Spatial pattern mining of tech clusters of dynamics and industry mix based on quantitative methods in England area, UK

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CASA0012, MSc Spatial Data Science and Visualisation Dissertation

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Repository: https://fang-zeqiang.github.io/CASA0012-Dissertation/

This dissertation is submitted in part requirement for the
MSc (Or MRes) in the Centre for Advanced Spatial Analysis,
Bartlett Faculty of the Built Environment, UCL

Word count: 8,000

2021-08-19

Abstract

Some abstract text

Declaration

I, Zeqiang Fang, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. It is xxx words in length

Acknowledgements

I would like to thank blah blah

Contents

List of Figures

List of Tables

Abbreviations

Term	**Abbreviation**
Digital Elevation Model	DEM
Digital Surface Model	DSM
Digital Terrain Model	DTM

Chapter 1

Introduction

1.1 Background

1. tech cluster development

https://technation.io/report2021/#uk-trends tech cluster & ttwa In fact, between 2007 and 2014, the number of creative enterprises grew faster than the overall company population in more than nine out of ten of the UK's 228 Travel-to-Work-Area geographies (Mateos-Garcia 2016).

There are high clustering effect among the England tech firms

By modeling the evolution of business growth and entry, this research contrasts the dynamics of the process by which regional clusters emerge in the US and UK computer industries. New enterprises are lured to both countries by industrial strength in specific sub-sectors in specific regions. Furthermore, incumbent firms in a cluster that is strong in their particular sub-sector of the industry expand at a quicker rate than the industry average. While there are significant second-order variations between the models estimated for the United States and the United Kingdom, the clustering dynamics appear to be comparable. There is no evidence that clustering effects are weaker in the United Kingdom than in the United States(Baptista and Swann, 1999).

2. dynamics cause better performance

dynamics and entry pattern Many industrial dynamics patterns appear to be shaped by the process by which knowledge is created, gathered, and subsequently destroyed, because it favors the admission of new enterprises, the coexistence of incumbents and new entrants, and, eventually, their selective or combined exit over time (Krafft,2004).

3. industry clustering pattern and economics performances

1.2 Research Question and Objectives

How does tech clusters' dynamics pattern change in UK from 1998 to 2018? / What factors can affect tech clusters' dynamics pattern change in UK?

To what extent will dynamic change affect tech clusters'performance

1.3 Report Structure

1. data clean
2. tech cluster recognition
3. dynamics index generation
4. hypothesis (OLS estimation)
5. regression
6. residual analysis
7. result interpretation

Chapter 2

Literature Review

2.1 Industry Cluster & Tech Cluster

Tech clusters like Silicon Valley play a central role for modern innovation, business competitiveness, and economic performance. This paper reviews what constitutes a tech cluster, how they function internally, and the degree to which policy makers can purposefully foster them. We describe the growing influence of advanced technologies for businesses outside of traditional tech fields, the strains and backlash that tech clusters are experiencing, and emerging research questions for theory and empirical work.

2.2 Cluster Dynamics

Industrial dynamics and clusters: a survey, regional research. This article reviews clusters and their impact on the entry, exit, and growth of firms, as well as the literature supporting the evolutionary dynamics of cluster formation. This extensive review shows strong evidence that clusters promote the entry of manufacturers, but the evidence that clusters can promote the growth and survival of firms is rather weak. From a number of open-ended questions, this research extracts various future research paths that emphasize the importance of manufacturer heterogeneity and the exact mechanism that supports the localized economy (Frenken, Cefis and Stam, 2014).

Relative researchers found that industry clustering not only increased firm entry but also firm exit rates. This implied that clusters could emerge and exist because they provide entry opportunities but they do not necessarily generate Marshallian economies that increase firm survival (Boschma, 2015).

by looking at how clusters influence entry, departure, and growth via localization economics, and by taking a long-term look at cluster emergence and evolution.

Entry is strongly influenced by clustering. Empirical research have consistently found that as cluster size grows, so does the rate of admission. Most potential entrepreneurs simply stay in their region of origin, therefore this empirical correlation does not imply that enterprises locate in a cluster because they gain from co-location.

Localization economies appear to play a role in entrance decisions in these research, but only for technologically trailing businesses who stand to gain the most and have the least to lose from co-location (ALCCER and CHUNG, 2007).

