerations. For example, entrepreneurship measures

[30] Accordingly, an analysis by Bosma and Sternberg (2014) based on data from 47 urban areas in 22 EU Member States could not find a general advantage of agglomerations for entrepreneurship. The study does, however, show a slightly higher share of opportunity-motivated entrepreneurship in cities.

could be built for the analysis that account for the innovative content of a firm, such as, at a basic level, start-ups in innovative industries[31] rather than general start-up or self-employment rates. An increasing strand of research suggests there is a need to consider the quality of entrepreneurship, i.e. productive entrepreneurship with growth potential (Morris et al., 2015; Guzman and Stern, 2020; Andrews et al. 2022; Stam and van de Ven 2021).

Future research actions

Here we propose three main directions for future research work to strengthen our understanding of policy levers for regional levelling up of entrepreneurship activity: (i) detailed case studies of regions that have experienced changes in performance, (ii) quantitative analyses such as those undertaken here, but including shorter period analyses, (iii) parallel research adopting comparable entrepreneurship metrics, time periods, geographical units, explanatory variables and methodologies in additional countries. More details are set out below.

Regional case studies

A particularly valuable future research direction is the use of rich regional case studies focused on the most interesting regional entrepreneurship development experiences, namely the leapfroggers and the plungers. These could combine quantitative ecosystem benchmarking on a range of entrepreneurship performance metrics and explanatory factors and qualitative stakeholder interviews discussing the main developments and the reasons for them in the region, taking into account the findings of the benchmarking work. The key focus would be on seeking policy insights from the experiences of different types of regions.

Careful attention has to be paid to the types of regions to be selected for such case study work. Crucially, rather than simply selecting "convenient" samples, case studies have to be selected based on an analysis of changes in their regional league table performance. For the United States, West Germany and England and Wales, the regions can be selected from the statistical analyses already undertaken to date. For other countries, new analysis could be undertaken to help select the most interesting regions.

Three main methods are possible:

- The first and simplest approach is to select the top leapfrogger regions and top plungers over a given time period. However, the analysis reported here has shown that changes in league table position can be "explained" by a range of factors. These include the sectoral composition of enterprises in the area and the human capital of the population. These factors can be applied to initially generate an expected end-period league table position for each region. This can then be compared with the observed league table position at the same end period.
- A second approach, then, is to select those regions with the greatest differences in expected and observed end-period league table positions. This method would focus on investigating those developments that cannot be explained by obvious factors such as sectoral composition or human capital of the population. This may be expected to reveal a set of particularly telling case studies.
- A third option is to use Fuzzy-set Qualitative Comparative Analysis (FsQCA) (Ragiv, 2000, 2008) to both select regional cases for analysis and provide more sophisticated analyses of the

[31] A problem with measures based on industry classifications for long time periods is that these classifications may be subject to considerable changes, with new industries emerging while some old industries lose importance. Moreover, the innovativeness of an industry may change over its life cycle; what is regarded as 'high-tech' today may in some years be fairly standard technologically.

findings. Although this is a relatively novel approach, it has been applied recently to both regional innovation (Filippopoulos and Fotopoulos, 2022) and entrepreneurial ecosystems research (Schrijvers et al, 2022; Alves et al, 2021; Xie et al, 2021; Munoz et al, 2020).

Shorter period analysis of regional league table changes is also needed.

A second important area we recommend for further research is quantitative analyses of explanations for changes over shorter – perhaps five-year – periods of time, set within a wider medium-term analysis such as that presented in this paper for the more recent time periods.

This would have three advantages:

1. It would document and distinguish the short- from medium- and long-term changes.
2. By using more recent, and therefore richer, data on dependent and independent variables, it would enable a more comprehensive analysis and examination of more relationships between factors and a more sophisticated measure of entrepreneurship than is permitted by a long-term trends assessment which is limited by data availability.
3. It may be able to identify policy levers that make a difference in a short, e.g. five-year, timescale, which falls more clearly in the timescale of politicians, such as changes in state taxes, major construction projects and changes in local regulations affecting entrepreneurship. There may indeed be some factors that are positive in a five-year period and continue to be positive in a medium- and long-term perspective.

The approach proposed is therefore to undertake shorter term national-level quantitative studies in the United States and other countries. The work would replicate the analysis in this paper over two decades, but then observe relationships between entrepreneurship performance and explanatory factors over successive five-year periods.

Extension of analysis to further countries

The analysis in this paper has examined the cases of England and Wales (Great Britain on certain measures), West Germany (all Germany on certain measures) and the United States. It is important to undertake similar studies in other countries to assess whether the overall issue of the long-run persistence of high and low performing regions in entrepreneurship is shared and whether the causes of changes in regional entrepreneurship performance of time are shared or different. In undertaking such comparisons it is important to ensure that, as far as possible, the datasets and analytical methods are comparable across countries, as we have done in this study. The OECD is well placed to co-ordinate such international analysis in a way that achieves both reliability and comparability of results and that can draw appropriate policy conclusions.

Conclusion

This section has sought to provide a realistic assessment of the extent to which the current state of knowledge on regional variations in entrepreneurship, set out in this paper, is of value to policy makers. It concludes that national and regional policy makers need to be aware of the stark variations in regional entrepreneurship rates which, because they are frequently of long standing, have the potential to cause “foregone economic potential” and “reduced social welfare”.

The realism is in the recognition that the analysis in the paper is not currently a blueprint for policy interventions to secure the required levelling-up of regions. The agenda set out is one seeking to raise policy-makers’ awareness of the issue, but also to highlight the gaps remaining in knowledge on regional entrepreneurship drivers and policy levers.

To begin to close that gap there is a strong case for new data analysis. The key theme is to acknowledge, and hence better understand, that regional entrepreneurship performance over time is characterised by both persistence and diversity. The analytical contribution of this paper is to point to this diversity but it is not yet able to document it in sufficient detail to give firm policy guidance on levers for improving performance in weaker regions.

Achieving this requires additional work, to develop deeper case studies of regions in the United States and countries that fall into different groups in terms of their performance over time – with a particular focus on leapfroggers and plungers, and to examine factors explaining changes in regional entrepreneurship performance over shorter-periods, more amenable to rapid policy action. The aim of these case studies would be to provide a better understanding of the policy-enabled factors of success and the avoidance of decline. Furthermore, an extension of the comparative approach in this paper to other countries would provide more evidence on the generalisability of the findings presented here.

References

Acs, Z J., P. Braunerhjelm, D.B. Audretsch and B. Carlsson (2009), “The knowledge spillover theory of entrepreneurship”, Small Business Economics, Vol. 32(1), 15–30. https://doi.org/10.1007/s11187-008-9157-3 Alves, A.C., B.B. Fischer and N.S. Vonortas (2021), “Ecosystems of entrepreneurship: Configurations and critical dimensions”, *Annals of Regional Science*, Vol. 67(1), 73–106. https://doi.org/10.1007/s00168-020-01041-y

Andrews, R.J., C. Fazio, J. Guzman, Y. Liu and S. Stern (2022), “The Startup Cartography Project: Measuring and mapping entrepreneurial ecosystems”, *Research Policy*, Vol. 51, 104437. https://doi.org/10.1016/j.respol.2021.104437

Audretsch, D.B. and M. Fritsch (1994), “On the Measurement of Entry Rates”, *Empirica*, Vol. 21, 105-113. https://doi.org/10.1007/BF01383974

Beresford, R. (2013), *Coal, coal mining and the enterprise culture. A study of Doncaster*, PhD thesis University of Warwick. http://wrap.warwick.ac.uk/80000

Boschma, R. (2005), “Proximity and Innovation: A Critical Assessment”, *Regional Studies*, Vol. 39, 61-74. https://doi.org/10.1080/0034340052000320887

Bosma, N. and R. Sternberg (2014), “Entrepreneurship as an Urban Event? Empirical Evidence from European Cities”, *Regional Studies*, Vol. 48, 1016-1033. http://dx.doi.org/10.1080/00343404.2014.904041

Cosci, S., V. Meliciani and M. Pini. (2022). “Historical Roots of Innovative Entrepreneurial Culture: the Case of Italian Regions”, *Regional Studies*, Vol. 56, 1683-1697.

Debbage, K. G., & Bowen, S. (2018). Non-farm proprietorship employment by US metropolitan area. *Journal of Enterprising Communities: People and Places in the Global Economy*. Vol. 12, 139-157, https://doi.org/10.1108/JEC-07-2017-0043

Djankov, S., R. La Porta, F. Lopez-de-Silanes and A. Shleifer (2002), “The Regulation of Entry”, *Quarterly Journal of Economics*, Vol. 67, 1 - 37. https://doi.org/10.1162/003355302753399436

Douglas, E.J., D.A. Shepherd and C. Prentice (2020), “Using fuzzy-set qualitative comparative analysis for a finer-grained understanding of entrepreneurship”, *Journal of Business Venturing*, Vol. 35, 1-17. https://doi.org/10.1016/j.jbusvent.2019.105970

Eurostat (2021), *Eurostat Regional Yearbook – 2021 Edition*. Luxembourg: Publications Office of the European Union.

Filippopoulos, N. and G. Fotopoulos (2022), “Innovation in economically developed and lagging European regions: A configurational analysis”, *Research Policy*, Vol. 51(2). https://doi.org/10.1016/j.respol.2021.104424

Florida, R., P. Adler and C. Mellander (2017), “The City as Innovation Machine”, *Regional Studies*, Vol. 51, 86–96. https://doi.org/10.1080/00343404.2016.1255324

Fotopoulos, G. (2014), “On the spatial stickiness of UK new firm formation rates”, *Journal of Economic Geography*, Vol. 14(3), 651–679. https://doi.org/10.1093/jeg/lbt011

Fotopoulos, G. (2022a), Persistence and Leapfrogging in Regional Start-up Rates: England and Wales 1981-2020, mimeo for OECD Centre for Entrepreneurship, SMEs, Regions and Cities.

Fotopoulos, G. (2022b), “Knowledge Spillovers, Entrepreneurial Ecosystems and the Geography of High Growth Firms”, *Entrepreneurship Theory and Practice*. https://doi.org/10.1177/10422587221111732

Fotopoulos, G. and D.J. Storey (2017), “Persistence and change in interregional differences in entrepreneurship: England and Wales, 1921–2011”, *Environment and Planning A*, Vol. 49(3), 670–

702. https://doi.org/10.1177%2F0308518X16674336

Fotopoulos, G. and D.J. Storey (2019), "Public policies to enhance regional entrepreneurship: Another programme failing to deliver?" *Small Business Economics*, Vol. 53(1), 189–209. https://doi.org/10.1007/s11187-018-0021-9

Fritsch, M. (2013), "New Business Formation and Regional Development—A Survey and Assessment of the Evidence", *Foundations and Trends in Entrepreneurship*, Vol. 9, 249–364. https://doi.org/10.1561/0300000043

Fritsch, M. and M. Wyrwich (2017), "The Effect of Entrepreneurship for Economic Development—An empirical analysis using regional entrepreneurship culture", *Journal of Economic Geography*, Vol. 17, 157-189. https://doi.org/10.1093/jeg/lbv049

Fritsch, M., A, Sorgner and M. Wyrwich (2019), "Self-Employment and Well-Being across Institutional Contexts", *Journal of Business Venturing*, Vol. 34, 105946. https://doi.org/10.1016/j.jbusvent.2019.105946

Fritsch, M. and S. Kublina (2019), "Persistence and Change of Regional New Business Formation in the National League Table" *Journal of Evolutionary Economics*, Vol. 29, 891-917. https://doi.org/10.1007/s00191-019-00610-5

Fritsch, M. and M. Wyrwich (2021a), "Is innovation (increasingly) concentrated in large cities? An international comparison", *Research Policy*, Vol. 50, 104237. https://doi.org/10.1016/j.respol.2021.104237

Fritsch, M. and M. Wyrwich (2021b), "Does Successful Innovation Require Large Cities? Germany as a Counterexample", *Economic Geography*, Vol. 97, 284-308. https://doi.org/10.1080/00130095.2021.1920391

Fritsch, M. and M. Wyrwich (2022), "Initial Conditions and Regional Performance in the Aftermath of Disruptive Shocks: The Case of East Germany after Socialism", *Industrial and Corporate Change*. https://doi.org/10.1093/icc/dtac033

Fritsch, M. and M. Wyrwich (2023) "Entrepreneurship in the Long-Run: Empirical Evidence and Historical Mechanisms", *Foundations and Trends in Entrepreneurship*, vol. 19.1, 1-125.

Fritsch, M., M. Greve and M. Wyrwich (2022), "The Long-run Effects of Communism and Transition to a Market System on Self-Employment: The Case of Germany", *Entrepreneurship Theory and Practice*. https://doi.org/10.1177/10422587221094498

Frydman, R., O. Khan and A. Rapaczynski (2011), "Entrepreneurship in Europe and the United States: Security, Finance, and Accountability". In Edmund S. Phelps and Hans-Werner Sinn (*eds*.): *Perspectives on the Performance of the Continental Economies,* Cambridge (MA): MIT Press, pp. 27-65.

Ghatak, M., M. Morelli and T. Sjostrom (2007), "Entrepreneurial talent, occupational choice and trickle up policies", *Journal of Economic Theory*, Vol. 137, 27-48. https://doi.org/10.1016/j.jet.2006.02.007

Glaeser E., S.P. Kerr and W. R. Kerr (2015), "Entrepreneurship and Urban Growth: An Empirical Assessment with Historical Mines", *Review of Economics and Statistics,* Vol. 97(2), 498–520. https://doi.org/10.1162/REST_a_00456

Global Entrepreneurship Monitor (GEM) (2022), *2021/2022 Global Report - Opportunity Amid Disruption*, London: GEM.

Grillitsch, M., M. Sotarauta and B. Asheim (2022), "Agency and economic change in regions: identifying routes to new path development using qualitative comparative analysis", *Regional Studies*. https://doi.org/10.1080/00343404.2022.2053095

Guzman, J. and S. Stern (2020), "The State of American Entrepreneurship: New Estimates of the Quantity and Quality of Entrepreneurship for 32 US States, 1988–2014", *American Economic Journal: Economic Policy*, Vol. 12 (4), 212–43. https://www.aeaweb.org/articles?id=10.1257/pol.20170498

Hamano, M. and F. Zanetti (2022), “Monetary policy, firm heterogeneity, and product variety”, *European Economic Review*, Vol. 144, 104089. https://doi.org/10.1016/j.euroecorev.2022.104089

Haynes, K.E., H. Qian and S.C. Turner,. (2012), “The location of business support programs: does the knowledge context matter?” In: Charlie Karlsson, Börje Johansson and Roger R. Stough (eds.): *Entrepreneurship, Social Capital and Governance*, Cheltenham: Elgar, pp. 302–324.

Morris, M.H., X. Neumeyer and D.F. Kuratko (2015), “A portfolio perspective on entrepreneurship and economic development”, *Small Business Economics*, Vol. 45, 713–728. https://doi.org/10.1007/s11187-015-9678-5

Motoyama, Y. (2014), “The state-level geographic analysis of high-growth companies”, *Journal of Small Business & Entrepreneurship*, Vol. 27, 213-227. https://doi.org/10.1080/08276331.2015.1012795

Motoyama, Y. and B. Danley (2012), “An analysis of the geography of entrepreneurship: Understanding the geographic trends of Inc. 500 companies over thirty years at the state and metropolitan levels”, Kansas City: Kauffman Foundation of Entrepreneurship. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2145480

Motoyama Y. and H. Mayer (2017), “Revisiting the roles of the university in regional economic development: a triangulation of data”, *Growth and Change*, Vol. 48, 787-804. https://doi.org/10.1111/grow.12186

Muñoz, P., Kibler, E., Mandakovic, V., Amorós, J.E., (2020), Local entrepreneurial ecosystems as configural narratives: A new way of seeing and evaluating antecedents and outcomes. *Research Policy*, Vol. 51.9, https://doi.org/10.1016/j.respol.2020.104065

North, D.C. (1994), “Economic performance through time”, *American Economic Review*, Vol. 84(3), 359–368. https://www.jstor.org/stable/2118057

Obschonka, M., M. Stuetzer, P.J. Rentfrow, L. Shaw-Taylor, M. Satchell, R.K. Silbereisen, J. Potter and S.D. Gosling (2018), “In the shadow of coal: How large-scale industries contributed to present-day regional differences in personality and well-being”, *Journal of Personality and Social Psychology*, Vol. 115(5), 903-927. http://psycnet.apa.org/record/2017-52083-001

OECD (2023), *Framework for the Evaluation of SME and Entrepreneurship Policies and Programmes 2023*, OECD Studies on SMEs and Entrepreneurship, Paris: OECD Publishing. https//doi.org/10.1787/a4c818d1-en

OECD (2019a) Local entrepreneurship ecosystems and emerging industries: case study of Malopolskie, Poland, OECD Local Economic and Employment Development (LEED) Papers, no. 2019/03, Paris: OECD Publishing. https://doi.org/10.1787/d99ba985-en

OECD (2019b), Local entrepreneurship ecosystems and emerging industries: case study of Mazowieckie, Poland, *OECD Local Economic and Employment Development (LEED) Papers*, No. 2019/06, Paris: OECD Publishing. https://doi.org/10.1787/e11d7a26-en

OECD (2019c), Local entrepreneurship ecosystems and emerging industries: case study of Pomorskie, Poland, *OECD Local Economic and Employment Development (LEED) Papers*, No. 2019/05, Paris: OECD Publishing. https://doi.org/10.1787/8fd63992-en

OECD (2019d), Local entrepreneurship ecosystems and emerging industries: case study of Coventry and Warwickshire, United Kingdom, *OECD Local Economic and Employment Development (LEED) Papers*, No. 2019/04, Paris: OECD Publishing. https://doi.org/10.1787/3b6277f9-en

OECD (2020), *Regions and Cities at a Glance 2020*. Paris: OECD Publishing. https://doi.org/10.1787/959d5ba0-en

OECD (2021), Local entrepreneurship ecosystems and emerging industries: case study of Cambridgeshire and Peterborough, United Kingdom, *OECD Local Economic and Employment Development (LEED) Papers*, No. 2021/01, Paris: OECD Publishing. https://doi.org/10.1787/044ffc1d-en

Office of Management and Budget (OMB) (2013), Revised Delineations of Metropolitan Statistical Areas, Micropolitan Statistical Areas, and Combined Statistical Areas, and Guidance on Uses of the Delineations of These Areas. Bulletin NO. 13-01. 2013.

Pagliarin, S. and L. Gerrits (2020), "Trajectory-based Qualitative Comparative Analysis: Accounting for case-based time dynamics", *Methodological Innovations*, Vol. 13(3). https://doi.org/10.1177/2059799120959170

Parker S.C. (2018), *The Economics of Entrepreneurship*. 2nd ed., Cambridge: Cambridge University Press.

