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Varieties of Capitalism and the Innovation Cluster Environment

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B.A., Emory University, 2011

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An abstract of
A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of

Master of Arts

In Political Science

2011

Abstract

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By Daniel S. Desatnik

Over the past two decades, scholars have successfully made the case for cluster policy. They have demonstrated the ability of clusters to serve as hotbeds of innovation and industrial upgrading by resolving problems of coordination, information asymmetries, and infrastructural capacity. In response, numerous countries have adopted the cluster model as a central part of their competitiveness agendas. While our understanding of the benefits of clusters has grown, it has yet to be matched with an understanding of the effects of the political-economic environment on cluster development.

This paper addresses this gap from the perspective of the varieties of capitalism (VOC) literature. The VOC literature provides a firm-centered framework for analyzing the differences in the political-economic terrain in which clusters are "nested." We posit a theory that the set of political-economic institutions associated with VOC type affects the incentives of firms to enter into a cluster, and thus results in observable cross-national differences in the prevalence, size, and type of clusters.

The empirical data support the theory by showing that the correlates of cluster formation are notably different at the two opposite poles of VOC typology: liberal-market economies (LMEs) and coordinated-market economies(CMEs).Whereas competition, capital mobility, and lack of institutions for coordination help necessitate the move to clusters in LMEs, these same factors do not assist cluster formation to the same degree, and can even hinder it in CMEs. Our findings lead us to conclude that there is utility in the VOC approach to cluster initiatives. While government-backed cluster initiatives must be still be tailored to the specific geographical region, the LME versus CME distinction provides a general script to be followed for cluster development.

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Table of Contents

CHAPTER ONE: INTRODUCTION 1

1.1 LITERATURE REVIEW 3
1.1.1 CLUSTERS AND CLUSTER FORMATION 4
1.1.2 CLUSTERS AND POLITICS 7
1.1.3 VARIETIES OF CAPITALISM 8
1.2 PAPER OVERVIEW AND ADDED VALUE 12

CHAPTER TWO: THEORY 14

2.1 ASSUMPTIONS AND PREFACE 14
2.2 RELATIVE BENEFITS OF THE CLUSTER ENVIRONMENT BY VOC TYPE 16
2.3 CAUSAL MECHANISM 24
2.4 HYPOTHESES 28

CHAPTER THREE: RESEARCH DESIGN AND EXPECTATIONS 30

3.1 UNIT OF ANALYSIS 30
3.2 INDEPENDENT VARIABLE: VARIETY OF CAPITALISM 31
3.3 DEPENDENT VARIABLE: MEASURING CLUSTERNESS 32
3.4 MEASURING INNOVATION: PATENTS 38
3.5 CONTROL VARIABLE: POPULATION DENSITY 40
3.6 DATA SOURCES 41
3.7 HYPOTHESIS TESTS 42

CHAPTER FOUR: EMPIRICAL TESTS 46

4.1 HYPOTHESIS 1:. 46
4.2 HYPOTHESIS 2: 55
4.3 HYPOTHESIS 3: 58

CHAPTER FIVE: DISCUSSION 72

5.1 POLICY IMPLICATIONS 72
5.2 FUTURE RESEARCH 74

REFERENCES 77

Tables and Graphs

CHAPTER ONE: INTRODUCTION 1

Figure 1: Porter Diamond Framework 5
Table 1: VOC characteristics by type 10

CHAPTER TWO: THEORY 14

Table 2: Cluster environment compatibility by VOC type 18
Table 3: LME cluster benefits 20
Table 4: CME cluster benefits 22
Figure 2: Diagram of Causal Mechanism 26

CHAPTER THREE: RESEARCH DESIGN AND EXPECTATIONS 30

Table 5: Cluster indicator types 33
Graph 1: GINI Innovation by Country 37
Graph 2: GINI innovation by VOC type 38
Table 6: Average GINI coefficients of innovation by VOC type 38

CHAPTER FOUR: EMPIRICAL TESTS 46

Graph 2: GINI innovation by VOC type 47
Table 7: Average GINI coefficients of innovation by VOC type 47
Table 8: Regression of GINI innovation by VOC dummy (no controls) 48
Table 9: Regression of GINI innovation by VOC dummy and population density (interaction) 49
Graph 3: Cluster Mapping Comparison by VOC type 51
Table 10: McKinsey data summary statistics and t-test 52
Graph 4: Share of population in the ten per cent of regions with the largest population 53
Graph 5: Index of geographic concentration by VOC type 54
Graph 6: Cluster diversity comparison by VOC 55
Graph 7: Cluster size comparison by VOC 56
Table 11: Cluster size and diversity comparison 56
Graph 8: Cluster diversity vs cluster size 57
Graph 9: Local Competition vs GINI innovation 60
Table 12: Regression of GINI innovation by local competition 61
Graph 10: Effectiveness of Monopoly Policy by VOC 62