Cluster effect on the whole England area Enterprise entry does play an important role in shaping the overall dynamics. The new entrants that survive in the cluster will become larger over time, resulting in broader expansion and overall impact (Clementi & Palazzo, 2016) https://pages.stern.nyu.edu/~gclement/Papers/Entry_exit.pdf

2.3 Industry Mix

On average, companies in large cities are more productive. There are two main explanations: corporate choice (big cities strengthen competition and only allow the most productive people to survive) and agglomeration economies (big cities promote interaction and increase productivity), which may be strengthened by the natural advantages of localization. In order to distinguish them, we nested a general version of the easy-to-handle company selection model and a standard agglomeration model. Stronger choices in large cities cut the distribution of productivity to the left, while stronger gatherings move to the right and expand the distribution. Using this forecast, French firm-level data, and new quantile methods, we show that firm choices cannot explain differences in spatial productivity. The results are applicable to various departments, city size thresholds, institutional samples and regional definitions.

The Herfindahl–Hirschman Index (HHI) is a commonly used economic concept in competition law, antitrust[1], and technology management. It's a measure of a company's size in relation to the industry it's in, as well as an indicator of how competitive it is (Liston-Heyes & Pilkington, 2004).

2.4 How location affect entry pattern in UK/Global

2.5 How time affect entry pattern in UK/Global

2.6 Other factor can affect dynamics pattern in UK

Firm density has a beneficial effect on entry rates in the early stages of an industry since each firm has the potential to bring in new entrants. Legitimation has been coined to describe this positive density impact. Higher company density levels, on the other hand, become a barrier to entrance as the industry evolves and grows, owing to fierce market competition (Boschma, 2015).

Chapter 3

Methodology

3.1 Research Framework

1. Data Clean & Select
2. Identifying Tech Cluster
3. Measuring the Dynamics & Industry Mix
4. Quantitative Method Research
5. Temporal Spatial Analysis

In this study, a data set containing all companies in UK will be cleaned and attribute selected, and technology companies will be identified and screened according to the classification and definition of technology companies on the official website of the British government. Before the quantitative study, this study is based on time and The spatial dimension counts the number of technology companies, and calculates the dynamic indicators of enterprise clusters and industrial combination indicators in a specific year and a specific region. Then this study conducts multiple regressions, univariate and bivariate variables Moran index testing to conduct spatial quantitative research, and finally combines Qualitative spatial pattern trend research on the spatial changes of indicators in three different time periods(1998, 2008 & 2018).

according to research method of Kumari's team(2019), the Moran's I of three time period will be calculated to analysis the dynamics change in spatial and temporal aspects.

3.2 Data Source and Processing

This raw dataset is collected from the core company data from Open Corporates master company database (Open Corporates, 2018). And the size of dataset accounts for 15 GB which is handled with `read_stata` and `get_chunk` function to read large data file in chunks, then increasing the reading speed. The "primary uk sic 2007" identification field is the basis of industry finding and the "birth year" is the key to measure dynamics variables . All rows whose these two values are empty are removed 17% incorperate date is missing and sic code is complete).

3.3 Identifying Tech Cluster

For the identification of science and technology companies, this study introduces the main 2007 sic code table to judge the science and technology industry, referring to the classification method of the Science and Technology Classification data set on the ons.gov.uk website; in order to better identify science and technology companies for the UK The economic contribution is officially based on the 2007 British Standard Economic Activity Classification, combined with different data sources, to classify and label science and technology companies (Office for National Statistics, 2015).

This research refers to the science and technology classification table provided by the government. The technology indicator is used to position the technology industry of all industries, and a total of 168 sic codes for the technology industry in 2007 were obtained, accounting for about 16% of all industry categories in the UK, including 5 industry categories such as Digital Technologies, Life Sciences

SIC07 type	5-digit SIC07 code	...3	Science and Technology category	Scienc
Class	26110	...	Digital Technologies	Compu
Class	58210	...	Digital Technologies	Digital
Class	62090	...	Digital Technologies	Digital
Class	63110	...	Digital Technologies	Digital
Class	27510	...	Other scientific/technological manufacture	Electri
Class	86230	...	Life Sciences & Healthcare	Health

& Healthcare, Publishing & Broadcasting , Other scientific/technological manufacture and Other scientific/technological services, details of the classification form will be attached in the attachment. There are almost 20% firms in the raw data belonging to tech firms according to the method of category as mentioned above.