Qian, H. (2013). Diversity versus tolerance: the social drivers of innovation and entrepreneurship in US cities. *Urban Studies*, Vol. 50(13), 2718-2735. https://doi.org/10.1177/0042098013477703

Qian, H. (2017), "Skills and knowledge-based entrepreneurship: evidence from US cities", *Regional Studies*, Vol. 51, 1469-1482. https://doi.org/10.1080/00343404.2016.1213383

Qian, H. and Z. Acs (2013), "An absorptive capacity theory of knowledge spillover entrepreneurship", *Small Business Economics*, Vol. 40(2), 185–197. https://doi.org/10.1007/s11187-011-9368-x

Reynolds, P. D. and Storey, D. J. (1993). Local and Regional Characteristics Affecting Small Business Formation: A Cross-National Comparison. Paris: OECD

Schrijvers, M., E. Stam and N. Bosma (2021), "Figuring it out: Configurations of high-performing entrepreneurial ecosystems in Europe", Utrecht University School of Economics Working Paper Series nr: 21-05. https://dspace.library.uu.nl/bitstream/handle/1874/419996/REBO_USE_WP_21_05.pdf

Shir, N. (2016), Entrepreneurial well-being—the payoff structure of business creation. Ph.D. Dissertation Stockholm School of Economics. https://ex.hhs.se/dissertations/849175-FULLTEXT02.pdf

Sleuwaegen, L. and S. Ramboer (2020), "Regional competitiveness and high growth firms in the EU: the creativity premium", *Applied Economics*, Vol. 52, 2325–2338. https://doi.org/10.1080/00036846.2019.1686454

Spigel, B. (2017), "The Relational Organization of Entrepreneurial Ecosystems", *Entrepreneurship: Theory and Practice*, Vol. 41, 49–72. https://doi.org/10.1111/etap.12167

Stam, E. and A. van de Ven (2021), "Entrepreneurial ecosystem elements", *Small Business Economics*, Vol. 56, 809–832. https://doi.org/10.1007/s11187-019-00270-6

Sterk, V., P. Sedlacek and B. Pugsley (2021), "The nature of firm growth", *American Economic Review*, Vol. 111, 547–79. https://doi.org/10.1257/aer.20190748

Sternberg, R., J. von Bloh and A. Coduras (2019), "A new framework to measure entrepreneurial ecosystems at the regional level", *Zeitschrift für Wirtschaftsgeographie*, Vol. 63, 103–117. https://doi.org/doi:10.1515/zfw-2018-0014

Stuetzer, M., M. Obschonka, D.B. Audretsch, M. Wyrwich, P.J. Rentfrow, M.J. Coombes, L. Shaw-Taylor and M. Satchell (2016), "Industry structure, entrepreneurship, and culture: An empirical analysis using historical coalfields", *European Economic Review*, Vol. 86, 52–72. https://doi.org/10.1016/j.euroecorev.2015.08.012

UK Government (2022), *Levelling Up the United Kingdom*. Department for Levelling Up, Housing and Communities, London.

Williamson, O.E. (2000), "The new institutional economics: Taking stock, looking ahead", *Journal of Economic Literature*, Vol. 38, 595–613. https://doi.org/10.1257/jel.38.3.595

Wurth, B., E. Stam, E. and B. Spigel (2022), "Toward an Entrepreneurial Ecosystem Research Program", *Entrepreneurship Theory and Practice*, Vol. 46, 729-778. https://doi.org/10.1177/1042258721998948

Xie, Z., X. Wang, L. Xie and K. Duan (2021), "Entrepreneurial *ecosystem* and the quality and quantity of regional entrepreneurship: A configurational approach", *Journal of Business Research*, Vol. 128, 499–509. https://doi.org/10.1016/j.jbusres.2021.02.015

Annex A. Additional tables

Table A.1. Top/bottom 5 CZs and MSAs on regional rank change

Indicator	Rank	CZs				MSAs			
		Top Performers (2015-19)	Top Leapfroggers (1980 to 2015-19)	Bottom Performers (2015-19)	Top Plungers (1980 to 2015-19)	Top Performers (2015-19)	Top Leapfroggers (1980 to 2015-19)	Bottom Performers (2015-19)	Top Plungers (1980 to 2015-19)
Self-Employment Rate	#1	Friday Harbor town, WA	Jordan town, MT	Welch city, WV	Norton city, KS	Santa Fe, NM	Charleston-North Charleston, SC	Dalton, GA	Texarkana, TX-AR
	#2	Vineyard Haven CDP, MA	Scobey city, MT	Rosebud CDP, SD	Kremmling town, CO	Barnstable Town, MA	Hilton Head Island-Bluffton, SC	Bloomington, IL	Wichita Falls, TX
	#3	Nantucket CDP, MA	Charleston city, SC	Clayton town, NM	Vernon city, TX	Naples-Marco Island, FL	New Orleans-Metairie, LA	Kankakee, IL	St. Joseph, MO-KS
	#4	McCall city, ID	Soda Springs city, ID	McLaughlin city, SD	Santa Rosa city, NM	Bend, OR	Bismarck, ND	Decatur, IL	Hanford-Corcoran, CA
	#5	Salida city, CO	New Orleans city, LA	Crossett city, AR	Clayton town, NM	The Villages, FL	Chicago-Naperville-Elgin, IL-IN-WI	Texarkana, TX-AR	Dalton, GA
Start-Up Rate	#1	Nantucket CDP, MA	Steele city, ND	Rosebud CDP, SD	Big Stone Gap town, VA	Bend, OR	Midland, MI	Elkhart-Goshen, IN	Houma-Thibodaux, LA
	#2	Jackson town, WY	St. Louis city, MO	Bennettsville city, SC	Spencer city, WV	St. George, UT	Charlotte-Concord-Gastonia, NC-SC	Columbus, IN	Grand Junction, CO
	#3	McCall city, ID	Chicago city, IL	Jordan town, MT	Lake Providence town, LA	Cheyenne, WY	St. Louis, MO-IL	Lima, OH	Jackson, TN
	#4	Friday Harbor town, WA	Wilmington city, DE	Defiance city, OH	Frederick city, OK	Ocean City, NJ	Chicago-Naperville-Elgin, IL-IN-WI	Oshkosh-Neenah, WI	Florence-Muscle Shoals, AL
	#5	Enterprise city, OR	Poughkeepsie city, NY	Lake Providence town, LA	Elko city, NV	Port St. Lucie, FL	New York-Newark-Jersey City, NY-NJ-PA	Dubuque, IA	Tuscaloosa, AL

Table A.2. CZ rankings and Rank Mobility Index (RMI)

CZ Code (1990)	CZ City Name (1990)	1990 Population	Self-Employment Rate Ranking						Startup Rate Ranking			
			2015-2019	1990	1980	1970	1920	*RMI 1980-2019*	2015-2019	1988-1992	1978-1982	*RMI 1978 - 2019*
100	Johnson City city, TN	524,270	421	543	591	601	606	*0.24*	633	645	625	*-0.01*
200	Morristown city, TN	180,775	276	363	333	515	582	*0.08*	428	286	471	*0.06*
301	Middlesborough city, KY	64,382	620	388	304	422	685	*-0.44*	603	442	372	*-0.32*
302	Knoxville city, TN	634,523	329	500	573	608	494	*0.34*	451	328	426	*-0.03*
401	Winston-Salem city, NC	423,152	357	567	602	578	506	*0.34*	418	426	584	*0.23*
402	Martinsville city, VA	90,577	653	625	659	659	679	*0.01*	617	670	719	*0.14*
500	Greensboro city, NC	904,324	379	597	605	633	618	*0.31*	467	508	602	*0.19*
601	North Wilkesboro town, NC	81,602	208	384	314	385	607	*0.15*	646	689	678	*0.04*
602	Galax city, VA	59,132	187	347	447	525	666	*0.36*	638	672	689	*0.07*
700	Spartanburg city, SC	316,059	496	680	593	650	661	*0.13*	511	561	591	*0.11*
800	Gastonia city, NC	367,044	464	668	655	666	674	*0.26*	504	661	672	*0.23*
900	Charlotte city, NC	1,098,606	353	639	669	621	654	*0.44*	164	190	462	*0.41*
1001	Boone town, NC	65,585	55	208	198	210	406	*0.20*	182	84	260	*0.11*
1002	Morganton city, NC	141,277	312	450	558	501	580	*0.34*	699	709	703	*0.01*
1100	Hickory city, NC	309,596	279	642	640	665	646	*0.50*	342	537	583	*0.33*
1201	Franklin town, NC	35,147	27	28	25	174	708	*0.00*	49	28	87	*0.05*
1202	Cullowhee CDP, NC	45,310	193	152	263	201	690	*0.10*	172	235	382	*0.29*
1203	Asheville city, NC	333,521	38	302	431	435	278	*0.55*	76	219	363	*0.40*
1204	Andrews town, NC	46,072	36	55	69	237	696	*0.05*	191	160	395	*0.28*
1301	Bennettsville city, SC	67,938	641	665	548	488	719	*-0.13*	721	718	721	*0.00*
1302	Florence city, SC	466,378	249	522	527	439	712	*0.39*	189	115	325	*0.19*
1400	Fayetteville city, NC	563,232	636	700	691	717	636	*0.08*	667	686	660	*-0.01*
1500	Wilmington city, NC	278,374	106	296	346	390	439	*0.33*	153	114	329	*0.24*
1600	Rocky Mount city, NC	199,296	526	690	676	587	548	*0.21*	668	599	554	*-0.16*
1701	Raleigh city, NC	1,033,266	370	600	620	609	514	*0.35*	210	257	479	*0.37*
1702	Henderson city, NC	56,157	553	699	579	596	692	*0.04*	687	714	570	*-0.16*
1800	Goldsboro city, NC	191,958	318	580	556	492	668	*0.33*	714	712	654	*-0.08*
1900	Greenville city, NC	485,375	570	695	629	696	499	*0.08*	605	636	578	*-0.04*
2000	Virginia Beach city, VA	1,046,518	640	719	721	721	259	*0.11*	426	546	610	*0.26*
2100	Washington city, NC	113,371	75	103	211	203	489	*0.19*	120	113	284	*0.23*
2200	South Boston city, VA	144,503	375	499	454	504	599	*0.11*	456	589	662	*0.29*
2300	Lynchburg city, VA	206,226	522	563	618	664	409	*0.13*	431	531	605	*0.24*
2400	Richmond city, VA	901,877	474	676	715	706	187	*0.33*	284	276	533	*0.35*
2500	Newport News city, VA	507,398	672	709	711	719	538	*0.05*	531	584	649	*0.16*
2600	Roanoke Rapids city, NC	133,384	539	662	511	605	672	*-0.04*	708	641	608	*-0.14*
2700	Biloxi city, MS	388,725	533	521	458	457	321	*-0.10*	623	468	465	*-0.22*
2800	Laurel city, MS	113,460	528	397	303	173	641	*-0.31*	690	582	473	*-0.30*
2900	Hattiesburg city, MS	140,181	416	439	363	182	638	*-0.07*	417	323	343	*-0.10*
3001	Kosciusko city, MS	40,085	716	366	201	266	642	*-0.71*	554	620	456	*-0.14*
3002	Yazoo City city, MS	37,640	661	528	380	444	697	*-0.39*	705	530	482	*-0.31*

3003	Jackson city, MS	489,514	402	557	569	477	619	*0.23*	378	316	303	*-0.10*
3101	McComb city, MS	99,784	320	373	320	264	637	*0.00*	327	279	380	*0.07*
3102	Brookhaven city, MS	42,736	623	376	239	127	584	*-0.53*	356	236	477	*0.17*
3201	Jonesville town, LA	24,727	494	259	366	57	695	*-0.18*	60	388	310	*0.35*
3202	Natchez city, MS	71,664	564	356	416	352	544	*-0.21*	379	300	327	*-0.07*
3203	Vicksburg city, MS	80,366	608	705	680	670	213	*0.10*	556	543	514	*-0.06*
3300	New Orleans city, LA	1,328,455	167	616	609	482	78	*0.61*	269	382	391	*0.17*
3400	Houma city, LA	263,681	486	443	395	323	586	*-0.13*	578	379	138	*-0.61*
3500	Baton Rouge city, LA	709,562	382	664	643	583	630	*0.36*	370	381	335	*-0.05*
3600	Alexandria city, LA	188,241	472	495	473	456	401	*0.00*	481	455	436	*-0.06*
3700	Lake Charles city, LA	321,386	576	667	627	691	226	*0.07*	460	614	457	*0.00*
3800	Lafayette city, LA	496,579	147	475	392	326	512	*0.34*	264	327	89	*-0.24*
3901	Monroe city, LA	247,645	556	454	483	460	686	*-0.10*	273	319	237	*-0.05*
3902	Lake Providence town, LA	21,802	594	433	357	303	710	*-0.33*	718	680	250	*-0.65*
4001	Magnolia city, AR	35,334	665	262	214	263	709	*-0.63*	558	326	247	*-0.43*
4002	Shreveport city, LA	481,136	423	512	544	497	463	*0.17*	348	439	355	*0.01*
4003	Ruston city, LA	73,719	466	481	601	526	472	*0.19*	351	497	367	*0.02*
4004	Many town, LA	22,646	687	180	216	90	707	*-0.65*	156	258	366	*0.29*
4101	Crossett city, AR	24,319	718	332	502	472	711	*-0.30*	717	688	558	*-0.22*
4102	Pine Bluff city, AR	168,631	617	584	437	481	660	*-0.25*	598	592	501	*-0.13*
4103	El Dorado city, AR	92,733	676	438	299	305	634	*-0.52*	545	357	234	*-0.43*
4200	Little Rock city, AR	554,185	438	558	570	522	428	*0.18*	245	241	350	*0.15*
4301	Stuttgart city, AR	42,504	411	145	208	143	522	*-0.28*	388	297	344	*-0.06*
4302	Searcy city, AR	83,140	399	420	272	208	510	*-0.18*	358	428	292	*-0.09*
4401	Corbin city, KY	128,186	588	323	279	222	716	*-0.43*	535	452	244	*-0.40*
4402	Richmond city, KY	98,880	612	514	391	369	667	*-0.31*	654	673	639	*-0.02*
4501	Jackson city, KY	46,312	450	256	166	169	617	*-0.39*	449	575	291	*-0.22*
4502	Hazard city, KY	125,405	683	565	496	342	699	*-0.26*	500	205	261	*-0.33*
4601	Campbellsville city, KY	75,804	331	130	99	157	701	*-0.32*	594	683	581	*-0.02*
4602	Somerset city, KY	110,053	315	171	165	198	691	*-0.21*	568	291	314	*-0.35*
4701	Greenwood city, MS	80,521	441	451	368	311	673	*-0.10*	377	377	485	*0.15*
4702	Clarksdale city, MS	131,220	512	568	376	402	693	*-0.19*	387	523	500	*0.16*
4800	Greenville city, MS	151,652	598	655	575	485	665	*-0.03*	490	559	490	*0.00*
4901	Jackson city, TN	173,871	470	502	446	512	648	*-0.03*	526	277	474	*-0.07*
4902	Dyersburg city, TN	84,911	558	515	435	376	663	*-0.17*	711	577	551	*-0.22*
4903	Lexington city, TN	38,928	224	140	227	278	717	*0.00*	537	435	580	*0.06*
5000	Tupelo city, MS	177,410	506	459	324	301	706	*-0.25*	464	337	439	*-0.03*
5100	Corinth city, MS	117,738	460	229	286	334	676	*-0.24*	509	346	476	*-0.05*
5201	New Albany city, MS	49,654	410	547	432	164	658	*0.03*	709	708	667	*-0.06*
5202	Memphis city, TN	1,017,324	573	663	665	682	250	*0.13*	575	403	496	*-0.11*
5300	West Memphis city, AR	139,552	430	527	434	508	643	*0.01*	669	532	397	*-0.38*
5401	Bowling Green city, KY	141,219	514	496	354	338	609	*-0.22*	525	494	535	*0.01*
5402	Glasgow city, KY	83,277	211	245	191	307	684	*-0.03*	614	594	643	*0.04*
5500	Columbia city, TN	128,093	348	422	421	452	566	*0.10*	593	547	592	*0.00*
5600	Nashville-Davidson (remain, TN	996,401	235	409	555	540	191	*0.44*	240	158	375	*0.19*
5700	Tullahoma city, TN	110,196	307	367	443	412	520	*0.19*	620	548	556	*-0.09*
5800	Paris city, TN	120,782	242	252	265	306	683	*0.03*	570	385	520	*-0.07*