Graph 11: Effectiveness of Anti-Monopoly Policy vs GINI Innovation 63
Table 13: Regression of GINI innovation by LME Anti-Monopoly Effectiveness 63
Table 14: Regression of GINI innovation by CME Anti-Monopoly Effectiveness 63
Graph 12: Rigidity of Employment Index by VOC 66
Graph 13: Rigidity of Employment vs GINI innovation 67
Table 15: Regression of GINI innovation by LME Rigidty of Employment 67
Graph 14: VC availability by GINI innovation 69
Graph 15: Supplier Score vs GINI coefficient 71

Chapter One: Introduction

Policies that strengthen innovation and competitiveness represent the next frontier in economic development. For advanced industrialized democracies, this *innovation-driven* stage of development is characterized by a push to improve the capacity of economic actors to generate, and engage in, cutting-edge products and processes. Amidst this push, the concept of regional clustering has been both championed by scholars (Best 1990, Porter 1990; 1996; 1998) and enthusiastically embraced by countries as a modern industrial blueprint for driving innovation and enhancing competitiveness (OECD 2000).Clusters are attractive to policy-makers and economic actors alike due to their ability to increase the productivity of member firms, ease coordination across firms, allow for rapid diffusion of best practices, and, importantly, stimulate and enable innovations through inter-firm linkages and knowledge spillovers (Porter 2010).

Given the benefits of clusters, one of the tasks of the researcher is to identify the factors and practices that contribute to their development and success. While the literature has grown our understanding of the benefits of clusters and has documented 'best practices' that have contributed to cluster success, it is not matched by an understanding of the effects of the political-economic environment on cluster development. This gap is partly the result of a field of study that is largely the purview of a small number of economists and business strategists. In this realm, clusters are often perceived as "private-sector driven" phenomena that emerge spontaneously without government intervention.[1] Where comparative political approaches have been taken, scholars have found that the context-specific realities of a region make mechanically transferring successful cluster models to different locations difficult, ill-advised, and primed for failure.[2] The combination of these factors has resulted in numerous regional and locality specific cluster studies, but also a lack of general theories of regional clustering that are fused with political content.

The purpose of this paper is to address the gap between cluster studies and politics by enhancing the understanding of the effects of the political-economic environment on cluster development. We do this by adopting the varieties of capitalism (VOC) framework to the question of cross-national differences in clustering. The VOC approach blends policy-related questions with firm-related questions. By locating the firm at the center of the analysis, VOC helps "build bridges between business studies and comparative political economy, two disciplines that are all too often disconnected." [3]

The VOC approach provides us with great leverage on the question of clusters. This is because VOC parallels and overlaps with cluster theory on a number of key dimensions. First, by locating the firm at the center of the analysis, both VOC and cluster models integrate game-theoretical, strategic perspectives on the firm. Second, both serve an important role in connecting microeconomic analysis to the macroeconomic outcome. Finally, VOC unveils the complementary sets of political-economic institutions that comprise the "terrain" in which firms and clusters are "nested." As an approach that

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[1] See: "Michael Porter on Competitiveness". <http://www.youtube.com/watch?v=y5I_cnpP99U>

[2] Hospers, Gert-Jan, and Sjoerd Beugelsdijk. "Regional Cluster Policies: Learning by Comparing." *KYKLOS* 55 (2002): 381-402. Print.

[3] Soskice, David. "An Introduction to Varieties of Capitalism."*Varieties of Capitalism*.By Peter A. Hall.Oxford UP, 2001.1-29. Print.

weighs heavily on the systematic differences in a firm's structure and strategies, it appears to have utility in explaining observed differences in cross-national clustering activity.

We ask: Does the variety of capitalism in an innovation-driven economy affect the prevalence, size, and form of clusters? We believe that it does, and if so, we can uncover valuable insights into the effects of the political-economic environment on cluster development. Even in the event that VOC does not have any substantial impact, this finding would mean that the clustering phenomena can truly exist and thrive in varying political-economic conditions.

This chapter proceeds by giving an overview of the existing literature and sets the stage for the pertinence of the research topic. It explains why innovation-driven economies are turning to regional, micro-economic level policies aimed at establishing globally competitive clusters. Furthermore, it introduces the varieties of capitalism literature and reveals how the VOC literature has important overlapping attributes with the cluster literature. This chapter concludes by providing an outline from which the rest of the paper will proceed.