3.4 Quatitative Analysis and Methods

3.4.1 Time Range Selection

The reason why this research choose tech firms which incorporate from 1998 to 2018 is because the number of technology companies established in the UK in the past 20 years is significantly higher than before 1998, as shown in below figure.

3.4.2 Tech Cluster Identifying

Travel to Work Locations is official statistics that capture local labour markets, i.e., areas where the majority (approximately 70%) of the people who live there work. These measures are based on responses to the 2011 and are used to define the TTWAs algorithmically. There are currently 228 TTWAs in the UK. When it is recognised that the activity of interest may be scattered across administrative boundaries such as local authority districts or NUTS areas, TTWAs are widely utilised in industrial clustering investigations (Prothero, 2021).

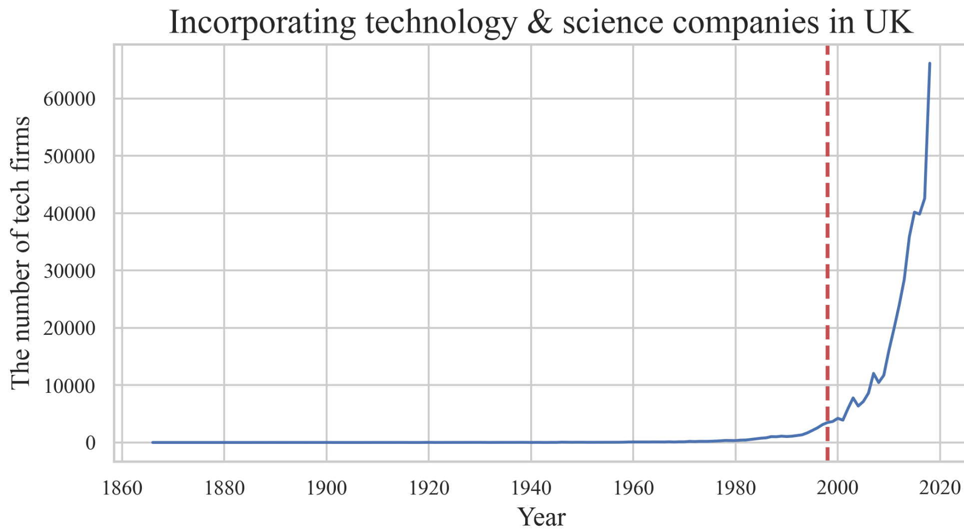

Figure 3.1: Incorporating technology and science companies in UK

Relevant studies have shown that commuting across towns has become more common in England and Wales. People are not limited to living and working in the same administrative area. In addition, studies have found that low-skilled workers tend to rely on the public to work locally. Strong skill-oriented jobs are more dependent on cars, and they are also the main force for cross-city commuting. The technology industry has a greater demand for those strong skill-oriented workers which suggest that travel to work area(TTWA) is used as a cluster of technology companies compared to traditional administrative Region would be a good choice (Titheridge & Hall,2006)

The University of Cambridge had funded some researchers to undertake the Wisbech 2020 Vision project to analyse the current problem, mining the potential future space for employment growth with alternative macro-economic scenario to help drive a high value-added growth plan in the local area (Burgess & et al., 2014)

This geographical division can better reflect the relationship between population, company and work. In terms of geographic research, related researchers have combined the Business Structure Database (BSD) from the Office for National Statistics (ONS) and industry classification methods to use the ONS geographic area of TTWA to survey the commuting patterns and labour market of the population in 2011. Most scholars state that this might be an effective measure for the research of industrial clusters at the sub-regional level (Mateos-Garcia 2016).

3.4.3 Dynamics Measuring Index

Firm entry is the result of the interaction between the characteristics of an actor, on the one hand, and the surrounding environment, on the other hand (Frenken, Cefis and Stam, 2014).