5900	Clarksville city, TN	207,237	682	651	663	704	568	*-0.03*	670	713	696	*0.04*
6000	Huntsville city, AL	452,760	544	593	581	673	657	*0.05*	470	398	524	*0.07*
6100	Gadsden city, AL	273,119	268	403	365	349	595	*0.13*	665	447	506	*-0.22*
6200	Florence city, AL	208,379	368	411	479	426	623	*0.15*	499	444	495	*-0.01*
6301	McMinnville city, TN	72,288	169	225	332	224	456	*0.23*	642	640	571	*-0.10*
6302	Cookeville city, TN	82,854	161	328	233	309	705	*0.10*	433	533	409	*-0.03*
6401	Chattanooga city, TN	446,572	300	510	600	610	388	*0.42*	454	359	518	*0.09*
6402	Crossville city, TN	83,418	243	233	192	335	698	*-0.07*	634	490	356	*-0.39*
6501	Blue Ridge city, GA	29,360	13	123	150	245	714	*0.19*	158	108	417	*0.36*
6502	Cleveland city, TN	168,312	355	430	399	463	577	*0.06*	698	593	603	*-0.13*
6600	Rome city, GA	346,443	495	599	560	545	615	*0.09*	508	491	521	*0.02*
6700	Tampa city, FL	2,067,959	172	474	334	260	19	*0.22*	68	57	95	*0.04*
6800	Lakeland city, FL	493,313	337	456	381	451	60	*0.06*	280	162	198	*-0.11*
6900	Sarasota city, FL	624,323	46	196	143	70	34	*0.13*	31	25	15	*-0.02*
7000	Miami city, FL	3,270,606	41	540	468	438	7	*0.59*	25	31	56	*0.04*
7100	West Palm Beach city, FL	1,177,580	42	405	338	310	8	*0.41*	27	12	31	*0.01*
7200	Cape Coral city, FL	487,212	44	283	107	74	4	*0.09*	28	9	7	*-0.03*
7300	Palm Bay city, FL	489,186	122	513	440	675	44	*0.44*	73	63	124	*0.07*
7400	Orlando city, FL	1,256,429	217	588	489	393	40	*0.38*	55	51	118	*0.09*
7500	Daytona Beach city, FL	464,483	119	315	202	141	29	*0.12*	104	61	63	*-0.06*
7600	Jacksonville city (remaind, FL	963,876	342	685	584	619	33	*0.34*	111	136	288	*0.25*
7700	Lake City city, FL	119,581	406	494	340	332	677	*-0.09*	328	358	287	*-0.06*
7800	Ocala city, FL	288,348	95	255	83	147	136	*-0.02*	117	35	29	*-0.12*
7900	Gainesville city, FL	260,538	303	637	397	554	228	*0.13*	258	211	229	*-0.04*
8000	Sumter city, SC	193,123	482	686	656	698	694	*0.24*	707	665	620	*-0.12*
8100	Columbia city, SC	622,711	516	674	653	669	656	*0.19*	440	364	532	*0.13*
8201	Barnwell city, SC	67,108	626	711	641	546	682	*0.02*	650	642	677	*0.04*
8202	Charleston city, SC	541,252	259	627	705	712	299	*0.62*	148	298	507	*0.50*
8300	Greenville city, SC	767,140	363	631	645	623	651	*0.39*	341	493	538	*0.27*
8401	South Augusta CDP, GA	461,606	639	706	696	655	542	*0.08*	602	542	606	*0.01*
8402	Washington city, GA	31,747	113	370	293	495	704	*0.25*	325	356	498	*0.24*
8501	Fitzgerald city, GA	24,894	689	421	426	366	505	*-0.36*	672	373	536	*-0.19*
8502	Cordele city, GA	36,920	352	418	552	491	174	*0.28*	644	325	413	*-0.32*
8503	Valdosta city, GA	207,199	484	622	439	395	266	*-0.06*	427	353	458	*0.04*
8601	Waycross city, GA	100,330	366	472	370	519	564	*0.01*	381	287	309	*-0.10*
8602	Brunswick city, GA	82,207	133	364	341	534	22	*0.29*	180	106	199	*0.03*
8701	Hinesville city, GA	107,749	542	720	651	427	292	*0.15*	689	720	668	*-0.03*
8702	Statesboro city, GA	93,504	314	501	390	503	592	*0.11*	486	529	455	*-0.04*
8800	Savannah city, GA	359,972	206	623	599	674	51	*0.55*	171	101	213	*0.06*
8900	Macon city, GA	343,193	515	684	698	689	330	*0.25*	439	476	537	*0.14*
9001	Vidalia city, GA	98,515	583	480	448	370	398	*-0.19*	651	386	414	*-0.33*
9002	Milledgeville city, GA	72,803	585	707	670	651	689	*0.12*	463	608	595	*0.18*
9003	Dublin city, GA	67,429	519	644	476	363	434	*-0.06*	375	534	415	*0.06*
9100	Atlanta city, GA	2,725,351	186	550	612	647	389	*0.59*	128	103	243	*0.16*
9200	Griffin city, GA	119,345	535	555	635	558	652	*0.14*	553	658	637	*0.12*
9301	Athens city, GA	165,746	317	594	578	654	567	*0.36*	344	395	475	*0.18*
9302	Toccoa city, GA	78,568	413	465	345	333	703	*-0.09*	474	554	615	*0.20*

9400	Gainesville city, GA	190,941	228	320	325	379	670	*0.13*	302	329	480	*0.25*
9500	Talladega city, AL	137,248	555	608	597	542	639	*0.06*	681	706	614	*-0.09*
9600	Anniston city, AL	396,926	448	624	559	555	675	*0.15*	540	583	611	*0.10*
9701	Columbus city (remainder), GA	289,795	671	715	722	720	614	*0.07*	544	633	720	*0.24*
9702	Americus city, GA	60,437	503	629	538	585	602	*0.05*	621	487	469	*-0.21*
9800	Auburn city, AL	123,116	510	717	697	672	659	*0.26*	581	699	634	*0.07*
9900	Tallahassee city, FL	349,748	458	609	497	530	610	*0.05*	266	294	311	*0.06*
10000	Panama City city, FL	147,465	189	380	236	293	18	*0.07*	135	53	104	*-0.04*
10101	Bainbridge city, GA	40,801	257	646	283	346	529	*0.04*	295	519	427	*0.18*
10102	Thomasville city, GA	59,265	321	375	557	374	170	*0.33*	318	225	562	*0.34*
10200	Albany city, GA	166,849	584	677	667	573	477	*0.12*	532	482	493	*-0.05*
10301	Eufaula city, AL	55,880	530	638	353	493	640	*-0.25*	462	522	448	*-0.02*
10302	Dothan city, AL	210,225	434	601	464	643	629	*0.04*	502	389	418	*-0.12*
10400	Meridian city, MS	148,315	651	620	382	361	465	*-0.37*	616	438	563	*-0.07*
10501	Columbus city, MS	92,611	606	603	542	490	664	*-0.09*	487	434	451	*-0.05*
10502	Starkville city, MS	98,221	655	476	462	367	688	*-0.27*	517	654	461	*-0.08*
10600	Birmingham city, AL	153,230	345	413	274	246	718	*-0.10*	584	483	433	*-0.21*
10700	Birmingham city, AL	940,211	404	602	636	595	316	*0.32*	333	289	486	*0.21*
10801	Tuscaloosa city, AL	243,485	581	659	666	639	680	*0.12*	625	488	579	*-0.06*
10802	Demopolis city, AL	65,429	697	582	449	461	721	*-0.34*	353	445	526	*0.24*
10900	Pensacola city, FL	515,942	200	591	568	694	80	*0.51*	161	198	346	*0.26*
11001	Mobile city, AL	534,425	296	572	513	506	73	*0.30*	241	208	273	*0.04*
11002	Atmore city, AL	73,540	706	653	465	561	653	*-0.33*	521	526	402	*-0.17*
11101	Montgomery city, AL	327,067	646	682	589	626	350	*-0.08*	505	314	373	*-0.18*
11102	Troy city, AL	77,708	429	552	403	394	650	*-0.04*	597	416	374	*-0.31*
11201	Bluefield city, WV	202,920	615	570	628	652	552	*0.02*	495	250	282	*-0.30*
11202	Welch city, WV	64,223	722	619	704	710	722	*-0.02*	484	310	544	*0.08*
11203	Big Stone Gap town, VA	85,936	645	612	525	317	452	*-0.17*	637	93	93	*-0.75*
11301	Fredericksburg city, VA	170,410	664	561	613	600	591	*-0.07*	468	244	443	*-0.03*
11302	Baltimore city, MD	2,348,219	452	704	712	713	147	*0.36*	364	472	651	*0.40*
11303	Colonial Beach town, VA	52,862	92	93	116	120	457	*0.03*	321	98	307	*-0.02*
11304	Arlington CDP, VA	4,019,817	383	641	695	716	317	*0.43*	270	396	566	*0.41*
11401	Marquette city, MI	125,941	436	683	652	574	470	*0.30*	376	406	597	*0.31*
11402	Marinette city, WI	110,064	364	410	349	269	574	*-0.02*	406	451	449	*0.06*
11403	Sault Ste. Marie city, MI	51,041	299	470	441	331	248	*0.20*	345	121	301	*-0.06*
11500	Jackson city, MI	284,663	433	650	657	562	376	*0.31*	701	687	695	*-0.01*
11600	Detroit city, MI	5,071,793	477	716	717	708	451	*0.33*	354	544	665	*0.43*
11700	Lansing city, MI	432,674	660	678	706	703	386	*0.06*	632	667	694	*0.09*
11800	Mount Pleasant city, MI	118,558	566	534	461	499	498	*-0.15*	658	576	621	*-0.05*
11900	Saginaw city, MI	526,596	426	660	689	649	523	*0.36*	539	656	699	*0.22*
12001	Big Rapids city, MI	104,544	293	429	326	325	475	*0.05*	588	407	540	*-0.07*
12002	Ludington city, MI	46,802	286	249	355	298	526	*0.10*	360	275	555	*0.27*
12100	Kalamazoo city, MI	479,510	509	643	678	661	361	*0.23*	686	666	698	*0.02*
12200	Grand Rapids city, MI	1,108,630	451	628	616	582	364	*0.23*	516	551	657	*0.20*
12301	Traverse City city, MI	124,682	73	128	243	262	338	*0.24*	141	38	90	*-0.07*
12302	Petoskey city, MI	67,906	59	270	322	152	196	*0.36*	107	32	144	*0.05*
12401	Alpena city, MI	84,702	196	377	369	433	517	*0.24*	206	239	431	*0.31*

12402	Houghton Lake CDP, MI	85,452	152	238	120	24	545	-0.04	199	37	55	-0.20
12501	Dayton city, OH	1,168,246	652	687	693	699	245	0.06	685	675	666	-0.03
12502	Washington city, OH	98,609	462	477	387	431	102	-0.10	713	681	629	-0.12
12600	Richmond city, IN	104,942	677	604	576	549	165	-0.14	700	700	693	-0.01
12701	Cincinnati city, OH	1,798,792	589	649	679	663	333	0.12	513	514	623	0.15
12702	Maysville city, KY	49,753	280	325	230	464	572	-0.07	712	655	708	-0.01
12800	Greensburg city, IN	119,729	473	520	389	466	374	-0.12	692	694	664	-0.04
12901	Lexington-Fayette, KY	452,598	381	516	530	611	306	0.21	400	340	442	0.06
12902	Mount Sterling city, KY	34,345	597	322	284	449	432	-0.43	677	616	589	-0.12
12903	Danville city, KY	76,413	261	277	358	215	481	0.13	619	651	630	0.02
13000	Fort Knox CDP, KY	162,451	674	661	671	722	662	0.00	674	704	714	0.06
13101	Louisville city, KY	1,005,917	488	652	660	678	315	0.24	407	423	598	0.26
13102	Madison city, IN	45,179	577	392	485	514	203	-0.13	683	674	631	-0.07
13103	Bardstown city, KY	56,650	442	394	306	417	414	-0.19	559	549	656	0.13
13200	Owensboro city, KY	168,349	572	458	524	414	635	-0.07	548	580	441	-0.15
13300	Findlay city, OH	240,597	673	606	619	547	183	-0.07	715	690	682	-0.05
13400	Lima city, OH	258,066	670	633	662	537	298	-0.01	716	697	669	-0.07
13501	Toledo city, OH	816,865	650	688	699	683	346	0.07	655	632	676	0.03
13502	Defiance city, OH	96,794	587	613	642	575	290	0.08	719	719	655	-0.09
13600	South Bend city, IN	629,902	575	654	622	618	462	0.07	613	578	653	0.06
13700	Elkhart city, IN	323,967	468	571	567	592	295	0.14	577	461	593	0.02
13800	Wabash city, IN	119,203	532	531	407	430	215	-0.17	569	590	590	0.03
13900	Kokomo city, IN	184,899	704	673	637	697	433	-0.09	649	693	700	0.07
14000	Muncie city, IN	413,851	680	648	683	634	255	0.00	652	703	691	0.05
14100	Fort Wayne city, IN	505,239	551	671	682	657	263	0.18	551	565	642	0.13
14200	Indianapolis city (remaind, IN	1,282,031	523	645	672	629	240	0.21	288	320	553	0.37
14300	Columbus city, IN	146,039	517	586	563	656	252	0.06	660	503	679	0.03
14400	Terre Haute city, IN	246,739	642	551	515	447	377	-0.18	663	564	680	0.02
14500	Lafayette city, IN	327,328	634	632	595	603	161	-0.05	662	662	658	-0.01
14600	Bloomington city, IN	255,816	508	508	487	589	454	-0.03	472	545	604	0.18
14700	Evansville city, IN	368,692	667	575	596	539	353	-0.10	536	566	512	-0.03
14801	Olney city, IL	57,748	336	132	105	178	405	-0.32	432	474	349	-0.12
14802	Vincennes city, IN	55,856	662	358	481	267	181	-0.25	694	524	466	-0.32
14900	Gary city, IN	643,037	669	718	720	718	528	0.07	479	649	697	0.30
15000	Canton city, OH	664,018	333	529	626	646	425	0.41	627	610	646	0.03
15100	Lorain city, OH	404,145	649	710	716	709	302	0.09	691	692	711	0.03
15200	Cleveland city, OH	2,588,518	479	692	709	705	426	0.32	373	492	624	0.35
15300	Parkersburg city, WV	198,078	595	578	639	642	444	0.06	574	587	489	-0.12
15400	Zanesville city, OH	178,179	593	590	553	516	471	-0.06	695	652	600	-0.13
15500	Steubenville city, OH	142,523	709	713	719	668	446	0.01	704	695	710	0.01
15600	Wheeling city, WV	203,852	702	634	684	559	516	-0.02	592	598	675	0.12
15700	Portsmouth city, OH	215,234	644	542	603	552	534	-0.06	696	659	618	-0.11
15800	Athens city, OH	138,668	679	614	607	616	608	-0.10	710	668	622	-0.12
15900	Columbus city, OH	1,450,425	531	656	681	690	160	0.21	457	507	560	0.14
16000	Mansfield city, OH	313,537	628	587	615	617	309	-0.02	688	707	683	-0.01
16100	State College borough, PA	292,130	565	455	506	568	531	-0.08	591	591	650	0.08
16200	Altoona city, PA	419,708	559	467	562	523	594	0.00	566	601	670	0.14

16300	Pittsburgh city, PA	2,597,833	571	576	634	641	541	*0.09*	424	528	663	*0.33*
16400	Youngstown city, OH	818,144	417	617	674	671	487	*0.36*	624	600	690	*0.09*
16500	Erie city, PA	654,568	461	478	504	577	354	*0.06*	666	650	671	*0.01*
16600	Roanoke city, VA	433,524	548	679	677	679	543	*0.18*	453	450	567	*0.16*
16701	Elkins city, WV	60,238	657	442	477	373	411	*-0.25*	534	313	416	*-0.16*
16702	Morgantown city, WV	253,304	694	640	582	653	588	*-0.16*	466	421	531	*0.09*
16703	Buckhannon city, WV	40,090	499	372	360	487	360	*-0.19*	384	506	371	*-0.02*
16801	Beckley city, WV	173,668	630	497	505	598	631	*-0.17*	316	166	305	*-0.02*
16802	Summersville town, WV	58,171	395	390	470	409	624	*0.10*	488	88	279	*-0.29*
16901	Charleston city, WV	350,721	690	669	701	677	627	*0.02*	489	318	481	*-0.01*
16902	Spencer city, WV	23,005	546	149	319	377	715	*-0.31*	697	253	156	*-0.75*
17000	Pikeville city, KY	212,757	693	425	406	359	702	*-0.40*	380	54	158	*-0.31*
17100	Huntington city, WV	339,337	705	675	664	628	466	*-0.06*	618	495	508	*-0.15*
17200	Harrisonburg city, VA	149,569	367	486	500	566	413	*0.18*	520	448	612	*0.13*
17300	Staunton city, VA	174,460	311	532	512	645	294	*0.28*	482	489	626	*0.20*
17400	Hagerstown city, MD	363,619	621	509	587	632	429	*-0.05*	682	623	688	*0.01*
17501	Cumberland city, MD	151,186	467	447	503	527	561	*0.05*	541	500	576	*0.05*
17502	Winchester city, VA	96,269	287	310	411	428	77	*0.17*	369	285	513	*0.20*
17600	Charlottesville city, VA	225,466	174	395	514	517	417	*0.47*	283	272	453	*0.24*
17700	Syracuse city, NY	1,107,773	536	618	617	581	322	*0.11*	524	606	702	*0.25*
17800	Oneonta city, NY	159,510	143	167	268	398	154	*0.17*	595	460	645	*0.07*
17900	Binghamton city, NY	304,877	578	530	565	662	355	*-0.02*	564	711	712	*0.21*
18000	Buffalo city, NY	2,350,758	590	681	694	687	334	*0.14*	437	630	704	*0.37*
18100	Elmira city, NY	348,168	428	466	510	631	310	*0.11*	661	702	706	*0.06*
18201	Olean city, NY	198,552	529	416	456	465	359	*-0.10*	676	639	641	*-0.05*
18202	St. Marys borough, PA	40,791	485	694	586	612	565	*0.14*	480	527	717	*0.33*
18300	Watertown city, NY	249,713	511	611	463	498	184	*-0.07*	600	648	705	*0.15*
18400	Plattsburgh city, NY	169,661	309	577	509	505	169	*0.28*	476	350	510	*0.05*
18500	Amsterdam city, NY	111,451	613	490	539	386	10	*-0.10*	573	676	715	*0.20*
18600	Albany city, NY	1,035,703	440	556	577	541	262	*0.19*	352	498	659	*0.43*
18700	Sunbury city, PA	187,362	547	507	491	565	362	*-0.08*	631	701	713	*0.11*
18800	Scranton city, PA	802,085	453	424	374	388	579	*-0.11*	519	404	638	*0.17*
18900	Williamsport city, PA	222,963	599	504	494	620	455	*-0.15*	561	638	701	*0.19*
19000	Allentown city, PA	595,081	604	564	650	648	521	*0.06*	542	568	687	*0.20*
19100	Reading city, PA	1,025,674	457	533	523	563	484	*0.09*	612	664	707	*0.13*
19200	Harrisburg city, PA	958,912	591	610	608	576	476	*0.02*	629	660	709	*0.11*
19300	Poughkeepsie city, NY	801,690	252	569	520	471	108	*0.37*	211	369	575	*0.50*
19400	New York city, NY	10,890,583	191	566	592	543	53	*0.56*	69	248	408	*0.47*
19500	Brick Township CDP, NJ	986,327	205	538	536	484	11	*0.46*	147	217	399	*0.35*
19600	Newark city, NJ	5,358,601	358	670	686	627	239	*0.45*	175	338	525	*0.49*
19700	Philadelphia city, PA	5,379,644	475	636	630	579	176	*0.21*	310	464	586	*0.38*
19800	Wilmington city, DE	513,293	631	714	718	715	438	*0.12*	190	202	594	*0.56*
19901	Dover city, DE	357,029	238	484	478	467	241	*0.33*	216	139	384	*0.23*
19902	Cambridge city, MD	139,615	80	184	176	185	75	*0.13*	297	171	425	*0.18*
19903	Chincoteague town, VA	44,764	319	64	123	107	200	*-0.27*	434	362	528	*0.13*
20001	Bangor city, ME	281,530	93	87	193	308	253	*0.14*	165	169	388	*0.31*
20002	Calais city, ME	35,308	68	23	13	17	84	*-0.08*	195	302	446	*0.35*