1.1 Literature Review

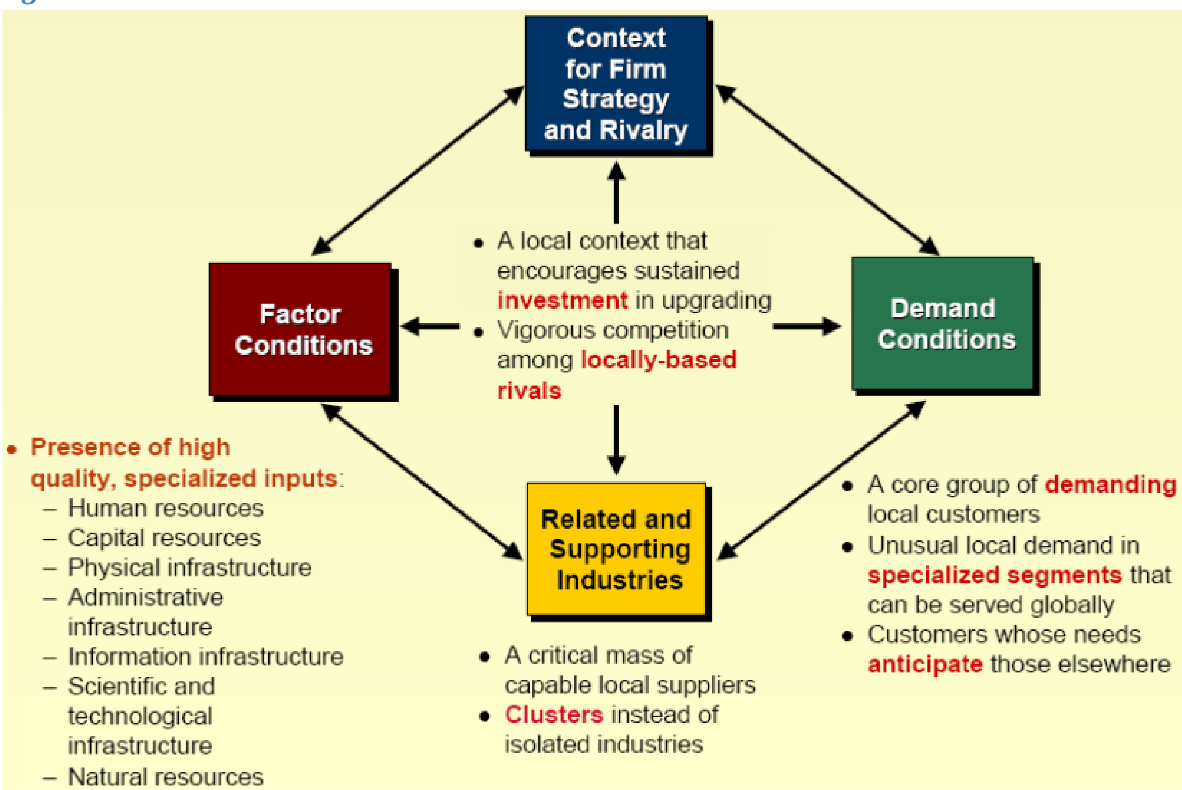
We begin by providing a brief overview of the benefits and structure of the cluster environment. We do this because an understanding of the workings of clusters and their attraction to firms and policy makers is an important component of our theory. We then proceed to discuss some of the approaches to the cluster concept taken by policy makers. The difficulties in formulating general theories of cluster formation are listed in order to explain why there is a lack of political content on the subject. Finally, we go into the VOC literature in more depth in order to expose overlapping elements with cluster theory.

1.1.1 Clusters and Cluster formation

Clusters are geographic concentrations of interconnected companies, specialized suppliers, service providers, and associated institutions in a particular field that are present in a nation or region. The advantages that they confer to member firms results in a disproportionate amount of a country's innovation and commercialization of new products taking place in these environments. For countries in the *innovation-driven* stage of development, the cluster strategy provides a model for upgrading the sophistication of business networks and interactions. As the Cluster Initiative Greenbook points out: "Cluster development initiatives are an important new direction in economic policy, [that builds on] earlier efforts in macroeconomic stabilization, privatization, market opening, and reducing the costs of doing business."