To measure the degree of dynamic change of a cluster, it is necessary to calculate the entry rate of the technology cluster. Brandt used the enterprise's entry rate and exit rate to measure the dynamics attributes of a company (2005). This research refers to the researcher's calculation method. The number of enterprises entering and quitting a sector as a percentage of the total number of firms in the same sector in a given year is used to compute entry rate in this tech cluster dynamics research(ibid). The calculation method is as follows.

$$Entry\ Rate_{i,t} = \frac{Incorporating\ Firms_{i,t}}{Total\ Firms_i}$$

Where i means location(travel to work area), t means year

3.4.4 Industry Mix Measuring Index

It is necessary to calculate the Herfindahl-Hirschman Index or location quotient of the technology cluster to measure the degree of industrial concentration in a cluster area,. However, only the former method is used because the employment data corresponding to the corresponding region year is missing; Here is a reference to the quantitative method of industrial concentration of Chao Lu's research team (2017). HHI is calculated by squaring the market share of each competing company and then adding the results, where the market share is given in the form of scores or points (ibid). Increases in the Herfindahl index generally indicate a decrease in competition and an increase of market power, whereas decreases indicate the opposite (Hall & et al., 2009), as the calculation method shown below.

$$Herfindahl - Hirschman\ Index\ _{i,t} = \sum_{j=1}^{N} \left(\frac{Tech\ Firms_{j,i,t}}{Total\ Tech\ Firms_{i,t}}\right)^2$$

Where: N is the overall number of individual tech firm contained. k represents the kth industry in location i and year t. $TechFirms_j$ is the number of j-th individual tech firm $TotalTechFirms$ represents the number of total tech firms in a specific location and year.

3.4.5 Research Objectivities

Independent Variables	Type	Description
Firms	numeric	The number of tech firms
Density	numeric	The density of tech firms
Herfindahl-Hirschman Index	numeric	The index measuring the industry mix
Year	category	Years from 1998 to 2018
Location	category	Top ten clusters of companies in England

3.4.6 Moran's I

One of the most popular and often used measures of spatial autocorrelation is Moran's Index. Based on the locations and values of the feature, the Global Moran's I tool analyzes the pattern of a data set spatially and decides if it is scattered, clustered, or random. The program calculates the Moran's I Index value, as well as the z-score and p-value, to statistically validate the Index. It is computed using the formula below (Kumari & et al., 2019).

$$Moran's\ Index = \frac{n}{S_0} \frac{\sum_{x=1}^{n} \sum_{y=1}^{n} w_{x,y} z_x z_y}{\sum_{x=1}^{n} z_x^2}$$

$$S_0 = \sum_{x=1}^{n} \sum_{y=1}^{n} w_{x,y}$$

Where z_x stands for deviation of an attribute from its mean $(x_i - X)$ for feature X, $w_{x,y}$ is the spatial weight among feature X and Y, n is the total number of features and So is the summation of all spatial weights

The statistic's z_j score is given below

$$z_x = \frac{I - E[I]}{\sqrt{V[I]}}$$

where

$$E[I] = \frac{-1}{(n-1)}$$

$$V[I] = E[I^2] - E[I]^2$$

The Moran's Index(I) has a range of values from -1 to 1. Index value 1 indicates that the observed pattern is spatially clustered. On the other hand value -1 indicates scattering or dispersion. Moran's I assign a value of near or equal to zero to the lack of auto correlation. The z-score and p-value of the Index are only used to form final judgments regarding the observed pattern.

3.5 Limitations

In term of missing value in the original dataset, there are almost 99.8% missing value in dissolution date. This means that most companies do not have a dissolution date, which might not mean that some companies survive, nor can it accurately reflect the company's exit numbers in a specific year and region.

Moreover, the company's incorporation date data (including firms birth year) is also missing about 17.26%. These two difficulties make the data after cleaning process may have the risk of insufficient accuracy in representing the dynamics of the industry. The model prediction after fitted to this dataset might not reach the same situation as the real world level.

1. ttwa

- ttwa might not be a data-driven method
- ttwa data is not up-to-date because it is 2015 statistics
- ttwa's change (Ozkul,2014)

Ozkul, B., 2014. Changing home-to-work travel in England and Wales. Regional Studies, Regional Science, 1(1), pp.32-39.

The value of this statistical data(Herfindahl-Hirschman Index) for identifying monopoly development, on the other hand, is directly dependent on the precise definition of a market (Kwoka, 1977). For instances, geographical considerations might influence market share. This dilemma can arise when there are nearly equal market share of tech businesses in a given sector, but they each operate exclusively in distinct regions of the travel to work area, resulting in each firm having a monopoly inside the specific marketplace in which it conducts business, which might make it more difficult to measure the industry mix in a specific location and year. Furthermore, one IT firm may control as much as 70% of the market for a certain area of the digital industry (i.e. the sale of one specific equipment). As a result, that company would have a near-total monopoly on the manufacturing and sale of that commodity.