20003	Presque Isle city, ME	86,936	313	473	531	604	458	*0.30*	282	331	467	*0.26*
20100	Portland city, ME	659,567	135	266	337	510	342	*0.28*	176	195	434	*0.36*
20200	Burlington city, VT	291,889	156	312	336	446	384	*0.25*	248	107	281	*0.05*
20301	Berlin city, NH	93,132	70	97	148	425	421	*0.11*	385	154	393	*0.01*
20302	Claremont city, NH	248,653	81	131	179	475	356	*0.14*	267	96	223	*-0.06*
20401	Providence city, RI	1,509,789	537	658	690	686	532	*0.21*	339	427	628	*0.40*
20402	Nantucket CDP, MA	6,012	3	6	5	1	3	*0.00*	1	3	5	*0.01*
20403	Vineyard Haven CDP, MA	11,639	2	1	2	9	1	*0.00*	15	6	8	*-0.01*
20500	Boston city, MA	4,680,127	341	553	633	660	368	*0.40*	294	486	616	*0.45*
20600	Manchester city, NH	1,055,369	250	343	400	553	435	*0.21*	340	173	396	*0.08*
20700	Keene city, NH	111,709	64	209	257	462	307	*0.27*	311	161	321	*0.01*
20800	Springfield city, MA	672,970	444	596	675	695	524	*0.32*	626	657	685	*0.08*
20901	Bridgeport city, CT	3,287,116	241	523	598	625	392	*0.50*	397	390	565	*0.23*
20902	Pittsfield city, MA	175,197	79	265	442	560	492	*0.50*	281	159	502	*0.31*
21001	Ashland city, WI	45,915	89	137	102	137	427	*0.02*	235	251	251	*0.02*
21002	Houghton city, MI	45,101	335	526	673	572	620	*0.47*	368	511	437	*0.10*
21003	Ironwood city, MI	33,059	199	287	294	381	587	*0.13*	305	231	280	*-0.03*
21004	Rhinelander city, WI	58,162	67	84	101	25	518	*0.05*	47	30	68	*0.03*
21101	Rice Lake city, WI	83,782	104	176	207	117	556	*0.14*	193	168	295	*0.14*
21102	Amery city, WI	47,857	173	177	174	183	589	*0.00*	478	311	270	*-0.29*
21201	Hutchinson city, MN	67,242	258	396	367	400	246	*0.15*	576	647	550	*-0.04*
21202	Redwood Falls city, MN	34,927	219	110	134	101	229	*-0.12*	259	436	293	*0.05*
21301	Mankato city, MN	144,025	456	407	394	357	113	*-0.09*	538	671	573	*0.05*
21302	Owatonna city, MN	97,991	478	517	498	476	358	*0.03*	601	669	596	*-0.01*
21400	St. Cloud city, MN	209,591	427	417	386	507	431	*-0.06*	483	517	559	*0.11*
21501	Minneapolis city, MN	2,496,889	405	574	668	707	288	*0.36*	286	418	548	*0.36*
21502	Mora city, MN	34,066	209	158	281	330	585	*0.10*	571	560	587	*0.02*
21600	Hibbing city, MN	119,328	87	117	100	103	311	*0.02*	192	127	253	*0.08*
21701	Rochester city, MN	203,412	541	457	482	511	201	*-0.08*	507	626	644	*0.19*
21702	Austin city, MN	70,445	618	426	466	496	391	*-0.21*	703	635	609	*-0.13*
21801	Mason City city, IA	79,484	349	313	383	434	142	*0.05*	320	563	341	*0.03*
21802	Decorah city, IA	71,937	273	257	217	194	260	*-0.08*	496	581	472	*-0.03*
21900	Marshalltown city, IA	109,523	538	434	377	358	98	*-0.22*	643	679	582	*-0.08*
22001	Waterloo city, IA	217,058	554	423	532	569	185	*-0.03*	636	585	549	*-0.12*
22002	Iowa Falls city, IA	30,458	210	173	196	217	233	*-0.02*	254	271	316	*0.09*
22100	Iowa City city, IA	184,611	567	560	501	580	92	*-0.09*	647	698	588	*-0.08*
22200	Cedar Rapids city, IA	225,270	492	525	614	630	94	*0.17*	492	574	523	*0.04*
22300	Ottumwa city, IA	139,246	304	211	280	300	209	*-0.03*	450	505	516	*0.09*
22400	Sheboygan city, WI	184,298	614	698	687	591	611	*0.10*	702	717	716	*0.02*
22500	Appleton city, WI	489,344	609	672	647	602	441	*0.05*	628	615	635	*0.01*
22601	Green Bay city, WI	269,388	491	607	571	486	459	*0.11*	477	515	542	*0.09*
22602	Antigo city, WI	60,552	361	324	235	233	621	*-0.17*	607	405	534	*-0.10*
22700	Wausau city, WI	343,633	455	541	551	509	562	*0.13*	522	653	599	*0.11*
22800	Eau Claire city, WI	283,822	422	464	493	489	395	*0.10*	550	628	569	*0.03*
22900	La Crosse city, WI	200,301	540	524	517	520	537	*-0.03*	599	573	561	*-0.05*
23000	Monroe city, WI	111,619	431	378	262	324	243	*-0.23*	567	691	577	*0.01*
23100	Madison city, WI	509,140	552	605	574	597	261	*0.03*	420	540	543	*0.17*

23200	Dubuque city, IA	159,168	346	448	474	405	273	*0.18*	506	541	546	*0.06*
23301	Charleston city, IL	97,830	658	361	351	404	251	*-0.43*	679	643	564	*-0.16*
23302	Effingham city, IL	97,130	362	223	352	189	396	*-0.01*	355	440	459	*0.14*
23400	Bloomington city, IL	184,997	713	595	550	500	123	*-0.23*	675	622	574	*-0.14*
23500	Decatur city, IL	375,709	663	635	590	667	120	*-0.10*	582	682	633	*0.07*
23600	Burlington city, IA	137,543	513	471	428	407	130	*-0.12*	572	631	539	*-0.05*
23700	Galesburg city, IL	148,898	656	444	490	479	155	*-0.23*	678	677	681	*0.00*
23801	Davenport city, IA	374,685	643	626	646	614	339	*0.00*	587	611	636	*0.07*
23802	Clinton city, IA	70,990	377	487	427	416	119	*0.07*	452	619	585	*0.18*
23900	Peoria city, IL	516,618	681	583	580	584	320	*-0.14*	579	597	647	*0.09*
24000	Racine city, WI	517,725	647	703	702	684	519	*0.08*	557	617	684	*0.18*
24100	Milwaukee city, WI	1,576,491	635	712	710	701	533	*0.10*	411	562	661	*0.35*
24200	Kankakee city, IL	127,042	699	615	471	531	280	*-0.32*	608	644	632	*0.03*
24300	Chicago city, IL	7,332,926	384	702	707	693	277	*0.45*	203	478	617	*0.57*
24400	Rockford city, IL	567,043	603	579	583	622	347	*-0.03*	657	637	673	*0.02*
24500	Fort Leonard Wood CDP, MO	104,894	707	428	546	714	569	*-0.22*	448	467	652	*0.28*
24600	Farmington city, MO	123,822	569	389	344	387	257	*-0.31*	194	422	504	*0.43*
24701	St. Louis city, MO	2,221,983	563	701	703	688	304	*0.19*	105	372	557	*0.63*
24702	Mexico city, MO	34,954	596	285	247	294	324	*-0.48*	610	409	491	*-0.17*
24801	Jacksonville city, IL	84,129	607	357	309	272	275	*-0.41*	693	603	572	*-0.17*
24802	Springfield city, IL	254,766	579	545	488	494	291	*-0.13*	543	553	607	*0.09*
24900	Alton city, IL	368,497	632	585	543	588	460	*-0.12*	635	624	619	*-0.02*
25000	Quincy city, IL	146,027	332	331	347	268	274	*0.02*	435	475	568	*0.18*
25101	Mountain Home city, AR	51,785	63	11	33	4	681	*-0.04*	244	109	60	*-0.26*
25102	West Plains city, MO	80,043	141	60	30	38	447	*-0.15*	134	213	188	*0.07*
25103	Harrison city, AR	62,458	146	31	21	18	553	*-0.17*	289	206	226	*-0.09*
25104	Heber Springs city, AR	43,194	28	14	14	33	713	*-0.02*	221	155	177	*-0.06*
25105	Batesville city, AR	56,665	391	143	34	53	616	*-0.50*	357	214	298	*-0.08*
25200	Henderson city, KY	148,734	654	445	430	432	478	*-0.31*	497	509	412	*-0.12*
25300	Union City city, TN	111,076	476	359	307	223	563	*-0.23*	659	613	648	*-0.02*
25401	Paducah city, KY	131,411	493	342	308	327	461	*-0.26*	260	374	503	*0.34*
25402	Murray city, KY	30,735	385	250	260	436	600	*-0.17*	473	457	421	*-0.07*
25500	Mount Vernon city, IL	135,989	545	406	276	285	443	*-0.37*	583	431	365	*-0.30*
25601	Carbondale city, IL	262,229	586	462	401	360	500	*-0.26*	549	571	547	*0.00*
25602	Harrisburg city, IL	38,649	469	352	249	156	570	*-0.31*	529	368	347	*-0.25*
25701	Cape Girardeau city, MO	175,893	435	369	275	339	430	*-0.22*	132	232	289	*0.22*
25702	Poplar Bluff city, MO	68,126	195	105	40	36	372	*-0.21*	36	125	180	*0.20*
25800	Blytheville city, AR	112,558	602	492	413	292	605	*-0.26*	197	646	438	*0.33*
25900	Jonesboro city, AR	177,546	274	289	155	122	554	*-0.17*	447	430	369	*-0.11*
26001	Roseau city, MN	19,102	136	391	141	163	539	*0.01*	383	685	530	*0.20*
26002	Duluth city, MN	279,645	605	544	692	692	546	*0.12*	527	535	640	*0.16*
26003	Grand Marais city, MN	3,868	16	4	8	61	107	*-0.01*	17	13	94	*0.11*
26004	International Falls city, MN	16,299	251	697	508	205	555	*0.36*	313	366	432	*0.17*
26101	Moberly city, MO	55,761	277	327	104	159	382	*-0.24*	265	502	450	*0.26*
26102	Marshall city, MO	48,863	447	308	178	211	144	*-0.37*	443	570	385	*-0.08*
26103	Brookfield city, MO	23,087	281	139	147	123	485	*-0.19*	312	499	403	*0.13*
26104	Trenton city, MO	14,259	183	48	59	131	54	*-0.17*	413	394	398	*-0.02*

26105	Unionville city, MO	11,405	487	39	22	28	284	*-0.64*	615	410	405	*-0.29*
26106	Centerville city, IA	29,880	198	94	86	106	199	*-0.16*	412	420	435	*0.03*
26107	Kirksville city, MO	38,117	354	300	287	188	216	*-0.09*	304	459	376	*0.10*
26201	Bismarck city, ND	106,477	351	468	654	644	397	*0.42*	249	335	225	*-0.03*
26202	Elgin city, ND	3,549	376	330	270	685	573	*-0.15*	46	347	359	*0.43*
26203	Linton city, ND	11,698	103	51	97	191	244	*-0.01*	238	110	235	*0.00*
26204	Steele city, ND	3,332	592	74	90	521	415	*-0.70*	50	265	627	*0.80*
26301	Devils Lake city, ND	24,289	192	163	384	249	293	*0.27*	183	252	364	*0.25*
26302	Carrington city, ND	6,934	96	63	94	177	357	*0.00*	125	147	129	*0.01*
26303	Belcourt CDP, ND	16,399	698	383	410	406	513	*-0.40*	515	415	240	*-0.38*
26304	Minot city, ND	75,620	638	432	610	635	365	*-0.04*	214	496	362	*0.21*
26305	Rugby city, ND	13,064	124	59	292	63	437	*0.23*	62	393	390	*0.45*
26401	Buffalo town, SD	3,172	137	269	252	599	576	*0.16*	35	663	387	*0.49*
26402	Baker city, MT	3,103	25	37	396	564	367	*0.51*	40	100	64	*0.03*
26403	Bowman city, ND	4,503	334	153	241	119	491	*-0.13*	119	60	52	*-0.09*
26404	Lemmon city, SD	10,551	153	61	91	140	328	*-0.09*	90	156	187	*0.13*
26405	Scobey city, MT	2,266	62	50	585	44	318	*0.73*	169	70	108	*-0.08*
26406	Wolf Point city, MT	13,275	463	415	648	441	581	*0.26*	319	678	444	*0.17*
26407	Plentywood city, MT	4,732	179	47	79	39	227	*-0.14*	38	116	96	*0.08*
26408	Glasgow city, MT	13,402	157	134	564	368	625	*0.56*	218	402	248	*0.04*
26409	Glendive city, MT	12,804	256	203	572	413	593	*0.44*	151	260	107	*-0.06*
26410	Dickinson city, ND	27,945	437	212	507	423	422	*0.10*	30	175	28	*0.00*
26411	Sidney city, MT	24,120	344	188	183	251	453	*-0.22*	8	247	44	*0.05*
26412	Williston city, ND	27,030	294	126	371	195	497	*0.11*	11	87	13	*0.00*
26501	Brookings city, SD	37,639	695	452	417	329	143	*-0.39*	458	634	420	*-0.05*
26502	Madison city, SD	13,822	223	109	288	171	157	*0.09*	230	510	484	*0.35*
26503	Sioux Falls city, SD	166,686	543	469	419	483	96	*-0.17*	232	212	333	*0.14*
26504	Watertown city, SD	36,597	160	210	200	139	168	*0.06*	143	185	194	*0.07*
26601	Milbank city, SD	19,120	150	116	250	234	190	*0.14*	184	200	378	*0.27*
26602	Sisseton city, SD	21,736	392	100	261	221	104	*-0.18*	212	339	487	*0.38*
26603	McLaughlin city, SD	7,956	719	546	658	442	232	*-0.08*	684	721	674	*-0.01*
26604	Mobridge city, SD	8,052	171	161	342	125	373	*0.24*	71	163	193	*0.17*
26605	Aberdeen city, SD	53,889	213	344	282	403	117	*0.10*	231	301	422	*0.26*
26701	Bemidji city, MN	90,557	155	90	87	89	282	*-0.09*	323	267	345	*0.03*
26702	Grafton city, ND	34,909	305	224	254	196	238	*-0.07*	257	196	233	*-0.03*
26703	Thief River Falls city, MN	28,824	432	346	561	282	502	*0.18*	555	473	454	*-0.14*
26704	Grand Forks city, ND	114,353	691	549	661	676	197	*-0.04*	606	572	552	*-0.07*
26801	Fargo city, ND	186,935	624	435	529	548	305	*-0.13*	361	424	429	*0.09*
26802	Lisbon city, ND	16,577	397	292	205	295	135	*-0.27*	290	263	299	*0.01*
26803	Jamestown city, ND	40,169	465	186	267	448	219	*-0.27*	276	501	313	*0.05*
26804	Cooperstown city, ND	3,303	703	53	356	80	440	*-0.48*	110	290	252	*0.20*
26901	Fergus Falls city, MN	107,013	158	101	131	172	490	*-0.04*	287	303	381	*0.13*
26902	Little Falls city, MN	66,121	231	151	98	253	390	*-0.18*	392	612	511	*0.17*
27001	O'Neill city, NE	16,382	197	17	149	43	308	*-0.07*	116	186	152	*0.05*
27002	Ord city, NE	10,999	37	104	50	100	285	*0.02*	103	234	263	*0.22*
27003	Ainsworth city, NE	6,705	83	42	242	204	225	*0.22*	80	83	88	*0.01*
27004	Winner city, SD	12,283	53	24	172	69	146	*0.17*	108	207	361	*0.35*

27005	Yankton city, SD	46,006	163	230	219	345	134	*0.08*	271	293	379	*0.15*
27006	Mitchell city, SD	26,465	263	253	297	286	91	*0.05*	275	243	278	*0.00*
27007	Huron city, SD	20,678	504	243	408	244	319	*-0.13*	215	256	190	*-0.03*
27008	Parkston city, SD	21,139	102	118	132	136	314	*0.04*	308	172	509	*0.28*
27009	Chamberlain city, SD	10,882	111	305	253	128	547	*0.20*	307	458	254	*-0.07*
27010	Miller city, SD	5,968	140	202	343	259	271	*0.28*	45	278	332	*0.40*
27011	Pierre city, SD	18,859	675	295	388	702	64	*-0.40*	144	150	300	*0.22*
27012	Gettysburg city, SD	3,190	24	85	251	5	15	*0.31*	41	77	113	*0.10*
27101	Willmar city, MN	83,321	325	207	229	277	340	*-0.13*	398	380	470	*0.10*
27102	Marshall city, MN	51,976	401	179	126	168	180	*-0.38*	207	595	519	*0.43*
27201	Sioux Center city, IA	57,299	202	129	73	118	124	*-0.18*	315	344	317	*0.00*
27202	Worthington city, MN	61,396	270	181	138	130	254	*-0.18*	461	556	440	*-0.03*
27301	Spencer city, IA	61,754	116	175	108	93	58	*-0.01*	177	187	230	*0.07*
27302	Fairmont city, MN	51,420	246	124	238	133	48	*-0.01*	409	411	423	*0.02*
27401	Storm Lake city, IA	54,752	292	157	124	187	79	*-0.23*	444	479	308	*-0.19*
27402	Fort Dodge city, IA	102,471	236	301	204	280	152	*-0.04*	386	536	368	*-0.02*
27501	Des Moines city, IA	524,193	582	581	604	594	109	*0.03*	322	484	424	*0.14*
27502	Creston city, IA	34,795	439	326	180	206	131	*-0.36*	673	588	338	*-0.46*
27503	Atlantic city, IA	35,692	123	92	162	71	189	*0.05*	331	322	352	*0.03*
27504	Carroll city, IA	48,243	149	201	136	104	24	*-0.02*	298	308	337	*0.05*
27601	Rapid City city, SD	145,322	212	246	290	391	121	*0.11*	113	132	168	*0.08*
27602	North Eagle Butte CDP, SD	7,743	717	666	588	202	303	*-0.18*	641	710	718	*0.11*
27603	Philip city, SD	5,435	110	80	206	199	559	*0.13*	81	104	239	*0.22*
27604	Murdo city, SD	1,324	490	26	37	45	106	*-0.63*	14	20	224	*0.29*
27605	Rosebud CDP, SD	10,489	721	708	708	681	515	*-0.02*	722	722	722	*0.00*
27701	Scottsbluff city, NE	66,000	180	284	244	225	114	*0.09*	263	292	283	*0.03*
27702	Cheyenne city, WY	86,744	497	440	522	593	525	*0.03*	39	485	306	*0.37*
27703	Torrington town, WY	20,518	78	333	452	146	540	*0.52*	279	261	351	*0.10*
27704	Pine Ridge CDP, SD	19,858	633	278	373	75	162	*-0.36*	706	629	613	*-0.13*
27801	Norfolk city, NE	54,691	339	197	195	287	81	*-0.20*	363	367	312	*-0.07*
27802	Columbus city, NE	58,502	365	282	298	291	151	*-0.09*	475	518	497	*0.03*
27901	Hastings city, NE	41,027	409	198	475	411	63	*0.09*	374	462	401	*0.04*
27902	York city, NE	27,206	297	88	115	289	88	*-0.25*	338	221	249	*-0.12*
27903	Grand Island city, NE	71,884	627	334	420	378	100	*-0.29*	300	309	266	*-0.05*
28001	Sioux City city, IA	174,136	502	431	385	375	212	*-0.16*	580	469	428	*-0.21*
28002	West Point city, NE	24,921	372	141	209	175	153	*-0.23*	393	520	411	*0.02*
28101	Lincoln city, NE	273,359	500	506	516	658	177	*0.02*	371	579	527	*0.22*
28102	Nebraska City city, NE	40,159	184	98	106	148	116	*-0.11*	415	550	492	*0.11*
28201	Red Oak city, IA	49,152	214	206	181	161	97	*-0.05*	403	466	460	*0.08*
28202	Omaha city, NE	720,297	534	630	638	638	166	*0.14*	296	453	517	*0.31*
28301	Sterling city, CO	35,522	177	160	112	151	125	*-0.09*	301	222	192	*-0.15*
28302	Ogallala city, NE	16,878	207	147	66	67	25	*-0.20*	88	112	132	*0.06*
28303	Oshkosh city, NE	2,460	7	319	31	227	149	*0.03*	77	42	169	*0.13*
28304	Valentine city, NE	8,331	49	52	53	66	265	*0.01*	94	78	167	*0.10*
28305	Broken Bow city, NE	13,796	23	165	122	314	208	*0.14*	146	223	334	*0.26*
28306	North Platte city, NE	33,932	666	446	606	340	503	*-0.08*	367	441	370	*0.00*
28401	Colorado Springs city, CO	443,681	225	379	433	640	12	*0.29*	129	262	155	*0.04*