To begin studying the differences in cross-country clustering activity and to assess the quality of cluster strategy proposals, we must have an understanding of the characteristics, causes, and types of clusters. Michael Porter, often recognized as the preeminent champion of cluster of strategy, introduces a framework for developing and sustaining a cluster environment. According to Porter's "diamond" framework, there are four critical dimensions of a geographical location's microeconomic environment that affect the rate of innovation and overall competitiveness of the cluster: (1) strong and sophisticated local demand; (2) a local base of related and supporting industries to support the export industry; (3) favorable factor (resource) conditions; (4) a competitive climate driving firm productivity. Many of the 'best practices' for cluster development are focused on simultaneously improving or providing aspects of the diamond framework. Figure 1 displays Porter's diamond framework and the factors involved in each dimension.

Figure 1: Porter Diamond Framework



Source: Michael Porter, Institute for Strategy and Competitiveness, Harvard

The benefits that are generated as a result of this cluster environment are well-documented. Foremost, presence within a cluster produces powerful positive externalities and spillovers that endow firms with advantages in both perceiving the need for innovative activity and in sourcing the components to carry out that innovative activities.[4] By co-locating with local suppliers, firms can more easily turn new ideas into realities and can improve the quality of their supplier relations through repeated interactions. Indeed, firms are far more likely to innovate when own-sector employment in its home region is strong.[5] Associated institutions such as schools, universities, and other skill training facilities can provide firms in clusters with experienced personnel. Furthermore, while technology and other forms of codifiable knowledge are tradable assets, it is the set of untradeable interdependencies and tacit knowledge that emerge in the cluster environment that constitute the backbone of technological development (Gambarotto and Solari 2004). This embedded tacit knowledge in a certain geographical proximity matters because knowledge does not move frictionlessly among economic actors.

Clusters are reinforced by a positive feedback process based on the set of competitive advantages that arise from the geographical agglomeration of industrial activities. Firms gravitate towards clusters to take part in these competitive advantages. In technology oriented clusters such as Silicon Valley, firms are attracted due to cluster advantages such as research institutions, venture capital linkages, relations with other industry leaders, and educational institutions. While most clusters enjoy some combination of these advantages to different degrees, established clusters develop their own unique knowledge and brand that gives them global supremacy in their particular field.

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[4]Porter, Michael R; Stern, Scott."National Innovative Capacity." Harvard Business Review (2000)
[5]Baptista, Rui& Swann, Peter, 1998. "Do firms in clusters innovate more?," Research Policy, Elsevier, vol. 27(5), pages 525-540, September.

1.1.2 Clusters and Politics

Thus far, implementation of cluster programs and initiatives has been based on the recommendations of lead scholars (such as Porter) through cluster studies and comparative cluster analyses. Success stories of certain key clusters, - from Silicon Valley (Saxenian 1994), the Emilia-Romagna region of Italy (Scott 1993), and the Baden Württemburg region of Germany (Strambach et al. 2001) – have initiated the search for ‘best practices’ that can be used to generate or evolve similar clusters in other countries. These often include, but are not limited to: driving economic development to the regional level, upgrading institutions for collaboration, enhancing public-private collaboration, matching funds of action plans, and even inviting tourism.[6]

While these practices have some success at nursing nascent clusters, the government-driven implementation of new clusters has largely been a failure. As Hospers and Beugelsdijk (2002) point out, the spontaneous nature of the cluster phenomena makes it difficult, if not impossible, for governments to transfer successful cluster models mechanically. In general, creating clusters from scratch involves high costs and requires much time before they become embedded in their environment (Castells and Hall 1994). Indeed, in a lecture on clusters to the Columbus Partnership on competitiveness, Porter declared: “If you see economic development as something the government does, it will never get done. Government-backed initiatives fail. Private sector driven ones can succeed.”[7]In essence, regional cluster policy can be ‘inspired’ by successful cases and

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[6] Porter, Michael. "Competitiveness and Economic Development:Where Does Texas Stand?" *Texas Economic Summit*. 14 Nov. 2006. Web.

[7] See: "Michael Porter on Competitiveness”. <http://www.youtube.com/watch?v=y5I_cnpP99U>

best practices, but only in conjunction with context-specific considerations such as the structural and cultural specificities of the region. The process of cultivating clusters has been likened to the process of innovation itself, with policy-makers and private-sector actors experimenting with "new combinations" of best practices and context-specific considerations.

These realities of cluster development have important implications for researchers and policy makers. The question of why successful models of clusters cannot be transferred from one locality to another could be illuminated by an understanding of the political-economic variables involved. Furthermore, the necessity of taking into account the cultural and structural specifics of the region does not mean that general theories of cluster development are not applicable. Instead, by understanding the similarities and differences across regions, and the way certain environmental variables affect cluster development, we can better target the areas of cluster development that can benefit from government intervention.