3.6 Ethical Statement

The data for this project comes from OpenCorporates, a firm which aggregates company-level data from around the world(https://opencorporates.com/). In this case, OpenCorporates have taken data from the UK Companies House register (https://www.gov.uk/government/organisations/companies-house). As detailed by Nathan and Rosso (2015), all limited companies in the UK need to registers with Companies House when they are set up, and provide annual returns and financial statements. These include details of directors and company secretary, registered office address, shares and shareholders, as well as company type and principal business activity. Thus, all the data used here is already in the public domain.

The research objectives are tech firms in the UK for this project and the individual data will not be collected and measured in this project. For issues of deanonymisation or privacy, traceable information such as the real companies name and ID will not be utilised in the research. The raw data will be cleaned and filtered by several key variables include industries instead of the company's name or other sensitive information before doing the research. Through data cleaning, pre-processing, desensitisation or other processing methods, the risks of damage to company interests (such as social reputation, economic benefits and etc.) will be mitigated to an as low as possible level in the research process.

Besides, this project will not cause discrimination of industries or job categories. The final analysis results, such as the different industry concentration in each region, will not deepen some people's stereotypes and prejudices about the region (This content will be fully discussed in the project discussion section). It is necessary to point out and declare the objectivity of the analysis and the non-absoluteness of the results in the disclaimer. Consider the feelings of people and governments in different parts of the UK, this research will prevent the influence of personal preferences and subjective emotions.

The leakage of companies' name and information will be protected. For example, in the reflection of the results section of academic research, the name and related information of the companies that moved may be revealed. Although this information may be open to the public you need to know that this information may be used by people with other ulterior motives. This project will desensitise the company name and information at the stage of chart presentation, such as using A, B, and C to replace them to achieve this purpose.

Chapter 4

Results

4.1 Visualisation and Analysis of Tech Cluster

4.1.1 Distribution

From 1998 to 2018, the entry rate of each Travel to work area (TTWA) in England will change drastically every ten years. For example, in 1998 the darker colored areas were mostly around the Greater London area and the entire southern part of England. The overall entry rate in 2008 was higher than that in 1998 and showed a trend of new companies entering the north of England. In this year, some ttwa areas on the edge of England have more prominent entry rates, such as Malton, Minehead and Bridport. However, the overall entry rate in 2018 was about twice as high as the average in 2008. Moreover, ttwa with high entry rate is mostly concentrated in the north and the surrounding areas of Greater London.

The figure below is the spatial distribution change in entry rate of tech clusters(ttwa) in England. The trend can be witnessed that there is an increasing trend in the overall level of entry rate from 1998 (average about 1.06%) to 2018 (average about 14.33%)