28402	Limon town, CO	4,529	40	254	54	23	423	*0.02*	33	193	101	*0.09*
28501	Springfield town, CO	4,556	108	82	75	54	671	*-0.05*	306	605	163	*-0.20*
28502	Pueblo city, CO	165,577	419	535	457	533	326	*0.05*	404	387	336	*-0.09*
28503	Trinidad city, CO	19,774	35	62	139	138	575	*0.14*	101	255	216	*0.16*
28504	Burlington city, CO	11,225	568	159	41	99	400	*-0.73*	59	179	236	*0.25*
28601	Oberlin city, KS	7,425	72	75	185	105	112	*0.16*	209	383	181	*-0.04*
28602	Norton city, KS	5,947	715	195	43	65	21	*-0.93*	208	604	140	*-0.09*
28603	Phillipsburg city, KS	11,668	394	43	119	41	410	*-0.38*	137	135	296	*0.22*
28604	Colby city, KS	17,613	148	133	163	283	404	*0.02*	179	157	66	*-0.16*
28605	Goodland city, KS	8,747	74	241	295	243	370	*0.31*	72	165	145	*0.10*
28606	St. Francis city, KS	5,825	118	30	81	20	442	*-0.05*	102	111	221	*0.17*
28607	McCook city, NE	21,058	58	96	154	304	46	*0.13*	174	69	208	*0.05*
28608	Kearney city, NE	51,732	359	365	398	319	175	*0.05*	224	456	268	*0.06*
28609	Lexington city, NE	44,047	278	190	113	79	188	*-0.23*	346	215	267	*-0.11*
28701	Salida city, CO	12,684	5	13	128	167	37	*0.17*	7	18	30	*0.03*
28702	Glenwood Springs city, CO	83,451	21	115	84	158	61	*0.09*	12	4	1	*-0.02*
28703	Kremmling town, CO	7,966	708	32	51	6	644	*-0.91*	16	7	4	*-0.02*
28704	Laramie city, WY	32,402	471	548	554	550	344	*0.12*	277	397	141	*-0.19*
28800	Fort Collins city, CO	339,896	181	303	291	384	85	*0.15*	121	224	134	*0.02*
28900	Denver city, CO	1,875,828	144	386	469	528	31	*0.45*	66	94	142	*0.11*
29001	Pratt city, KS	19,236	323	183	151	110	127	*-0.24*	122	99	170	*0.07*
29002	Coldwater city, KS	2,313	445	66	29	51	20	*-0.58*	324	284	231	*-0.13*
29003	Dodge City city, KS	37,454	388	236	213	186	182	*-0.24*	518	259	256	*-0.36*
29004	Great Bend city, KS	49,931	301	164	203	126	214	*-0.14*	334	216	185	*-0.21*
29005	Hutchinson city, KS	79,585	611	345	330	355	210	*-0.39*	498	333	463	*-0.05*
29006	Hays city, KS	37,533	407	217	259	288	496	*-0.21*	243	230	128	*-0.16*
29007	Plainville city, KS	9,582	159	99	82	83	482	*-0.11*	278	76	290	*0.02*
29008	Ness City city, KS	6,408	88	71	77	257	495	*-0.02*	78	201	179	*0.14*
29101	Concordia city, KS	21,756	289	136	71	166	279	*-0.30*	285	324	394	*0.15*
29102	Superior city, NE	12,421	97	81	85	209	205	*-0.02*	246	341	360	*0.16*
29103	Beloit city, KS	12,070	115	89	36	86	139	*-0.11*	65	210	357	*0.40*
29104	Salina city, KS	58,588	550	321	289	315	118	*-0.36*	512	315	286	*-0.31*
29201	Hiawatha city, KS	21,574	240	125	60	31	159	*-0.25*	471	307	315	*-0.22*
29202	Marysville city, KS	18,778	282	142	61	94	256	*-0.31*	255	288	410	*0.21*
29203	Manhattan city, KS	148,034	668	621	566	637	179	*-0.14*	611	696	686	*0.10*
29204	Topeka city, KS	292,055	507	519	535	556	103	*0.04*	596	425	488	*-0.15*
29301	Wichita city, KS	495,499	520	493	467	473	67	*-0.07*	359	399	377	*0.02*
29302	Newton city, KS	71,184	481	279	312	254	164	*-0.23*	514	413	445	*-0.10*
29303	Arkansas City city, KS	52,496	524	146	135	91	39	*-0.54*	653	569	499	*-0.21*
29401	Ottawa city, KS	48,551	290	178	168	155	163	*-0.17*	425	408	326	*-0.14*
29402	Emporia city, KS	46,157	610	437	424	571	82	*-0.26*	533	538	529	*-0.01*
29403	Bartlesville city, OK	147,891	449	219	231	228	101	*-0.30*	590	371	319	*-0.38*
29501	Kansas City city, KS	81,303	701	693	623	429	281	*-0.11*	640	715	692	*0.07*
29502	Kansas City city, MO	1,567,702	400	562	594	590	71	*0.27*	202	269	419	*0.30*
29503	St. Joseph city, MO	148,656	622	419	335	392	192	*-0.40*	390	516	505	*0.16*
29504	Sedalia city, MO	77,797	226	168	117	73	198	*-0.15*	226	220	259	*0.05*
29505	Maryville city, MO	35,200	415	286	140	216	235	*-0.38*	459	596	468	*0.01*

29506	Bethany city, MO	17,757	201	114	55	59	133	*-0.20*	414	332	211	*-0.28*
29601	Columbia city, MO	257,549	557	592	521	538	237	*-0.05*	317	470	541	*0.31*
29602	Eldon city, MO	63,769	105	49	12	16	622	*-0.13*	56	14	48	*-0.01*
29700	Springfield city, MO	361,945	316	273	199	265	222	*-0.16*	159	151	285	*0.17*
29800	Monett city, MO	102,422	215	44	23	22	375	*-0.27*	145	64	171	*0.04*
29901	Joplin city, MO	237,379	425	297	237	242	110	*-0.26*	423	317	264	*-0.22*
29902	Nevada city, MO	49,895	232	120	68	84	337	*-0.23*	229	432	447	*0.30*
30000	Russellville city, AR	117,317	386	235	167	135	550	*-0.30*	395	375	386	*-0.01*
30100	Fort Smith city, AR	291,240	390	353	224	226	399	*-0.23*	416	312	322	*-0.13*
30200	Muskogee city, OK	137,327	380	311	190	252	269	*-0.26*	585	454	348	*-0.33*
30300	Fayetteville city, AR	267,534	328	294	187	184	467	*-0.20*	205	228	269	*0.09*
30401	Stillwater city, OK	72,552	525	449	450	229	140	*-0.10*	343	558	148	*-0.27*
30402	Tulsa city, OK	820,055	291	337	323	299	145	*0.04*	251	181	151	*-0.14*
30403	Okmulgee city, OK	48,041	527	121	111	176	323	*-0.58*	609	684	302	*-0.43*
30501	Woodward city, OK	27,536	265	170	92	78	335	*-0.24*	74	95	42	*-0.04*
30502	Enid city, OK	103,019	326	127	88	154	289	*-0.33*	236	361	125	*-0.15*
30601	El Paso city, TX	730,035	414	589	649	700	207	*0.33*	436	304	331	*-0.15*
30602	Alamogordo city, NM	64,147	127	276	526	445	111	*0.55*	372	164	112	*-0.36*
30603	Truth or Consequences city, NM	9,912	182	56	15	8	2	*-0.23*	233	11	9	*-0.31*
30604	Deming city, NM	51,744	580	244	412	328	501	*-0.23*	309	143	204	*-0.15*
30605	Van Horn town, TX	3,407	126	479	318	88	678	*0.27*	170	481	24	*-0.20*
30701	Roswell city, NM	106,454	562	316	329	240	70	*-0.32*	253	203	83	*-0.24*
30702	Santa Rosa city, NM	6,408	712	67	95	284	558	*-0.86*	329	82	67	*-0.36*
30801	Hobbs city, NM	91,892	489	231	361	256	468	*-0.18*	152	140	80	*-0.10*
30802	Lubbock city, TX	270,417	408	314	296	320	206	*-0.16*	335	226	200	*-0.19*
30901	Clovis city, NM	68,772	711	362	480	297	234	*-0.32*	552	360	342	*-0.29*
30902	Littlefield city, TX	31,206	267	214	221	207	38	*-0.06*	589	465	214	*-0.52*
30903	Amarillo city, TX	210,999	347	240	313	239	45	*-0.05*	336	245	164	*-0.24*
30904	Pampa city, TX	60,977	350	204	258	281	76	*-0.13*	421	296	117	*-0.42*
30905	Wellington city, TX	9,452	57	112	26	52	449	*-0.04*	382	343	120	*-0.36*
30906	Memphis city, TX	9,572	84	21	47	46	16	*-0.05*	242	282	183	*-0.08*
30907	Matador town, TX	1,532	227	7	9	13	504	*-0.30*	446	68	111	*-0.46*
30908	Plainview city, TX	51,301	356	264	152	142	55	*-0.28*	656	477	318	*-0.47*
31001	Garden City city, KS	43,371	378	272	228	302	158	*-0.21*	262	354	126	*-0.19*
31002	Ulysses city, KS	14,540	188	402	222	113	469	*0.05*	314	233	215	*-0.14*
31003	Scott City city, KS	9,821	114	35	89	348	68	*-0.03*	219	170	91	*-0.18*
31004	Liberal city, KS	29,013	420	268	164	179	483	*-0.36*	422	117	166	*-0.36*
31005	Perryton city, TX	18,119	505	193	80	55	35	*-0.59*	389	71	109	*-0.39*
31006	Guymon city, OK	26,058	616	102	232	111	329	*-0.53*	510	334	219	*-0.40*
31007	Dumas city, TX	26,960	424	191	121	248	27	*-0.42*	326	525	147	*-0.25*
31101	Victoria city, TX	149,963	338	288	269	235	509	*-0.10*	349	414	205	*-0.20*
31102	La Grange city, TX	38,478	91	77	70	170	655	*-0.03*	198	183	76	*-0.17*
31103	Gonzales city, TX	17,205	245	404	133	354	645	*-0.16*	546	342	114	*-0.60*
31201	Austin city, TX	887,999	151	354	327	396	473	*0.24*	112	174	105	*-0.01*
31202	Marble Falls city, TX	34,308	12	9	3	2	126	*-0.01*	75	23	10	*-0.09*
31301	San Antonio city, TX	1,418,118	387	483	547	536	93	*0.22*	337	345	320	*-0.02*
31302	Beeville city, TX	37,590	601	498	486	341	632	*-0.16*	178	618	340	*0.22*

31303	Kerrville city, TX	53,508	15	19	19	42	283	*0.01*	54	48	40	*-0.02*
31304	Mason city, TX	3,423	8	5	44	58	436	*0.05*	127	153	160	*0.05*
31401	Odessa city, TX	253,938	310	215	266	261	66	*-0.06*	91	79	26	*-0.09*
31402	Pecos city, TX	37,700	700	341	315	419	301	*-0.53*	51	433	175	*0.17*
31403	Fort Stockton city, TX	18,753	302	108	218	401	419	*-0.12*	142	281	47	*-0.13*
31404	Alpine city, TX	17,264	101	154	46	150	549	*-0.08*	168	149	62	*-0.15*
31501	Crystal City city, TX	22,595	483	657	459	276	613	*-0.03*	491	607	404	*-0.12*
31502	Pearsall city, TX	18,726	619	78	48	351	420	*-0.79*	149	218	189	*0.06*
31503	Laredo city, TX	147,627	165	349	278	219	87	*0.16*	222	41	81	*-0.20*
31600	Brownsville city, TX	701,888	71	381	402	279	141	*0.46*	547	264	245	*-0.42*
31700	Corpus Christi city, TX	465,297	288	393	372	418	173	*0.12*	399	299	186	*-0.30*
31800	Bryan city, TX	169,826	549	559	405	350	669	*-0.20*	394	504	139	*-0.35*
31900	Lake Jackson city, TX	268,590	560	503	541	380	445	*-0.03*	501	627	358	*-0.20*
32000	Houston city, TX	3,601,782	237	488	534	415	90	*0.41*	227	229	146	*-0.11*
32100	Beaumont city, TX	453,230	659	482	537	469	332	*-0.17*	503	392	430	*-0.10*
32201	Lufkin city, TX	164,552	403	340	225	214	649	*-0.25*	438	378	137	*-0.42*
32202	Nacogdoches city, TX	94,372	239	189	125	232	687	*-0.16*	419	355	294	*-0.17*
32301	San Angelo city, TX	107,939	266	258	246	197	65	*-0.03*	396	391	157	*-0.33*
32302	Brady city, TX	23,116	85	106	35	60	366	*-0.07*	401	349	135	*-0.37*
32303	Junction city, TX	6,374	39	25	16	10	407	*-0.03*	299	81	53	*-0.34*
32304	Uvalde city, TX	32,153	112	218	173	56	59	*0.08*	234	240	103	*-0.18*
32305	Del Rio city, TX	43,250	443	385	518	529	351	*0.10*	604	555	220	*-0.53*
32306	Eagle Pass city, TX	36,378	710	573	688	615	17	*-0.03*	664	266	276	*-0.54*
32401	Big Spring city, TX	53,452	418	355	169	274	633	*-0.35*	188	209	98	*-0.12*
32402	Sweetwater city, TX	21,436	306	68	310	64	488	*0.01*	362	521	277	*-0.12*
32403	Snyder city, TX	27,660	99	339	248	81	223	*0.21*	252	437	100	*-0.21*
32501	Abilene city, TX	178,818	322	228	177	149	86	*-0.20*	274	192	61	*-0.30*
32502	Childress city, TX	8,200	170	8	39	96	578	*-0.18*	493	138	77	*-0.58*
32503	Stamford city, TX	16,595	131	162	27	30	628	*-0.14*	123	238	191	*0.09*
32601	Wichita Falls city, TX	140,375	600	281	220	343	47	*-0.53*	445	363	228	*-0.30*
32602	Graham city, TX	26,987	66	38	18	40	371	*-0.07*	95	119	25	*-0.10*
32603	Seymour city, TX	4,385	76	3	4	11	272	*-0.10*	261	242	127	*-0.19*
32604	Vernon city, TX	22,198	685	199	38	95	381	*-0.90*	563	365	202	*-0.50*
32701	Brownwood city, TX	54,013	203	111	93	77	379	*-0.15*	350	177	136	*-0.30*
32702	Stephenville city, TX	49,105	132	119	58	29	418	*-0.10*	268	280	86	*-0.25*
32801	Waco city, TX	249,106	446	399	301	316	352	*-0.20*	391	400	274	*-0.16*
32802	Corsicana city, TX	89,355	125	317	109	112	647	*-0.02*	442	352	184	*-0.36*
32900	Killeen city, TX	268,822	688	696	700	711	363	*0.02*	648	716	601	*-0.07*
33000	Fort Worth city, TX	1,443,402	308	485	445	454	220	*0.19*	292	330	197	*-0.13*
33100	Dallas city, TX	2,584,139	255	441	460	421	137	*0.28*	173	118	110	*-0.09*
33200	Paris city, TX	163,014	295	242	137	153	474	*-0.22*	429	552	392	*-0.05*
33300	Tyler city, TX	366,249	230	205	158	145	551	*-0.10*	256	273	174	*-0.11*
33400	Longview city, TX	269,555	343	293	240	181	557	*-0.14*	293	270	143	*-0.21*
33500	Texarkana city, TX	218,995	574	351	273	230	571	*-0.42*	469	419	323	*-0.20*
33601	Lawton city, OK	167,446	561	537	455	607	327	*-0.15*	530	621	483	*-0.07*
33602	Altus city, OK	50,463	360	329	156	97	508	*-0.28*	680	567	383	*-0.41*
33603	Frederick city, OK	10,384	678	248	96	68	479	*-0.81*	630	471	162	*-0.65*