1.1.3 Varieties of Capitalism

In our effort to inject political content into an area of research that has largely been dominated by economists and business strategists, we turn to the varieties of capitalism (VOC) literature. As discussed earlier, the varieties of capitalism is an approach to political economy that produces a myriad of hypotheses with respect to corporate governance, monetary policy, welfare programs, labor reform, and for our purposes, innovation. At its core, VOC theory examines how a given political-economic institutional structure affects the relationships, behaviors, and characteristics of firms, labor, and investors. Differences across countries' political systems give countries different comparative advantages. In majoritarian electoral systems, wider policy swings result in a greater reliance on market mechanisms to help firms adjust and maintain flexibility in the face of shifts in policy.[8] Through a recognition of the interplay of the political-economic institutional environment on firm behaviors,. VOC scholars have inserted political science into numerous areas of economic research from which it has been all but absent.

VOC theory differentiates national political-economic institutional structures based on a number of dimensions. The core dimension involves the degree to which a country relies on either market mechanisms or hierarchies to form the context in which economic actors organize, conduct their relationships, and solve coordination problems.[9] Traditionally, VOC can be viewed as capitalism by gradation with two ideal types – liberal market economies (LMEs) and coordinated market economies (CMEs) – at opposite poles of the spectrum. However, scholars have found this dichotomous formulation to be too narrow in scope and OECD-centric.[10] Schneider (2008) expands upon the VOC classifications by identifying the principles of allocation that comprise the underlying logic of four ideal-typical VOCs: LMEs, CMEs, network-market economies (NMEs) and hierarchical market economies (HMEs). According to Schneider, different logics inform relations among economic agents in each variety – markets, negotiation, trust, and command, respectively – and lead to marked differences in these four varieties

[8] Soskice, David. "An Introduction to Varieties of Capitalism."*Varieties of Capitalism*.By Peter A. Hall.Oxford UP, 2001.1-29. Print.

[9] Taylor, MZ "Empirical Evidence Against Varieties of Capitalism's Theory of Technological Innovation." *International Organization*, Vol. 58, No. 3, 2004

[10]Pontusson, Jonas, and David Rueda."The Politics of Inequality and Partisan Polarization in OECD Countries."

in labor and employee relations, corporate governance, inter-firm relations and skill regimes.

Applying a VOC framework to our study can give us many insights into the broader set of institutions in which firm activities are "nested." Institutions are relevant because they shape the environment in which economic activity plays out. The package of institutions associated with certain VOC typologies affects both firm characteristics and the national industrial environment. By understanding cross-national differences in the political-economic institutional environment, we have a framework for analyzing cross-national differences in clustering activity.

Table 1: VOC characteristics by type

	Liberal Market Economies	**Coordinated Market Economies**	**Network Market Economies**	**Hierarchical Market Economies**
Allocative Principal	Markets	Negotiation	Trust	Hierarchy
Characteristic interaction among stakeholders	Spot exchange	Institutionalized meeting	Reiterated exchange	Order or directive
Length of relationships (all types)	Short	Long	Long	Variable
Stock ownership	Dispersed	Blockholding	Blockholding and cross-ownership	Family block-holding

Predominant type of large firms	Specialized managerial corporations, MNCs	Bank controlled firms, business groups	Informal business groups (keiretsu)	Hierarchical business groups
Firm relations within sectors	Competitive	Sectoral associations	Associations and informal ties	oligopolistic
Firm relations across sectors	Few	Encompassing associations	Informal connections	Few (save acquisitions)
Supplier relationships	Competitive, bidding	Long term, negotiated	Long term, informal	Vertical integration
Employment relations	Short term, market	Long term, negotiated	Life time employment	Short term, market
Labor-management committees	No	Yes	Yes	no
Skills	General	Sector specific	Firm specific	low
Comparative institutional advantages	Radical innovation, services	Incremental innovation, manufacturing	Incremental innovation, manufacturing	Commodities, global production networks
Representative Case	United States	Germany	Japan	Chile

As we can see from Table 1, there are notable differences across VOC type in key dimensions discussed in the cluster literature. These include the allocative principle, length of relationships, firm relations within and across sectors, supplier relations, employee relations, and skill regimes. We know that clusters intensify competition, extend relationships through co-location, improve supplier relations and the ability of firms to source new materials, and enhance employee relations and skill regimes through closer integration with educational and training institutions. It is due to these overlapping dimensions and the marked differences of these dimensions across VOC type, that our theory of the effect of VOC on clustering is constructed.