In terms of herfindahl-Hirschman index of tech industry in ttwa of England

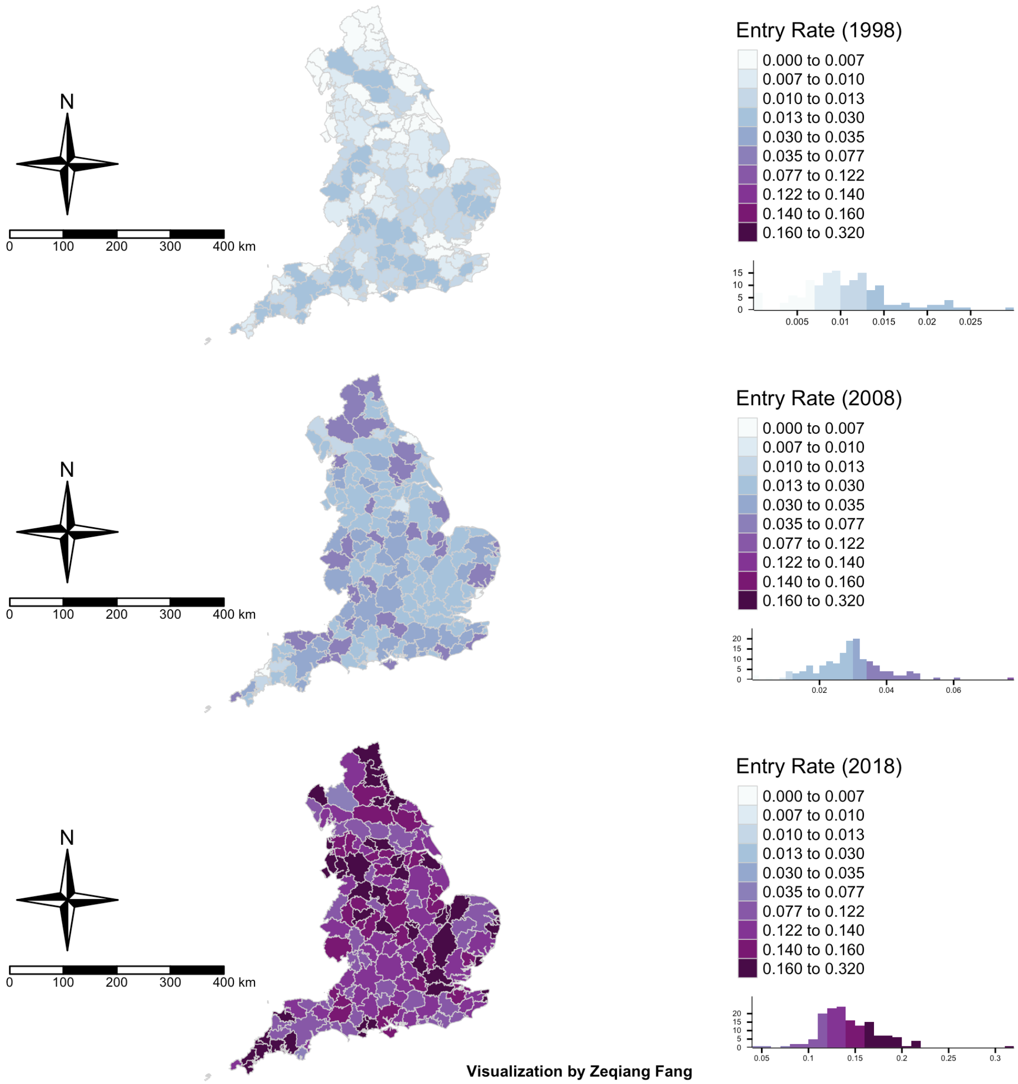

Figure 4.1: The distribution of the entry rate of the England tech clusters(ttwa) from 1998 to 2018