33700	Ardmore city, OK	110,584	260	144	52	76	36	*-0.29*	185	306	154	*-0.04*
33801	Elk City city, OK	61,297	244	138	74	47	450	*-0.24*	84	184	23	*-0.08*
33802	Chickasha city, OK	71,297	272	338	127	82	331	*-0.20*	402	463	176	*-0.31*
33803	Oklahoma City city, OK	1,026,679	222	436	375	353	171	*0.21*	186	237	122	*-0.09*
33901	Ada city, OK	65,700	412	222	78	62	224	*-0.46*	366	513	210	*-0.22*
33902	Sherman city, TX	151,914	218	275	189	270	249	*-0.04*	528	512	389	*-0.19*
34001	Hot Springs city, AR	184,167	298	221	212	116	480	*-0.12*	291	189	207	*-0.12*
34002	Idabel city, OK	90,716	233	113	45	49	527	*-0.26*	410	449	339	*-0.10*
34201	Havre city, MT	26,677	480	216	328	290	612	*-0.21*	347	321	123	*-0.31*
34202	Cut Bank city, MT	23,600	629	194	184	108	383	*-0.62*	494	204	121	*-0.52*
34203	Great Falls city, MT	91,696	194	227	378	532	276	*0.26*	225	227	330	*0.15*
34204	Lewistown city, MT	12,602	18	54	67	275	296	*0.07*	126	89	238	*0.16*
34301	Cody city, WY	33,703	100	91	210	218	132	*0.15*	48	43	51	*0.00*
34302	Worland city, WY	13,197	164	306	157	231	393	*-0.01*	64	55	74	*0.01*
34303	Riverton city, WY	33,662	45	260	438	220	41	*0.55*	100	62	72	*-0.04*
34304	Sheridan city, WY	41,044	51	271	404	236	186	*0.49*	21	126	65	*0.06*
34305	Miles City city, MT	13,080	185	247	348	162	313	*0.23*	155	197	258	*0.14*
34306	Jordan town, MT	1,589	60	722	624	312	720	*0.78*	720	586	545	*-0.24*
34307	Colstrip CDP, MT	13,469	696	647	451	399	597	*-0.34*	455	557	464	*0.01*
34308	Billings city, MT	133,053	128	185	256	165	178	*0.18*	99	85	69	*-0.04*
34309	Harlowton city, MT	4,065	30	72	65	48	378	*0.05*	32	66	196	*0.23*
34401	Butte-Silver Bow (remainde, MT	8,424	56	10	145	115	138	*0.12*	26	36	50	*0.03*
34402	Bozeman city, MT	74,220	17	69	171	114	172	*0.21*	13	34	37	*0.03*
34403	Butte-Silver Bow (remainde, MT	58,752	166	234	321	347	26	*0.21*	98	148	150	*0.07*
34404	Butte-Silver Bow (remainde, MT	53,387	247	309	472	567	343	*0.31*	162	152	328	*0.23*
34501	Bonners Ferry city, ID	8,332	19	45	7	318	583	*-0.02*	22	17	84	*0.09*
34502	Libby city, MT	17,481	22	73	277	551	348	*0.35*	42	39	130	*0.12*
34503	Kalispell city, MT	88,928	26	29	144	98	195	*0.16*	24	21	43	*0.03*
34504	Missoula city, MT	107,012	54	70	194	160	202	*0.19*	53	45	71	*0.02*
34601	Gillette city, WY	41,182	371	382	644	92	598	*0.38*	154	92	12	*-0.20*
34602	Rawlins city, WY	16,659	692	400	533	258	493	*-0.22*	61	130	70	*0.01*
34603	Casper city, WY	72,354	262	237	423	364	221	*0.22*	67	52	32	*-0.05*
34604	Lusk town, WY	2,499	398	387	76	7	28	*-0.45*	29	72	49	*0.03*
34801	Las Vegas city, NM	42,932	117	348	188	144	596	*0.10*	272	249	182	*-0.12*
34802	Santa Fe city, NM	174,526	32	41	129	468	603	*0.13*	138	40	78	*-0.08*
34803	Tucumcari city, NM	11,810	498	291	255	72	268	*-0.34*	125	134	82	*-0.06*
34804	Clayton town, NM	4,124	720	12	103	32	448	*-0.86*	330	128	106	*-0.31*
34805	Alamosa city, CO	40,207	77	135	226	336	167	*0.21*	201	283	265	*0.09*
34901	Albuquerque city, NM	599,416	369	368	495	586	345	*0.17*	430	176	178	*-0.35*
34902	Socorro city, NM	17,327	518	187	444	132	402	*-0.10*	441	412	262	*-0.25*
35001	Phoenix city, AZ	2,278,696	221	461	545	480	211	*0.45*	217	105	115	*-0.14*
35002	Safford city, AZ	34,562	648	689	611	478	218	*-0.05*	671	446	522	*-0.21*
35100	Tucson city, AZ	794,180	253	412	484	544	341	*0.32*	408	194	201	*-0.29*
35201	Grand Junction city, CO	144,496	52	79	160	212	258	*0.15*	57	50	18	*-0.05*
35202	Gunnison city, CO	10,740	43	40	42	190	511	*0.00*	6	8	6	*0.00*
35300	Farmington city, NM	129,979	145	335	414	344	9	*0.37*	136	73	45	*-0.13*

35401	Flagstaff city, AZ	209,474	94	174	170	121	387	0.11	109	27	46	-0.09
35402	Cortez city, CO	32,797	168	290	422	502	535	0.35	157	146	85	-0.10
35500	Gallup city, NM	199,935	501	371	714	474	5	0.30	645	625	494	-0.21
35701	Twin Falls city, ID	97,938	120	156	62	321	129	-0.08	52	58	59	0.01
35702	Burley city, ID	38,893	264	232	311	424	300	0.07	239	480	478	0.33
35801	Boise City city, ID	340,801	139	267	264	397	52	0.17	82	131	165	0.12
35802	Ontario city, OR	51,022	220	213	153	271	236	-0.09	228	376	242	0.02
35803	McCall city, ID	9,363	4	46	11	21	49	0.01	3	5	14	0.02
35901	St. George city, UT	74,114	69	166	110	213	403	0.06	18	19	36	0.02
35902	Price city, UT	46,819	234	463	632	296	601	0.55	485	417	217	-0.37
35903	Moab city, UT	6,620	121	58	142	193	604	0.03	23	10	39	0.02
35904	Richfield city, UT	20,688	204	261	285	238	369	0.11	87	351	92	0.01
35905	Loa town, UT	2,177	6	57	6	12	700	0.00	19	80	35	0.02
36000	Provo city, UT	280,740	285	401	418	680	267	0.18	79	401	257	0.25
36100	Salt Lake City city, UT	1,129,963	340	554	549	636	156	0.29	131	246	206	0.10
36200	Logan city, UT	119,392	330	491	409	470	507	0.11	133	609	452	0.44
36301	Pocatello city, ID	237,736	269	427	519	557	408	0.35	150	443	400	0.35
36302	Salmon city, ID	11,032	9	27	32	37	43	0.03	9	90	33	0.03
36303	Jackson town, WY	14,611	20	22	17	14	349	0.00	2	1	2	0.00
36401	Craig city, CO	31,417	248	148	161	26	536	-0.12	10	22	17	0.01
36402	Vernal city, UT	34,856	271	274	223	337	560	-0.07	37	133	22	-0.02
36403	Soda Springs city, ID	13,047	175	336	621	313	464	0.62	200	254	324	0.17
36404	Rock Springs city, WY	77,411	324	414	540	382	530	0.30	89	141	54	-0.05
36501	Altamont CDP, OR	138,509	176	155	234	247	394	0.08	213	129	73	-0.19
36502	Burns city, OR	7,060	47	200	182	437	217	0.19	58	191	407	0.48
36503	Lakeview town, OR	7,186	29	65	57	180	32	0.04	83	102	159	0.11
36600	Redding city, CA	196,661	109	107	130	134	247	0.03	223	47	34	-0.26
36700	Eureka city, CA	132,181	14	83	186	200	242	0.24	365	142	149	-0.30
36800	Medford city, OR	209,038	48	76	72	109	23	0.03	86	59	75	-0.02
36901	Brookings city, OR	42,787	50	16	20	19	150	-0.04	106	26	41	-0.09
36902	Roseburg city, OR	154,922	142	150	114	250	62	-0.04	166	97	116	-0.07
37000	Modesto city, CA	611,683	373	360	415	365	325	0.06	565	370	203	-0.50
37100	Bakersfield city, CA	543,477	396	453	362	443	412	-0.05	523	348	212	-0.43
37200	Fresno city, CA	1,168,970	459	398	379	372	297	-0.11	562	429	255	-0.43
37300	Chico city, CA	345,836	216	192	118	241	270	-0.14	465	188	131	-0.46
37400	Sacramento city, CA	2,131,027	190	263	331	459	193	0.20	237	145	153	-0.12
37500	San Jose city, CA	2,119,668	275	350	436	518	30	0.22	204	336	297	0.13
37601	Elko city, NV	50,607	714	598	492	362	380	-0.31	560	295	99	-0.64
37602	Winnemucca city, NV	17,180	393	505	317	50	590	-0.11	405	539	119	-0.40
37603	Quincy-East Quincy CDP, CA	23,057	11	18	24	35	626	0.02	44	46	16	-0.04
37604	Reno city, NV	335,575	374	460	499	455	14	0.17	140	67	58	-0.11
37700	Santa Rosa city, CA	519,198	31	34	64	102	72	0.05	187	56	57	-0.18
37800	San Francisco city, CA	4,137,778	129	220	300	453	50	0.24	181	167	275	0.13
37901	Las Vegas city, NV	857,856	389	691	685	613	128	0.41	163	123	161	0.00
37902	Hawthorne CDP, NV	6,475	625	721	713	624	486	0.12	586	705	406	-0.25
37903	Mammoth Lakes town, CA	28,237	61	33	63	34	286	0.00	115	49	20	-0.13
38000	San Diego city, CA	2,498,016	130	298	359	606	6	0.32	139	199	209	0.10

38100	Yuma city, AZ	216,198	686	536	625	524	385	*-0.08*	622	274	304	*-0.44*
38200	Santa Barbara city, CA	586,770	90	95	159	322	57	*0.10*	160	120	102	*-0.08*
38300	Los Angeles city, CA	14,531,529	86	299	364	450	13	*0.39*	130	268	271	*0.20*
38401	Lewiston city, ID	79,411	327	226	271	273	95	*-0.08*	247	182	227	*-0.03*
38402	Pullman city, WA	69,392	637	539	631	513	312	*-0.01*	639	602	515	*-0.17*
38501	Moses Lake city, WA	68,361	684	518	305	356	230	*-0.53*	303	144	222	*-0.11*
38502	Wenatchee city, WA	78,455	138	408	429	389	416	*0.40*	97	65	246	*0.21*
38601	Spokane city, WA	497,428	154	307	339	408	89	*0.26*	92	86	173	*0.11*
38602	Spokane city, WA	70,593	107	239	350	383	336	*0.34*	114	137	241	*0.18*
38700	Longview city, WA	201,804	254	251	197	255	231	*-0.08*	196	75	195	*0.00*
38801	Portland city, OR	1,458,190	162	318	393	420	42	*0.32*	118	124	218	*0.14*
38802	City of the Dalles city, OR	57,120	98	304	316	458	148	*0.30*	70	91	272	*0.28*
38901	Eugene city, OR	788,525	283	280	245	371	99	*-0.05*	220	178	172	*-0.07*
38902	Newport city, OR	60,459	82	20	10	15	56	*-0.10*	93	24	38	*-0.08*
39000	Yakima city, WA	215,548	521	489	425	440	74	*-0.13*	332	305	353	*0.03*
39100	Kennewick city, WA	269,370	454	511	528	535	69	*0.10*	250	384	354	*0.14*
39201	La Grande city, OR	38,915	65	169	302	129	122	*0.33*	85	74	79	*-0.01*
39202	Enterprise city, OR	6,911	10	15	49	27	287	*0.05*	5	29	19	*0.02*
39203	Bend city, OR	102,745	34	86	56	87	264	*0.03*	20	15	11	*-0.01*
39204	Condon city, OR	3,113	229	122	175	124	424	*-0.07*	34	180	21	*-0.02*
39205	John Day city, OR	7,853	178	182	146	192	204	*-0.04*	63	44	133	*0.10*
39301	Friday Harbor town, WA	10,035	1	2	1	3	83	*0.00*	4	2	3	*0.00*
39302	Bellingham city, WA	127,780	134	172	215	410	115	*0.11*	96	33	97	*0.00*
39303	Port Angeles city, WA	76,610	33	36	28	85	194	*-0.01*	43	16	27	*-0.02*
39400	Seattle city, WA	3,147,582	284	374	453	570	105	*0.23*	167	122	232	*0.09*

Table A.3. MSA rankings and Rank Mobility Index (RMI)

MSA Code (2013)	MSA Name (2013)	2015-2019 population	Self-Employment Rate Ranking						Startup Rate Ranking			
			2015-2019	1990	1980	1970	1920	*RMI 1980-2019*	2015-2019	1988-1992	1978-1982	*RMI 1978-2019*
10180	Abilene, TX	170,669	160	49	40	37	138	*-0.32*	149	100	88	*-0.16*
10420	Akron, OH	703,845	206	286	359	362	330	*0.41*	320	312	332	*0.03*
10500	Albany, GA	148,436	279	322	307	177	235	*0.07*	207	174	169	*-0.10*
10540	Albany-Lebanon, OR	125,048	175	61	53	133	118	*-0.32*	88	117	117	*0.08*
10580	Albany-Schenectady-Troy, NY	880,736	282	278	278	186	182	*-0.01*	194	240	310	*0.31*
10740	Albuquerque, NM	912,108	141	82	146	198	166	*0.01*	170	98	92	*-0.21*
10780	Alexandria, LA	153,310	229	186	156	125	154	*-0.19*	218	131	136	*-0.22*
10900	Allentown-Bethlehem-Easton, PA-NJ	837,610	276	200	252	226	303	*-0.06*	278	273	367	*0.24*
11020	Altoona, PA	123,157	306	183	224	213	313	*-0.22*	333	325	293	*-0.11*
11100	Amarillo, TX	263,776	126	35	66	42	52	*-0.16*	156	140	132	*-0.06*
11180	Ames, IA	123,311	341	208	228	232	15	*-0.30*	192	369	153	*-0.10*
11460	Ann Arbor, MI	367,000	189	307	346	352	49	*0.42*	239	315	371	*0.35*
11500	Anniston-Oxford, AL	114,618	267	336	324	246	277	*0.15*	264	170	183	*-0.22*
11540	Appleton, WI	235,628	307	347	317	322	248	*0.03*	341	366	328	*-0.03*
11700	Asheville, NC	454,351	9	59	108	91	157	*0.26*	47	155	175	*0.34*
12020	Athens-Clarke County, GA	208,457	92	239	201	290	327	*0.29*	92	157	174	*0.22*
12060	Atlanta-Sandy Springs-Alpharetta, GA	5,862,424	72	189	234	239	282	*0.43*	98	168	204	*0.28*
12100	Atlantic City-Hammonton, NJ	266,105	271	255	190	40	13	*-0.22*	201	275	200	*0.00*
12220	Auburn-Opelika, AL	161,152	214	359	339	289	274	*0.33*	129	206	220	*0.24*
12260	Augusta-Richmond County, GA-SC	599,616	311	356	335	285	286	*0.06*	245	251	219	*-0.07*
12420	Austin-Round Rock-Georgetown, TX	2,114,441	59	87	67	98	211	*0.02*	50	94	67	*0.05*
12540	Bakersfield, CA	887,641	165	122	81	103	242	*-0.22*	106	77	64	*-0.11*
12580	Baltimore-Columbia-Towson, MD	2,796,733	197	346	355	356	101	*0.42*	214	238	282	*0.18*
12620	Bangor, ME	151,774	147	92	181	204	297	*0.09*	159	159	238	*0.21*
12700	Barnstable Town, MA	213,496	2	7	10	3	11	*0.02*	17	27	32	*0.04*
12940	Baton Rouge, LA	854,318	151	313	270	221	368	*0.32*	233	199	176	*-0.15*
12980	Battle Creek, MI	134,212	349	340	363	283	232	*0.04*	371	362	368	*-0.01*
13020	Bay City, MI	104,104	215	282	351	260	285	*0.36*	274	213	269	*-0.01*
13140	Beaumont-Port Arthur, TX	395,174	345	210	261	147	150	*-0.22*	301	216	245	*-0.15*
13220	Beckley, WV	118,828	344	212	194	262	366	*-0.40*	162	68	124	*-0.10*
13380	Bellingham, WA	220,821	51	24	28	88	86	*-0.06*	29	28	50	*0.06*
13460	Bend, OR	186,251	4	8	4	6	74	*0.00*	1	6	2	*0.00*
13740	Billings, MT	179,071	49	27	50	24	95	*0.00*	109	85	91	*-0.05*
13780	Binghamton, NY	241,874	309	221	240	307	190	*-0.18*	236	372	366	*0.35*
13820	Birmingham-Hoover, AL	1,085,330	179	258	288	220	220	*0.29*	235	239	254	*0.05*
13900	Bismarck, ND	127,503	134	133	312	337	215	*0.47*	172	184	113	*-0.16*