For our purposes, we focus on the differences across the dimensions for the polar opposite cases: LMEs and CMEs. We do this because variation should be greatest at opposite ends of the spectrum, and because the representative cases at the poles are more widely agreed upon by scholars. However, we do recognize the different distinctions in VOC type when selecting the countries that will be classified as LME or CME.

1.2 Paper Overview and Added Value

This paper proceeds as follows: In Chapter Two, we construct a theory about expected differences in clustering activity based on the interplay of the overlapping dimensions of VOC and cluster theory. We then delineate a series of hypotheses based upon the expectations of the model. Chapter Three expounds upon the research design and gives an explanation for how each hypothesis will be tested. Chapter Four performs empirical tests of the hypotheses based upon the research design in chapter three. Finally, Chapter Five summarizes our findings and notes areas for future research.

This paper contributes to the existing literature in a number of ways. First, by adopting a VOC approach to an issue of economic geography, a political dimension is added that illuminates policy prescription. Second, we examine existing measures of country-level clustering, identify their shortcomings, and introduce a new GINI measurement of clusterness that leverages intra-country disparities in the spatial distribution of innovative activity. Third, our findings reveal important cross-national differences in both the types and causes of clustering activity along the LME to CME dimension. Finally, the totality of this paper can be seen as lending support to the VOC approach to issues in the economic realm.

Chapter Two: Theory

The VOC conceptualization of society provides a potentially useful, yet thus far unexplored, framework for analyzing the effects that the institutional environment can play on firms' incentives to cluster. After outlining the marked differences across VOC typologies in the previous chapter, this chapter presents a theory for differences in clustering activity based on the interplay of VOC characteristics with what is understood to be the primary incentives driving firms towards clusters. We argue that the cluster model is both more compatible with LMEs, and that the relative benefits to be enjoyed in the cluster environment are greater for firms in LMEs than in CMEs. We derive three testable hypotheses that address our research question: 1)*LMEs should display greater overall clustering levels than CMEs;* 2) *clusters in LMEs should be larger and more diverse than clusters in CMEs;* and3)*firms in LMEs are drawn to clusters because they act as functional equivalents for industrial benefits that they lack relative to their CME counterparts.*

2.1 Assumptions and Preface

Before getting into the meat of our theory, it is important that we qualify the extent of its applicability and are explicit about our assumptions. As noted in Chapter 1, clusters are often private-sector driven phenomena that emerge spontaneously. Since every cluster faces unique, context-specific realities, we do not pretend to present an exact theory of cluster origins. Rather, we present a theory that produces general expectations with regards to differences in aggregate-level clustering activity across VOC type.

Recent attempts to explain clustering phenomena posit an initially random distribution of productive activity that is then followed by agglomeration because of either increasing returns to scale or network externalities (Saxenian 1994). In comparing aggregate level clustering activity in countries, we assume an initial random distribution of firms. In reality, factors as diverse as country age, culture and geography could greatly impact initial clustering levels and result in path dependent processes. Other than variation in our independent variable of VOC type, we assume that all other factors are held constant.

Incentives play an important role in our theory. In keeping with the view of clusters as 'private-sector' driven phenomena, we place the firm at the center of our analysis.The objective of the firm is to maximize shareholder wealth. In pursuing this objective, the firm should look to enhance their competitive edge. The cluster environment is one such solution for this need. Clusters provide a myriad of benefits to their members, and thus generate incentives among firms to enter into, or remain in, a cluster environment. The greater the competitive advantages the cluster confers to its members, the stronger the desire for new firms to enter the cluster. As the cluster solidifies its status as an ecosystem for increasing the innovative activity and competitiveness of a region, policy makers and economic actors are more likely to engage in activities that sustain existing clusters and promote clusters in other regions.

From this picture, it would appear that the driving force behind cluster growth and promotion is the *relative advantages* the cluster environment confers to its members. It is logical to assume that as the degree of relative advantages of the cluster increases, so should the prevalence of clusters as a favorable model of economic development. The more the cluster environment is compatible with, and superior to, the overarching industrial infrastructure, the more we would expect to see clusters thrive.

In constructing a theory around our belief, we assume the validity of the VOC classification system. Our purpose is not to evaluate the accuracy of the LME-CME classification system, but rather to use this classification to expose the affinities between the type of VOC and the cluster model. We anticipate that differences across VOC type impact clustering activity by altering the incentives faced by firms.