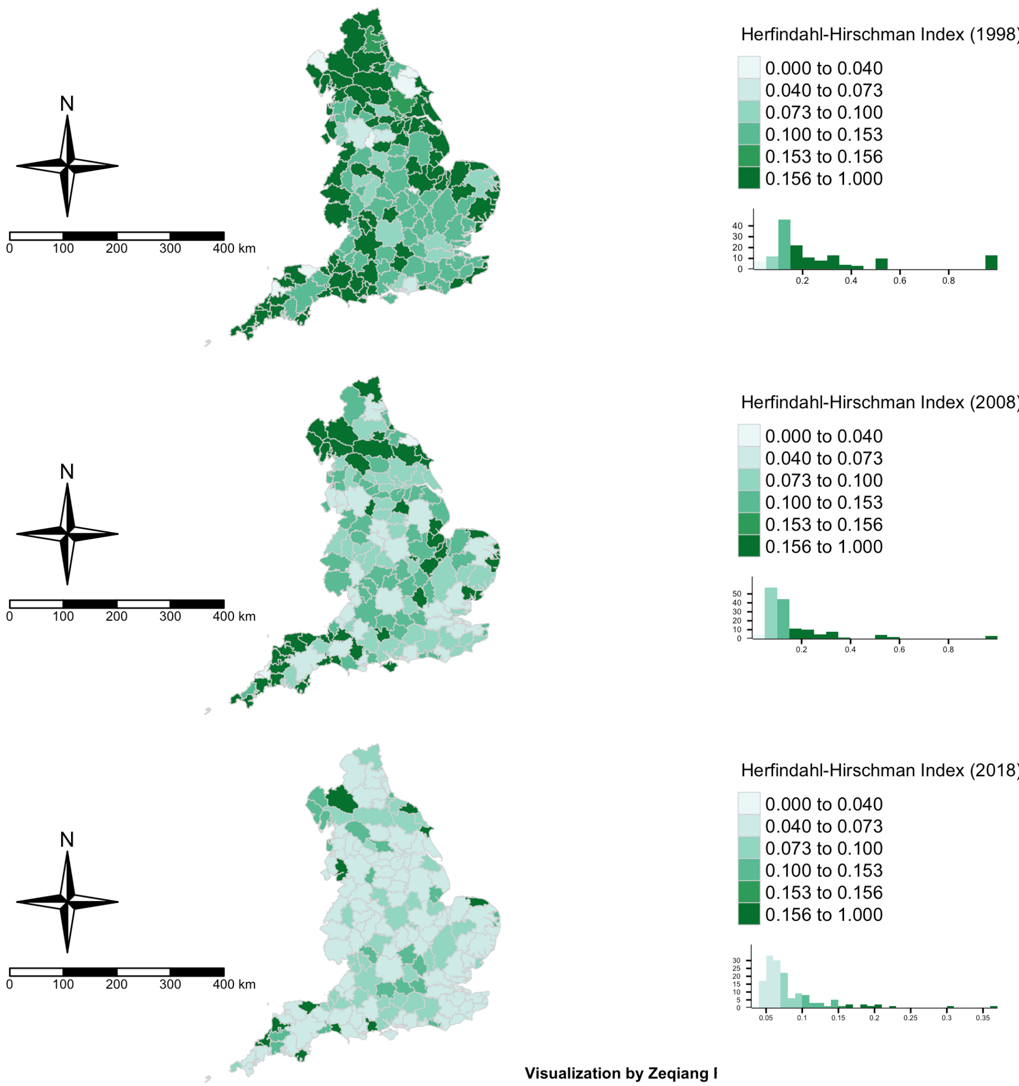

Figure 4.2: The distribution of the Herfindahl-Hirschman index of the England tech clusters(ttwa) from 1998 to 2018

4.1.2 Descriptive Analysis

4.2 Visualisation and Analysis of Dynamics

4.2.1 Regression

For Top 10 clusters regression on the dynamics with year and location

xxx illustrates the unconditional relation between exit hazard rate and age. Consistent with ..., the exit hazard rate decreases with age. This is the case because on average entrants are less productive than incumbents. As a cohort ages – see the right panel – the survivors' productivity and value increase, leading to lower exit rates.

From & Refer to https://pages.stern.nyu.edu/~gclement/Papers/Entry_exit.pdf

For Entry Rate & HHI

From & Refer to https://search.oecd.org/economy/growth/35027468.pdf

4.3 Spatial autocorrelation

Table 2 Spatio-temporal dynamics(entry rate) cluster analysis

Year	Moran's Index	p value	z-score
1998	0.436	0.00	10.077
2008	0.062	0.08	1.3483
2018	0.056	0.10	1.2382

Table 2. Entry rate regression[1, 2]

Dependent variable: entry rate of industry j in country i estimated over 1998-2000; fixed effect estimator

	I	II
	With an output gap variable	Also ICT-specific country effects
Constant	7.26***	6.14***
	(0.89)	(0.85)
Finland	−2.18***	−0.94*
	(0.50)	(0.50)
Belgium	−2.45***	−1.49**
	(0.65)	(0.63)
Netherlands	−0.76	0.15
	(0.46)	(0.48)
Sweden	−2.88***	−0.93
	(0.68)	(0.66)
Spain	0.66	1.60**
	(0.84)	(0.80)
Portugal	−1.74***	−0.09
	(0.48)	(0.48)
Italy	0.32	1.36*
	(0.74)	(0.72)
UK	−1.33	0.28
	(0.59)	(0.58)
ICT effects by country:		
Finland		−7.91***
		(1.05)
Belgium		−6.14***
		(1.06)
Netherlands		−5.76***
		(1.17)
Sweden		−12.42***
		(1.09)
Spain		−0.94
		(2.44)
Portugal		−10.50***
		(1.05)
Italy		−6.55***
		(1.05)
UK		−10.24***
		(1.05)
DUM99	−1.42***	−1.42***
	(0.27)	(0.26)
DUM2000	−1.94***	−1.93
	(0.38)	(0.36)
GAP	0.38*	0.39**
	(0.21)	(0.20)
Adjusted R^2	0.59	0.63
No. of observations	1 516	1 516

1. The reference group is the food, beverage and tobacco industry in Denmark.
2. Standard errors in parentheses.
*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.
Source: OECD estimations based on Eurostat data. Output gap variable from OECD (2002).