13980	Blacksburg-Christiansburg, VA	166,785	348	366	374	366	333	*0.07*	197	246	235	*0.10*
14010	Bloomington, IL	172,578	376	306	206	189	105	*-0.45*	357	355	267	*-0.24*
14020	Bloomington, IN	167,296	217	223	197	353	324	*-0.05*	136	146	135	*0.00*
14100	Bloomsburg-Berwick, PA	83,974	257	177	183	207	254	*-0.20*	359	330	315	*-0.12*
14260	Boise City, ID	710,743	46	39	43	67	43	*-0.01*	40	101	96	*0.15*
14460	Boston-Cambridge-Newton, MA-NH	4,832,346	145	192	256	275	205	*0.30*	266	326	339	*0.19*
14500	Boulder, CO	322,510	14	31	51	143	30	*0.10*	20	61	81	*0.16*
14540	Bowling Green, KY	174,498	261	117	83	72	364	*-0.47*	240	200	190	*-0.13*
14740	Bremerton-Silverdale-Port Orchard, WA	265,882	102	113	151	288	335	*0.13*	14	11	18	*0.01*
14860	Bridgeport-Stamford-Norwalk, CT	943,926	26	55	104	128	185	*0.21*	154	234	272	*0.31*
15180	Brownsville-Harlingen, TX	421,666	36	106	90	45	120	*0.14*	186	71	71	*-0.31*
15260	Brunswick, GA	117,400	50	84	68	162	24	*0.05*	56	81	107	*0.14*
15380	Buffalo-Cheektowaga, NY	1,130,175	314	362	349	320	195	*0.09*	269	314	329	*0.16*
15500	Burlington, NC	163,324	232	209	219	240	344	*-0.03*	231	321	302	*0.19*
15540	Burlington-South Burlington, VT	218,784	87	119	143	146	233	*0.15*	188	127	215	*0.07*
15680	California-Lexington Park, MD	112,290	317	281	247	339	338	*-0.19*	182	51	37	*-0.39*
15940	Canton-Massillon, OH	399,736	153	256	311	293	270	*0.42*	334	322	343	*0.02*
15980	Cape Coral-Fort Myers, FL	737,468	31	62	19	13	3	*-0.03*	8	20	22	*0.04*
16020	Cape Girardeau, MO-IL	96,976	182	178	64	129	231	*-0.31*	143	167	186	*0.11*
16060	Carbondale-Marion, IL	137,573	269	139	148	70	291	*-0.32*	204	95	126	*-0.21*
16180	Carson City, NV	54,773	118	89	150	31	162	*0.09*	24	34	13	*-0.03*
16220	Casper, WY	80,333	86	34	122	97	192	*0.10*	42	44	57	*0.04*
16300	Cedar Rapids, IA	270,056	220	188	266	273	93	*0.12*	327	324	268	*-0.16*
16540	Chambersburg-Waynesboro, PA	154,147	287	125	178	206	193	*-0.29*	305	292	304	*0.00*
16580	Champaign-Urbana, IL	226,323	329	325	326	350	51	*-0.01*	200	264	202	*0.01*
16620	Charleston, WV	264,113	347	273	325	268	301	*-0.06*	345	254	257	*-0.23*
16700	Charleston-North Charleston, SC	774,508	99	259	353	365	119	*0.68*	72	93	127	*0.15*
16740	Charlotte-Concord-Gastonia, NC-SC	2,545,560	129	294	300	244	360	*0.45*	114	262	303	*0.50*
16820	Charlottesville, VA	215,445	53	111	189	287	328	*0.36*	97	128	142	*0.12*
16860	Chattanooga, TN-GA	556,209	105	174	239	235	223	*0.36*	283	237	244	*-0.10*
16940	Cheyenne, WY	98,320	230	190	265	364	320	*0.09*	3	120	94	*0.24*
16980	Chicago-Naperville-Elgin, IL-IN-WI	9,508,605	176	350	352	325	174	*0.47*	171	307	336	*0.44*
17020	Chico, CA	225,817	55	14	5	16	108	*-0.13*	103	37	20	*-0.22*
17140	Cincinnati, OH-KY-IN	2,201,741	281	280	301	269	201	*0.05*	335	319	321	*-0.04*
17300	Clarksville, TN-KY	299,470	352	317	319	367	318	*-0.09*	145	145	146	*0.00*
17420	Cleveland, TN	122,563	122	123	121	111	246	*0.00*	332	276	264	*-0.18*
17460	Cleveland-Elyria, OH	2,056,898	239	351	361	354	222	*0.32*	279	327	354	*0.20*
17660	Coeur d'Alene, ID	157,322	28	9	34	18	175	*0.02*	6	8	9	*0.01*
17780	College Station-Bryan, TX	258,029	264	213	129	92	371	*-0.36*	99	73	34	*-0.17*
17820	Colorado Springs, CO	723,498	85	112	118	294	7	*0.09*	37	90	52	*0.04*
17860	Columbia, MO	205,369	240	234	191	200	115	*-0.13*	147	221	156	*0.02*

17900	Columbia, SC	824,278	235	305	290	303	367	*0.15*	195	178	171	*-0.06*
17980	Columbus, GA-AL	319,402	330	373	371	371	325	*0.11*	212	230	270	*0.15*
18020	Columbus, IN	82,481	180	266	212	277	225	*0.09*	376	323	372	*-0.01*
18140	Columbus, OH	2,077,761	245	290	308	311	124	*0.17*	272	287	265	*-0.02*
18580	Corpus Christi, TX	428,548	115	114	89	96	57	*-0.07*	208	89	111	*-0.26*
18700	Corvallis, OR	91,107	91	121	49	126	90	*-0.11*	84	87	65	*-0.05*
18880	Crestview-Fort Walton Beach-Destin, FL	272,056	32	181	106	369	317	*0.20*	10	33	26	*0.04*
19060	Cumberland, MD-WV	98,612	356	217	217	259	308	*-0.37*	291	225	241	*-0.13*
19100	Dallas-Fort Worth-Arlington, TX	7,320,663	98	124	130	100	112	*0.09*	140	180	172	*0.09*
19140	Dalton, GA	143,961	377	236	177	165	351	*-0.53*	367	345	234	*-0.35*
19180	Danville, IL	77,563	132	240	202	131	110	*0.19*	362	344	320	*-0.11*
19300	Daphne-Fairhope-Foley, AL	212,830	30	52	33	23	106	*0.01*	25	15	25	*0.00*
19340	Davenport-Moline-Rock Island, IA-IL	381,175	319	253	269	227	204	*-0.13*	348	310	318	*-0.08*
19380	Dayton, OH	803,543	340	344	362	360	164	*0.06*	352	348	312	*-0.11*
19460	Decatur, AL	152,271	247	182	168	196	358	*-0.21*	280	163	221	*-0.16*
19500	Decatur, IL	105,528	374	330	250	263	156	*-0.33*	360	356	346	*-0.04*
19660	Deltona-Daytona Beach-Ormond Beach, FL	646,288	37	57	24	15	18	*-0.03*	12	35	54	*0.11*
19740	Denver-Aurora-Lakewood, CO	2,892,066	63	109	153	161	34	*0.24*	61	132	157	*0.26*
19780	Des Moines-West Des Moines, IA	680,439	254	226	238	184	89	*-0.04*	268	311	246	*-0.06*
19820	Detroit-Warren-Dearborn, MI	4,317,848	210	374	368	351	259	*0.42*	221	286	322	*0.27*
20020	Dothan, AL	148,252	113	166	72	107	345	*-0.11*	217	183	163	*-0.14*
20100	Dover, DE	176,699	293	304	321	299	104	*0.07*	63	147	177	*0.30*
20220	Dubuque, IA	96,982	288	335	344	333	214	*0.15*	373	373	369	*-0.01*
20260	Duluth, MN-WI	289,247	294	187	332	315	312	*0.10*	285	215	256	*-0.08*
20500	Durham-Chapel Hill, NC	626,695	169	287	294	319	332	*0.33*	205	249	266	*0.16*
20700	East Stroudsburg, PA	168,032	183	83	63	46	92	*-0.32*	110	57	152	*0.11*
20740	Eau Claire, WI	167,406	154	147	193	215	98	*0.10*	252	243	210	*-0.11*
20940	El Centro, CA	180,701	302	168	237	134	213	*-0.17*	69	40	43	*-0.07*
21060	Elizabethtown-Fort Knox, KY	150,913	364	355	366	376	362	*0.01*	193	137	83	*-0.29*
21140	Elkhart-Goshen, IN	204,558	248	241	272	234	181	*0.06*	377	364	350	*-0.07*
21300	Elmira, NY	84,895	286	276	236	316	160	*-0.13*	370	367	363	*-0.02*
21340	El Paso, TX	840,477	201	237	315	346	102	*0.30*	123	111	145	*0.06*
21500	Erie, PA	273,835	289	232	210	242	208	*-0.21*	368	353	362	*-0.02*
21660	Eugene-Springfield, OR	373,340	61	25	26	56	66	*-0.09*	78	60	59	*-0.05*
21780	Evansville, IN-KY	314,960	332	228	214	195	218	*-0.31*	336	331	285	*-0.14*
22020	Fargo, ND-MN	240,421	320	127	182	225	128	*-0.37*	255	241	226	*-0.08*
22140	Farmington, NM	126,515	318	251	209	139	1	*-0.29*	209	107	87	*-0.32*
22180	Fayetteville, NC	519,101	354	367	358	374	251	*0.01*	184	160	154	*-0.08*
22220	Fayetteville-Springdale-Rogers, AR	514,259	133	75	41	38	250	*-0.24*	134	169	114	*-0.05*
22380	Flagstaff, AZ	141,274	138	162	135	60	123	*-0.01*	112	50	49	*-0.17*
22420	Flint, MI	407,875	253	371	376	372	329	*0.33*	234	291	364	*0.35*

22500	Florence, SC	205,502	337	268	221	117	375	-0.31	295	253	209	-0.23
22520	Florence-Muscle Shoals, AL	147,327	110	136	184	149	348	0.20	307	162	147	-0.43
22540	Fond du Lac, WI	102,597	350	354	287	175	296	-0.17	366	363	323	-0.11
22660	Fort Collins, CO	344,786	44	40	31	55	32	-0.03	15	42	29	0.04
22900	Fort Smith, AR-OK	249,777	190	104	62	52	230	-0.34	228	197	184	-0.12
23060	Fort Wayne, IN	406,305	273	345	360	326	228	0.23	337	361	348	0.03
23420	Fresno, CA	984,521	177	108	110	75	172	-0.18	121	125	82	-0.10
23460	Gadsden, AL	102,748	166	163	132	122	268	-0.09	276	247	247	-0.08
23540	Gainesville, FL	323,799	114	279	116	209	142	0.01	104	106	62	-0.11
23580	Gainesville, GA	198,667	75	79	131	71	264	0.15	173	211	203	0.08
23900	Gettysburg, PA	102,470	252	115	100	99	267	-0.40	262	257	243	-0.05
24020	Glens Falls, NY	125,892	82	54	70	132	143	-0.03	179	134	206	0.07
24140	Goldsboro, NC	123,603	292	284	297	216	349	0.01	226	289	228	0.01
24220	Grand Forks, ND-MN	101,745	359	219	329	345	94	-0.08	326	192	173	-0.41
24260	Grand Island, NE	75,480	310	69	124	82	81	-0.49	191	181	144	-0.13
24300	Grand Junction, CO	151,218	48	18	54	49	147	0.02	198	49	21	-0.47
24340	Grand Rapids-Kentwood, MI	1,062,392	199	257	251	199	189	0.14	344	318	314	-0.08
24420	Grants Pass, OR	86,251	16	6	2	2	36	-0.04	28	32	23	-0.01
24500	Great Falls, MT	81,625	79	42	123	230	109	0.12	131	92	121	-0.03
24540	Greeley, CO	305,345	94	93	114	172	117	0.05	35	151	74	0.10
24580	Green Bay, WI	319,401	283	312	264	150	269	-0.05	355	338	280	-0.20
24660	Greensboro-High Point, NC	762,063	140	230	242	251	337	0.27	271	294	308	0.10
24780	Greenville, NC	178,433	212	372	276	141	342	0.17	229	203	125	-0.28
24860	Greenville-Anderson, SC	895,942	135	246	281	210	363	0.39	185	339	316	0.35
25060	Gulfport-Biloxi, MS	412,115	268	191	161	137	84	-0.28	248	172	166	-0.22
25180	Hagerstown-Martinsburg, MD-WV	283,147	325	203	260	281	276	-0.17	265	228	291	0.07
25220	Hammond, LA	132,057	186	172	149	51	111	-0.10	153	75	61	-0.24
25260	Hanford-Corcoran, CA	150,691	362	310	158	157	114	-0.54	169	78	47	-0.32
25420	Harrisburg-Carlisle, PA	571,013	296	291	275	205	273	-0.06	338	357	358	0.05
25500	Harrisonburg, VA	133,557	188	202	186	241	168	-0.01	261	236	237	-0.06
25540	Hartford-East Hartford-Middletown, CT	1,207,677	171	297	343	334	278	0.46	292	341	357	0.17
25620	Hattiesburg, MS	168,177	170	101	79	25	283	-0.24	160	82	97	-0.17
25860	Hickory-Lenoir-Morganton, NC	366,678	159	245	291	296	370	0.35	323	371	344	0.06
25940	Hilton Head Island-Bluffton, SC	214,752	29	169	229	342	302	0.53	11	10	5	-0.02
25980	Hinesville, GA	80,041	365	377	377	314	376	0.03	93	29	4	-0.24
26140	Homosassa Springs, FL	145,169	23	15	1	1	29	-0.06	18	4	1	-0.05
26300	Hot Springs, AR	98,555	38	21	17	8	9	-0.06	74	55	89	0.04
26380	Houma-Thibodaux, LA	210,162	193	99	61	34	353	-0.35	311	118	108	-0.54
26420	Houston-The Woodlands-Sugar Land, TX	6,884,138	89	153	173	94	65	0.22	144	185	185	0.11
26580	Huntington-Ashland, WV-KY-OH	361,832	367	332	310	267	295	-0.15	310	176	207	-0.27
26620	Huntsville, AL	457,003	270	285	292	327	369	0.06	246	219	178	-0.18

26820	Idaho Falls, ID	145,507	70	107	139	167	210	*0.18*	64	190	191	*0.34*
26900	Indianapolis-Carmel-Anderson, IN	2,029,472	242	269	295	250	159	*0.14*	244	263	287	*0.11*
26980	Iowa City, IA	170,677	298	204	180	297	83	*-0.31*	267	272	139	*-0.34*
27060	Ithaca, NY	102,642	143	97	141	243	103	*-0.01*	363	368	326	*-0.10*
27100	Jackson, MI	158,636	203	308	350	274	265	*0.39*	325	278	327	*0.01*
27140	Jackson, MS	597,727	194	207	196	121	352	*0.01*	223	217	158	*-0.17*
27180	Jackson, TN	178,442	191	152	119	138	357	*-0.19*	358	191	194	*-0.44*
27260	Jacksonville, FL	1,503,574	120	319	215	231	33	*0.25*	60	123	168	*0.29*
27340	Jacksonville, NC	195,069	372	376	375	377	355	*0.01*	75	41	38	*-0.10*
27500	Janesville-Beloit, WI	162,152	343	342	305	336	260	*-0.10*	288	334	296	*0.02*
27620	Jefferson City, MO	151,273	277	218	128	127	137	*-0.40*	206	227	182	*-0.06*
27740	Johnson City, TN	202,049	167	118	220	169	341	*0.14*	277	265	231	*-0.12*
27780	Johnstown, PA	133,009	327	220	267	212	359	*-0.16*	343	313	333	*-0.03*
27860	Jonesboro, AR	131,241	109	68	39	36	292	*-0.19*	178	156	138	*-0.11*
27900	Joplin, MO	178,100	168	45	27	28	38	*-0.38*	254	222	181	*-0.19*
28020	Kalamazoo-Portage, MI	262,745	256	303	322	317	184	*0.18*	321	300	300	*-0.06*
28100	Kankakee, IL	110,637	375	323	203	300	167	*-0.46*	296	301	273	*-0.06*
28140	Kansas City, MO-KS	2,124,518	174	199	218	187	64	*0.12*	164	226	240	*0.20*
28420	Kennewick-Richland, WA	289,527	211	252	304	271	45	*0.25*	62	165	160	*0.26*
28660	Killeen-Temple, TX	444,716	353	337	340	357	217	*-0.03*	120	158	68	*-0.14*
28700	Kingsport-Bristol, TN-VA	306,546	152	233	253	236	340	*0.27*	314	328	288	*-0.07*
28740	Kingston, NY	178,665	21	65	86	73	56	*0.17*	16	62	164	*0.39*
28940	Knoxville, TN	853,337	119	160	200	217	294	*0.22*	281	196	201	*-0.21*
29020	Kokomo, IN	82,331	360	329	354	368	310	*-0.02*	306	375	375	*0.18*
29100	La Crosse-Onalaska, WI-MN	136,542	338	274	230	272	258	*-0.29*	361	329	255	*-0.28*
29180	Lafayette, LA	489,914	43	131	93	63	280	*0.13*	141	152	109	*-0.09*
29200	Lafayette-West Lafayette, IN	228,541	358	324	306	343	77	*-0.14*	253	266	250	*-0.01*
29340	Lake Charles, LA	208,549	260	263	263	168	25	*0.01*	215	204	199	*-0.04*
29420	Lake Havasu City-Kingman, AZ	207,695	76	29	29	9	48	*-0.13*	43	2	11	*-0.09*
29460	Lakeland-Winter Haven, FL	686,218	146	156	112	123	60	*-0.09*	94	149	165	*0.19*
29540	Lancaster, PA	540,999	111	137	154	151	219	*0.11*	290	337	359	*0.18*
29620	Lansing-East Lansing, MI	546,772	308	320	345	332	224	*0.10*	263	244	286	*0.06*
29700	Laredo, TX	273,526	66	80	55	47	58	*-0.03*	76	19	70	*-0.02*
29740	Las Cruces, NM	216,069	106	165	97	245	347	*-0.02*	118	52	98	*-0.05*
29820	Las Vegas-Henderson-Paradise, NV	2,182,004	173	360	348	310	212	*0.47*	108	166	167	*0.16*
29940	Lawrence, KS	120,290	181	173	223	228	55	*0.11*	146	105	137	*-0.02*
30020	Lawton, OK	127,620	321	363	216	361	234	*-0.28*	180	86	44	*-0.36*
30140	Lebanon, PA	139,729	284	159	164	258	299	*-0.32*	319	303	347	*0.07*
30300	Lewiston, ID-WA	62,638	185	37	46	53	23	*-0.37*	225	142	118	*-0.28*
30340	Lewiston-Auburn, ME	107,602	163	144	165	255	290	*0.01*	230	187	259	*0.08*
30460	Lexington-Fayette, KY	510,647	127	185	188	238	107	*0.16*	237	232	216	*-0.06*
30620	Lima, OH	103,175	361	261	316	193	161	*-0.12*	375	376	330	*-0.12*
30700	Lincoln, NE	330,329	241	193	199	347	132	*-0.11*	202	268	233	*0.08*