2.2 Relative benefits of the cluster environment by VOC type

Our theory explains differences in clustering activity, the dependent variable, as a function of the VOC type, the independent variable. An investigation of the differing dimensions of VOC type allows us to derive a series testable hypotheses relating to the influences of these dimensions on firm level decision making. We begin by asking: Is the cluster environment more compatible with one type of VOC than another?

Table 2 shows a breakdown of relevant environmental features versus the cluster environment, LME environment and CME environment. When lined up along these dimensions, we see that the cluster model is more compatible with LMEs than with CMEs for two primary reasons. First, both Porterian cluster models and LMEs rely heavily on market mechanisms to coordinate economic activity. Second, as a result of their reliance on market mechanisms, the structure of relationships among firms, suppliers, and employees in LMEs and the cluster environment follow similar paths.

Beginning with the first point, vigorous local competition constitutes the “heart” of the Porterian diamond framework. As we know, LMEs are characterized by a higher degree of reliance on mechanisms as compared to their CME counterparts. LMEs resort to market mechanisms to “coordinate” firm activity. Ironically, it is by intensifying these market mechanisms through vigorous local competition that enhanced coordination results. In this manner, it would appear that the cluster environment is not only more compatible with the LME environment, but it is also the natural successor to the LME economic model of development.

As a result of the greater reliance on market mechanisms, the structure of relationships between firms, suppliers, and employees in LMEs is more compatible with the cluster model than those of CMEs. Firms in LMEs structure their relationships with rival firms and suppliers based on competition and arms-length transactions. There are few within-sector or across-sector associations. Alternatively, CME firms allow for sector-specific and encompassing associations to help coordinate actions and tend to enjoy long-term, negotiated relationships with suppliers. Furthermore, the fact that employee relationships are short-term and market determined in LMEs makes it more likely that clusters in LMEs will experience knowledge spillovers in the form of poaching or job-hopping.

Table 2: Cluster environment compatibility by VOC type

Environmental feature	Cluster Literature (Porter Diamond Framework)	LMEs	CMEs
Allocative principal/Underlying mechanism	Vigorous competition among locally based rivals	• reliance on market mechanisms to coordinate firm actions • competitive relationships among firms	• negotiation and encompassing associations
Length of relationships	Improves upon the length and quality of relationships through geographical proximity and repeated interactions	• short	• long
Stock ownership	Emphasizes the need for an ample supply of "risk capital"	• Dispersed ownership • Lack of "patient capital" • More venture capital oriented	• Blockholding ownership • "Patient capital" with banks willing to sit on the board
Firm relationships within sectors	Based on intense local competition	• competitive	• sectoral associations reduce reliance on market mechanisms
Firm relationships across sectors	Necessitates strong linkages in order to exploit scientific and technical advances	• few	• encompassing associations
Supplier relations	Presence of capable local suppliers and related companies allows for higher quality interactions and the ability to	• competitive, bidding	• long term, negotiated

	more rapidly source elements to innovation		
Employment relations	Fluidity of personnel allows for powerful knowledge leakages	• short term, market	• long term, negotiated
Skills	High quality human resources, especially scientific, technical and managerial personnel	• general skill sets • comparative advantage in services	• sector-specific skill sets • comparative advantage in manufacturing

Having established that the cluster model is more compatible with LMEs, we now ask: Does VOC affect the relative advantages of firms when it comes to their decision to enter the cluster environment? A comparison of Tables 3 and 4 demonstrates that firms in LME's are likely to experience greater relative benefits by entering a cluster than firms in CME's. The geographical co-location of firms is useful in lowering inter-firm transaction costs. Since firms in LME's conduct much of their business through arms-length transactions, having complementary partners and suppliers in close range increases both their capacity and flexibility to innovate by helping them source new machinery, components, and services.

Whereas firms in CMEs, by definition, tend to work together to coordinate strategies, the cluster environment in LME's helps make up for the inherent lack of coordination by realigning the incentives of firms in the cluster. The health of the cluster bestows positive externalities to its members. The members, therefore, have an interest in the cluster's continued health. The co-location of firms becomes more than an agglomeration when firms partner together and resolve disputes through the formation of business associations. Furthermore, clusters allow repeated face-to-face interactions between firms and give them better information and insight as to their competitor's latest technologies- aspects of LME arrangements that are usually not present.