Figure 4.3: Regression results of tech clusters in England

Table 5. **Firm entry rate regressions on indicators summarising aspects of barriers to entrepreneurship II**[1, 2, 3]

Firm entry rates for manufacturing and services industries, 1998-2000

	Licenses and permits systems	Communication and simplification of rules and procedures	Administrative burdens for sole proprietor firms	Length of time creditors have claims on bankrupts' assets
Entry rates	–0.29***	–0.69	–0.14	–0.19***
	(0.09)	(0.55)	(0.23)	(0.02)
Hazard rates	–0.38	1.56	0.47	–0.39
	(0.77)	(2.79)	(1.35)	(0.57)

1. A two-step estimation method described in Bertrand *et al.* (2003) is applied. The first step is an estimation of industry firm entry rates on industry and time dummies and on country-specific ICT industry dummies. The resulting error terms are then averaged for each country across industries and regressed on each indicator separately.
2. Standard errors in parentheses.
3. The estimations are based on nine observations for entry rates and eight for hazard rates.

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Source: OECD calculations based on Eurostat firm entry data and indicators from the OECD regulatory database and UNICE, 2000.

Figure 4.4: Regression on industry mix and dynamics of tech clusters in England

Chapter 5

Discussion

Short introduction to the chapter, reviewing the previous chapter and detailing what this one aims to achieve and build upon.

To be done

5.1 Research significance

5.1.1 Global development goals

5.1.2 Local policy

5.1.3 Academic research

5.2 Limitations

To be done

5.3 Transferability

To be done

Chapter 6

Conclusion

case (Clementi & Palazzo,2016) This paper provides a framework to study the dynamics of the cross–section of firms and its implications for aggregate dynamics. When calibrated to match a set of moments of the investment process, our model delivers implications for firm dynamics and for the cyclicality of entry and exit that are consistent with the evidence.

The survival rate increases with size. The growth rate of employment is decreasing with size and age, both unconditionally and conditionally. The size distribution of firms is skewed to the right. When tracking the size distribution over the life a cohort, the skewness declines with age. The entry rate is positively correlated with current and lagged output growth. The exit rate is negatively correlated with output growth and positively associated with future growth.

Carefully modeling firm–level dynamics turns out to be key. The pro–cyclicality of entry and the positive association between age and firm growth deliver amplification and propagation of aggregate shocks in a plain-vanilla competitive framework.

A positive shock to aggregate productivity leads to an increase in entry. Consistent with the empirical evidence, entrants are smaller than incumbents. The skewness of the distribution of firms over idiosyncratic productivity increases.

As the exogenous component of aggregate productivity declines towards its unconditional mean, the new entrants that survive grow in productivity and size. That is, the distribution of idiosyncratic productivity improves. As a result, the response of output is stronger and more persistent than in an environment that abstracts from entry and exit.

Our numerical experiments reveal that on average, entry and exit account for about one fifth of the above–trend growth experienced by our economy over the 10 years following a 1.5 standard deviation innovation to aggregate productivity. As an alternative metric of the impact of entry and exit on aggregate dynamics, we assessed the effect on persistence. For a version of our model without entry or exit to generate a data–conforming persistence of output, the first–order auto correlation of aggregate productivity shocks must be 0.775. In the benchmark scenario with entry and exit, it needs only be 0.685.

Last, but not least, we show that according to our model there is a clear causal link between the exceptionally large drop in establishments during the great recession and the painfully low speed of the recovery from it. Whatever its exact nature, the adverse event that initiated the recession had a particularly strong effect on the 2008 and 2009 cohorts, severely reducing the ranks of small but high–conditional–growth plants and thereby suppressing the growth in aggregate labor demand for years to come.

In spite of the wealth of detail and descriptive realism achieved by the model, our framework could be extended in a variety of dimensions. In particular, we would like to gauge the quantitative effect of our mechanism when imbedded in a genuine general equilibrium framework. Relaxing our assumption that firms of different cohorts share the same technology is also of interest. Assuming, as it appears to be the case in reality, that entrants are more likely to adopt more recent vintages of capital, is likely to further enhance the amplification and propagation mechanism uncovered here. end (Clementi & Palazzo,2016)

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a b c d e f g h i j k l m n o p q r s t u v w x y z pay attention to the unity of format

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Appendix A Classification Form

Science and Technology Classification

Appendix B Proposal