30780	Little Rock-North Little Rock-Conway, AR	737,015	192	197	205	148	227	*0.03*	148	193	196	*0.13*
30860	Logan, UT-ID	137,629	112	151	92	102	263	*-0.05*	32	143	85	*0.14*
30980	Longview, TX	284,796	137	60	44	29	354	*-0.25*	174	126	100	*-0.20*
31020	Longview, WA	106,778	158	157	88	144	170	*-0.19*	142	186	218	*0.20*
31080	Los Angeles-Long Beach-Anaheim, CA	13,249,614	20	56	87	104	14	*0.18*	66	210	205	*0.37*
31140	Louisville/Jefferson County, KY-IN	1,257,088	218	292	286	292	183	*0.18*	308	269	292	*-0.04*
31180	Lubbock, TX	316,474	161	66	60	59	75	*-0.27*	152	97	119	*-0.09*
31340	Lynchburg, VA	261,652	237	198	241	279	241	*0.01*	238	295	289	*0.14*
31420	Macon-Bibb County, GA	229,504	184	314	342	208	134	*0.42*	211	233	214	*0.01*
31460	Madera, CA	155,433	224	33	42	22	266	*-0.48*	67	21	33	*-0.09*
31540	Madison, WI	653,725	263	267	233	237	145	*-0.08*	289	285	223	*-0.18*
31700	Manchester-Nashua, NH	413,035	207	164	179	298	315	*-0.07*	293	207	260	*-0.09*
31740	Manhattan, KS	132,928	363	333	318	370	153	*-0.12*	116	114	123	*0.02*
31860	Mankato, MN	100,749	251	214	126	154	82	*-0.33*	329	332	262	*-0.18*
31900	Mansfield, OH	121,100	323	235	296	194	191	*-0.07*	298	350	331	*0.09*
32580	McAllen-Edinburg-Mission, TX	855,176	18	96	105	44	226	*0.23*	115	53	75	*-0.11*
32780	Medford, OR	216,574	17	12	16	32	22	*0.00*	46	48	40	*-0.02*
32820	Memphis, TN-MS-AR	1,339,623	272	299	273	291	196	*0.00*	331	256	232	*-0.26*
32900	Merced, CA	271,382	305	167	185	153	284	*-0.32*	81	129	55	*-0.07*
33100	Miami-Fort Lauderdale-Pompano Beach, FL	6,090,660	11	179	133	93	4	*0.32*	19	43	73	*0.14*
33140	Michigan City-La Porte, IN	110,154	291	349	303	330	314	*0.03*	284	252	340	*0.15*
33220	Midland, MI	83,355	221	238	338	323	339	*0.31*	132	374	377	*0.65*
33260	Midland, TX	173,816	73	10	22	21	35	*-0.14*	100	47	78	*-0.06*
33340	Milwaukee-Waukesha, WI	1,575,223	316	369	365	355	322	*0.13*	324	354	365	*0.11*
33460	Minneapolis-St. Paul-Bloomington, MN-WI	3,573,609	162	195	277	344	173	*0.31*	251	297	301	*0.13*
33540	Missoula, MT	117,309	39	17	58	48	122	*0.05*	44	59	60	*0.04*
33660	Mobile, AL	430,655	228	277	222	178	10	*-0.02*	258	188	195	*-0.17*
33700	Modesto, CA	543,194	150	110	125	78	129	*-0.07*	133	108	69	*-0.17*
33740	Monroe, LA	203,457	222	141	138	114	306	*-0.22*	181	148	140	*-0.11*
33780	Monroe, MI	149,727	326	353	357	219	271	*0.08*	220	198	274	*0.14*
33860	Montgomery, AL	373,544	313	326	244	256	163	*-0.18*	260	189	197	*-0.17*
34060	Morgantown, WV	139,157	342	300	213	329	346	*-0.34*	227	136	129	*-0.26*
34100	Morristown, TN	140,912	136	132	117	265	144	*-0.05*	318	320	299	*-0.05*
34580	Mount Vernon-Anacortes, WA	125,612	67	11	8	35	169	*-0.16*	49	13	24	*-0.07*
34620	Muncie, IN	115,020	366	321	347	248	158	*-0.05*	273	349	290	*0.05*
34740	Muskegon, MI	173,297	346	327	336	305	253	*-0.03*	302	296	353	*0.14*
34820	Myrtle Beach-Conway-North Myrtle Beach, SC-NC	463,987	35	47	38	33	377	*0.01*	26	18	46	*0.05*
34900	Napa, CA	139,623	24	22	25	85	140	*0.00*	127	72	63	*-0.17*
34940	Naples-Marco Island, FL	371,453	3	30	12	5	2	*0.02*	7	7	15	*0.02*
34980	Nashville-Davidson--Murfreesboro--Franklin, TN	1,871,903	84	103	172	159	155	*0.23*	189	208	224	*0.09*
35100	New Bern, NC	124,786	315	206	258	328	199	*-0.15*	86	65	66	*-0.05*

35300	New Haven-Milford, CT	857,513	131	295	282	249	202	0.40	257	267	307	0.13
35380	New Orleans-Metairie, LA	1,267,777	60	248	245	124	70	0.49	165	235	239	0.20
35620	New York-Newark-Jersey City, NY-NJ-PA	19,294,236	83	231	248	182	63	0.44	85	212	249	0.44
35660	Niles, MI	154,133	103	161	198	181	141	0.25	270	283	281	0.03
35840	North Port-Sarasota-Bradenton, FL	803,709	10	28	21	10	31	0.03	36	45	35	0.00
35980	Norwich-New London, CT	267,390	213	302	309	282	216	0.26	242	259	306	0.17
36100	Ocala, FL	353,526	34	70	23	58	135	-0.03	23	30	36	0.03
36140	Ocean City, NJ	93,086	52	53	36	11	6	-0.04	4	14	7	0.01
36220	Odessa, TX	160,579	144	88	71	74	247	-0.19	122	88	86	-0.10
36260	Ogden-Clearfield, UT	662,875	202	262	204	340	236	0.01	51	171	105	0.14
36420	Oklahoma City, OK	1,382,841	74	116	95	68	87	0.06	101	116	115	0.04
36500	Olympia-Lacey-Tumwater, WA	279,711	142	134	91	130	97	-0.14	33	25	27	-0.02
36540	Omaha-Council Bluffs, NE-IA	931,779	244	265	284	266	133	0.11	222	274	251	0.08
36740	Orlando-Kissimmee-Sanford, FL	2,508,970	81	225	152	79	27	0.19	58	91	112	0.14
36780	Oshkosh-Neenah, WI	170,411	335	364	367	331	229	0.09	374	370	349	-0.07
36980	Owensboro, KY	118,477	301	158	211	142	305	-0.24	312	258	213	-0.26
37100	Oxnard-Thousand Oaks-Ventura, CA	847,263	41	32	80	190	127	0.10	54	96	80	0.07
37340	Palm Bay-Melbourne-Titusville, FL	585,507	65	215	142	335	62	0.20	34	70	116	0.22
37460	Panama City, FL	182,161	80	149	75	101	17	-0.01	45	38	45	0.00
37620	Parkersburg-Vienna, WV	90,758	334	318	298	278	240	-0.10	317	309	242	-0.20
37860	Pensacola-Ferry Pass-Brent, FL	488,246	116	244	254	286	41	0.37	90	80	128	0.10
37900	Peoria, IL	406,883	351	254	257	218	177	-0.25	350	333	355	0.01
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	6,079,130	216	283	280	222	139	0.17	210	271	297	0.23
38060	Phoenix-Mesa-Chandler, AZ	4,761,603	78	128	171	120	113	0.25	130	121	110	-0.05
38220	Pine Bluff, AR	90,865	223	334	170	173	356	-0.14	250	220	162	-0.23
38300	Pittsburgh, PA	2,331,447	258	216	259	252	311	0.00	316	305	345	0.08
38340	Pittsfield, MA	126,425	42	72	157	224	279	0.31	203	218	277	0.20
38540	Pocatello, ID	93,436	107	175	268	253	255	0.43	65	113	131	0.18
38860	Portland-South Portland, ME	532,075	33	43	69	160	151	0.10	107	124	198	0.24
38900	Portland-Vancouver-Hillsboro, OR-WA	2,445,761	64	64	84	87	40	0.05	83	139	155	0.19
38940	Port St. Lucie, FL	472,012	22	78	48	39	12	0.07	5	16	39	0.09
39140	Prescott, AZ	228,067	6	4	3	4	244	-0.01	13	1	3	-0.03
39300	Providence-Warwick, RI-MA	1,618,268	243	298	327	306	309	0.22	163	224	298	0.36
39340	Provo-Orem, UT	616,791	100	100	115	321	131	0.04	68	209	143	0.20
39380	Pueblo, CO	165,982	187	275	187	295	186	0.00	137	164	149	0.03
39460	Punta Gorda, FL	181,067	19	20	13	7	46	-0.02	31	3	10	-0.06
39540	Racine, WI	195,602	339	370	369	338	336	0.08	241	346	360	0.32
39580	Raleigh-Cary, NC	1,332,311	121	211	232	174	272	0.30	79	135	187	0.29
39660	Rapid City, SD	138,402	96	48	120	115	148	0.06	59	58	58	0.00
39740	Reading, PA	418,025	300	271	225	229	252	-0.20	340	365	370	0.08

39820	Redding, CA	179,212	25	16	18	14	194	*-0.02*	57	26	12	*-0.12*
39900	Reno, NV	460,924	130	129	162	135	5	*0.09*	105	138	120	*0.04*
40060	Richmond, VA	1,269,530	205	316	364	349	130	*0.42*	183	223	276	*0.25*
40140	Riverside-San Bernardino-Ontario, CA	4,560,470	93	71	57	84	91	*-0.10*	89	76	79	*-0.03*
40220	Roanoke, VA	313,009	226	315	255	270	289	*0.08*	287	284	279	*-0.02*
40340	Rochester, MN	217,964	278	146	159	152	126	*-0.32*	213	347	319	*0.28*
40380	Rochester, NY	1,072,877	238	243	313	304	203	*0.20*	282	358	356	*0.20*
40420	Rockford, IL	338,356	259	264	271	264	321	*0.03*	330	352	352	*0.06*
40580	Rocky Mount, NC	146,678	250	311	293	192	281	*0.11*	315	335	271	*-0.12*
40660	Rome, GA	97,369	108	357	243	247	316	*0.36*	243	306	294	*0.14*
40900	Sacramento-Roseville-Folsom, CA	2,315,980	71	50	76	145	237	*0.01*	73	64	72	*0.00*
40980	Saginaw, MI	191,821	231	368	373	341	275	*0.38*	369	359	361	*-0.02*
41060	St. Cloud, MN	198,581	285	148	113	155	221	*-0.46*	349	293	236	*-0.30*
41100	St. George, UT	165,811	12	13	11	19	298	*0.00*	2	5	14	*0.03*
41140	St. Joseph, MO-KS	126,173	355	145	101	113	125	*-0.68*	247	250	227	*-0.05*
41180	St. Louis, MO-IL	2,805,190	274	338	333	302	198	*0.16*	117	270	295	*0.47*
41420	Salem, OR	422,678	195	86	74	109	85	*-0.32*	53	54	51	*-0.01*
41500	Salinas, CA	433,410	69	73	85	185	96	*0.04*	82	56	56	*-0.07*
41540	Salisbury, MD-DE	404,417	57	91	82	65	165	*0.07*	87	83	133	*0.12*
41620	Salt Lake City, UT	1,201,043	123	180	166	183	73	*0.11*	167	214	170	*0.01*
41660	San Angelo, TX	120,837	97	44	45	26	21	*-0.14*	161	150	104	*-0.15*
41700	San Antonio-New Braunfels, TX	2,468,193	157	143	174	166	78	*0.05*	176	153	161	*-0.04*
41740	San Diego-Chula Vista-Carlsbad, CA	3,316,073	47	58	78	214	8	*0.08*	77	84	76	*0.00*
41860	San Francisco-Oakland-Berkeley, CA	4,701,332	40	26	56	95	42	*0.04*	119	154	192	*0.19*
41940	San Jose-Sunnyvale-Santa Clara, CA	1,987,846	149	135	160	171	26	*0.03*	216	279	229	*0.03*
42020	San Luis Obispo-Paso Robles, CA	282,165	13	3	7	12	80	*-0.02*	30	22	16	*-0.04*
42100	Santa Cruz-Watsonville, CA	273,962	15	2	6	17	16	*-0.02*	39	46	31	*-0.02*
42140	Santa Fe, NM	149,293	1	1	9	66	171	*0.02*	21	12	17	*-0.01*
42200	Santa Maria-Santa Barbara, CA	444,829	45	23	37	105	39	*-0.02*	70	104	101	*0.08*
42220	Santa Rosa-Petaluma, CA	499,772	8	5	14	20	37	*0.02*	55	36	30	*-0.07*
42340	Savannah, GA	386,036	117	288	231	257	28	*0.30*	157	175	188	*0.08*
42540	Scranton--Wilkes-Barre, PA	555,642	265	142	102	86	343	*-0.43*	328	304	313	*-0.04*
42660	Seattle-Tacoma-Bellevue, WA	3,871,323	101	94	140	201	68	*0.10*	91	119	141	*0.13*
42680	Sebastian-Vero Beach, FL	153,989	7	36	32	43	20	*0.07*	9	24	41	*0.09*
42700	Sebring-Avon Park, FL	103,437	58	19	15	30	47	*-0.11*	27	9	8	*-0.05*
43100	Sheboygan, WI	115,178	304	343	334	233	365	*0.08*	372	377	376	*0.01*
43300	Sherman-Denison, TX	131,014	62	41	35	61	79	*-0.07*	150	194	180	*0.08*
43340	Shreveport-Bossier City, LA	399,619	200	184	192	140	207	*-0.02*	187	202	193	*0.02*
43420	Sierra Vista-Douglas, AZ	125,867	172	98	109	223	300	*-0.17*	71	17	19	*-0.14*
43580	Sioux City, IA-NE-SD	143,846	295	150	136	77	136	*-0.42*	353	281	222	*-0.35*

43620	Sioux Falls, SD	259,348	227	130	98	112	72	*-0.34*	224	231	212	*-0.03*
43780	South Bend-Mishawaka, IN-MI	321,739	324	348	299	284	326	*-0.07*	339	280	311	*-0.07*
43900	Spartanburg, SC	307,617	233	331	226	309	373	*-0.02*	342	316	305	*-0.10*
44060	Spokane-Spokane Valley, WA	550,160	77	95	103	136	59	*0.07*	80	109	122	*0.11*
44100	Springfield, IL	209,167	275	229	176	156	200	*-0.26*	300	229	252	*-0.13*
44140	Springfield, MA	699,480	198	227	302	324	304	*0.28*	297	317	335	*0.10*
44180	Springfield, MO	462,434	124	63	47	69	99	*-0.20*	111	122	159	*0.13*
44220	Springfield, OH	134,726	297	339	323	348	245	*0.07*	365	351	309	*-0.15*
44300	State College, PA	161,960	312	250	227	312	176	*-0.23*	166	255	217	*0.14*
44420	Staunton, VA	121,651	139	201	208	318	121	*0.18*	199	201	284	*0.23*
44700	Stockton, CA	742,603	196	126	137	81	54	*-0.16*	126	130	106	*-0.05*
44940	Sumter, SC	140,714	208	361	285	359	361	*0.20*	347	242	261	*-0.23*
45060	Syracuse, NY	652,416	236	270	283	202	180	*0.13*	286	299	341	*0.15*
45220	Tallahassee, FL	382,197	219	301	246	254	374	*0.07*	52	74	48	*-0.01*
45300	Tampa-St. Petersburg-Clearwater, FL	3,097,859	68	138	65	41	19	*-0.01*	95	79	99	*0.01*
45460	Terre Haute, IN	186,908	331	176	175	110	257	*-0.41*	322	248	283	*-0.10*
45500	Texarkana, TX-AR	149,292	373	120	96	50	307	*-0.74*	190	144	179	*-0.03*
45540	The Villages, FL	125,044	5	81	20	54	350	*0.04*	38	23	6	*-0.09*
45780	Toledo, OH	644,137	322	328	341	313	197	*0.05*	354	336	324	*-0.08*
45820	Topeka, KS	232,778	266	171	155	163	88	*-0.30*	294	195	211	*-0.22*
45940	Trenton-Princeton, NJ	367,922	333	352	328	203	239	*-0.01*	275	282	325	*0.13*
46060	Tucson, AZ	1,027,207	88	105	147	170	61	*0.16*	155	102	93	*-0.16*
46140	Tulsa, OK	990,544	104	77	73	57	100	*-0.08*	177	161	150	*-0.07*
46220	Tuscaloosa, AL	250,681	246	309	314	261	372	*0.18*	309	173	151	*-0.42*
46340	Tyler, TX	227,449	95	38	52	27	149	*-0.11*	124	110	148	*0.06*
46540	Utica-Rome, NY	292,016	262	224	195	176	209	*-0.18*	299	277	278	*-0.06*
46660	Valdosta, GA	145,315	209	289	167	80	238	*-0.11*	158	141	130	*-0.07*
46700	Vallejo, CA	441,829	178	247	274	358	262	*0.26*	138	69	53	*-0.23*
47020	Victoria, TX	99,674	90	90	145	90	152	*0.15*	168	133	84	*-0.22*
47220	Vineland-Bridgeton, NJ	151,906	369	293	289	158	146	*-0.21*	259	298	317	*0.15*
47260	Virginia Beach-Norfolk-Newport News, VA-NC	1,761,729	336	375	372	373	206	*0.10*	175	179	208	*0.09*
47300	Visalia, CA	461,898	204	76	59	62	187	*-0.39*	125	103	77	*-0.13*
47380	Waco, TX	268,361	225	140	94	83	178	*-0.35*	256	245	189	*-0.18*
47460	Walla Walla, WA	60,365	56	85	127	164	50	*0.19*	96	182	225	*0.34*
47580	Warner Robins, GA	180,652	255	358	356	375	331	*0.27*	113	63	90	*-0.06*
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	6,196,585	155	260	330	363	179	*0.47*	151	205	230	*0.21*
47940	Waterloo-Cedar Falls, IA	169,556	328	155	279	280	116	*-0.13*	356	290	275	*-0.22*
48060	Watertown-Fort Drum, NY	112,842	357	341	163	89	71	*-0.52*	102	112	248	*0.39*
48140	Wausau-Weston, WI	163,140	234	205	207	188	334	*-0.07*	346	340	263	*-0.22*
48260	Weirton-Steubenville, WV-OH	118,213	368	365	370	276	256	*0.01*	303	343	374	*0.19*
48300	Wenatchee, WA	118,252	54	102	111	76	243	*0.15*	22	39	95	*0.19*
48540	Wheeling, WV-OH	141,475	370	249	337	197	288	*-0.09*	364	261	334	*-0.08*

48620	Wichita, KS	637,690	249	154	144	118	69	*-0.28*	232	260	253	*0.06*
48660	Wichita Falls, TX	150,715	290	51	30	64	44	*-0.69*	139	115	102	*-0.10*
48700	Williamsport, PA	114,330	303	196	169	211	261	*-0.36*	304	342	337	*0.09*
48900	Wilmington, NC	288,337	27	46	99	119	76	*0.19*	41	67	134	*0.25*
49020	Winchester, VA-WV	137,621	128	67	107	106	67	*-0.06*	219	177	258	*0.10*
49180	Winston-Salem, NC	666,216	125	222	235	191	293	*0.29*	249	302	338	*0.24*
49340	Worcester, MA-CT	941,338	156	272	320	301	319	*0.44*	196	288	351	*0.41*
49420	Yakima, WA	249,697	299	170	134	108	53	*-0.44*	128	99	103	*-0.07*
49620	York-Hanover, PA	445,565	280	242	249	179	249	*-0.08*	351	360	373	*0.06*
49660	Youngstown-Warren-Boardman, OH-PA	541,846	164	296	331	308	287	*0.44*	313	308	342	*0.08*
49700	Yuba City, CA	172,469	148	74	77	116	188	*-0.19*	48	31	28	*-0.05*
49740	Yuma, AZ	209,468	371	194	262	180	323	*-0.29*	135	66	42	*-0.25*