Table 3: LME cluster benefits

Environmental feature	LMEs	Benefits of Cluster environment
Allocative principal/Underlying mechanism	markets	The cluster represents the intensification of market mechanisms to the point where local competition is perceived as being a positive.
Length of relationships	short	Geographical proximity allows relationships to be longer, deeper, and more intensive.
Stock ownership	dispersed	LMEs lack the "patient capital" of CMEs. The dispersed ownership demands immediate returns. Cluster environments are compatible with this structure because they provide an ample supply of risk capital
Firm relationships within sectors	Competitive.	The competitive interactions already present among firms are beneficial both in incentivizing firms to enter the cluster, and in fostering the health of the cluster. In order to remain competitive, firms enter clusters for the benefits of upgrading. Intense local rivalry is at the heart of the Porterian diamond framework, as it drives the operation of a

		healthy cluster.
Firm relationships across sectors	Few	Clusters are more than geographical agglomerations of firms. A cluster includes deep linkages of firms across industries. By entering into the cluster environment, firms in LMEs mitigate one of their usual disadvantages in their environment.
Supplier relations	competitive, bidding	The relationship between firms and suppliers in a cluster environment still operates according to competitive mechanisms. However, the geographical proximity and repeated interactions improve the responsiveness of suppliers to firms' demands and allows them to quickly source the components to implement innovations.
Employment relations	Short-term, market	In an environment where employment is short term, employees would rather enter a cluster where they can quickly flow from one firm to another. Firms also find this effect desirable as it can lead to powerful knowledge spillovers and exchange of tacit knowledge.
Skills	general	Clusters attract, or are formed in part by, related and supporting institutions for education, research, and skill development. Firms are attracted to clusters because they provide high quality human resources, especially scientific, technical, and managerial personnel.

Table 4: CME cluster benefits

Environmental feature	CMEs	Benefits of Cluster environment
Allocative principal/Underlying mechanism	negotiation	Porter's diamond framework requires vigorous competition among local based rivals. Since clusters represent an intensification of market mechanisms, Porterian clusters would seem incompatible with CMEs. However, the possibility of alternative forms of cluster governance, such as network or hierarchical remain.
Length of relationships	long	Geographical proximity allows relationships to be longer, deeper, and more intensive. While this seems compatible with CMEs, the *relative* benefit of joining a cluster is reduced.
Stock ownership	blockholding	The blockholding ownership structure gives CMEs a "patient capital" aspect. Complementarities between long-term patient capital and a highly skilled workforce gives CMEs a comparative advantage in production of high-quality, high-value added commodities(Weiss2003).The relative benefit of joining a cluster compared to LME firms (that lack this comparative advantage) is reduced.
Firm relationships within sectors	Sectoral associations	Firms in CMEs already benefit from sectoral associations, thus diminishing any relative benefit of increased cooperation through clustering. The baseline of coordination for CMEs in higher than in LMEs. Sectoral associations also might make it more difficult for firms to enter into clusters.

Firm relationships across sectors	Encompassing associations	By definition, a cluster includes deep linkages of firms across industries. Again, while the encompassing associations of CMEs appears more compatible with the cluster environment, the relative benefit of entering a cluster is reduced because CME firms already enjoy a degree of linkages across sectors.
Supplier relations	Long-term, negotiated	Locating closer to their suppliers allows for longer term relationships and increased quality and compatibility. It could be argued that firms in CMEs have less to benefit, or it could be argued that it may be easier for them to join clusters because they would not need to alter their characteristics.
Employment relations	Long-term, negotiated	The long-term nature of employment makes it more likely for the firm to invest in training of labor. It also makes it more likely for the firm to capture the gains of this investment. Since long term employment reduces knowledge leakages in the forms of personnel transfers and job hopping, one of the primary benefits of clusters as ecosystems for spillovers is also reduced.
Skills	Sector specific	The existence of sector specific skills makes CMEs more compatible with cluster environments where there are high quality human resources. However, the relative benefits of entering the cluster in order to gain specialized labor are reduced.

In activities where CMEs have an inherent advantage, firms in LMEs can realize similar benefits through clusters. CMEs typically extend long-term, permanent, or even life-time positions to their employees. These firms tend to invest in “high skill” firm-specific training for their employees since assurances of long-term employment make these employees less likely to “job hop”. In contrast, LME’s do not extend the same type of employment assurances to employees. Firms in LMEs are less likely to invest in employee training. Workers in LMEs will typically invest in general skills that are more portable to allow for inter-firm movement. As Hall and Soskice (2001) note: “top management has unilateral control over the firm, including the substantial freedom to hire and fire…in these markets, it is relatively easy for firms to release or hire labor in order to take advantage of new opportunities.”

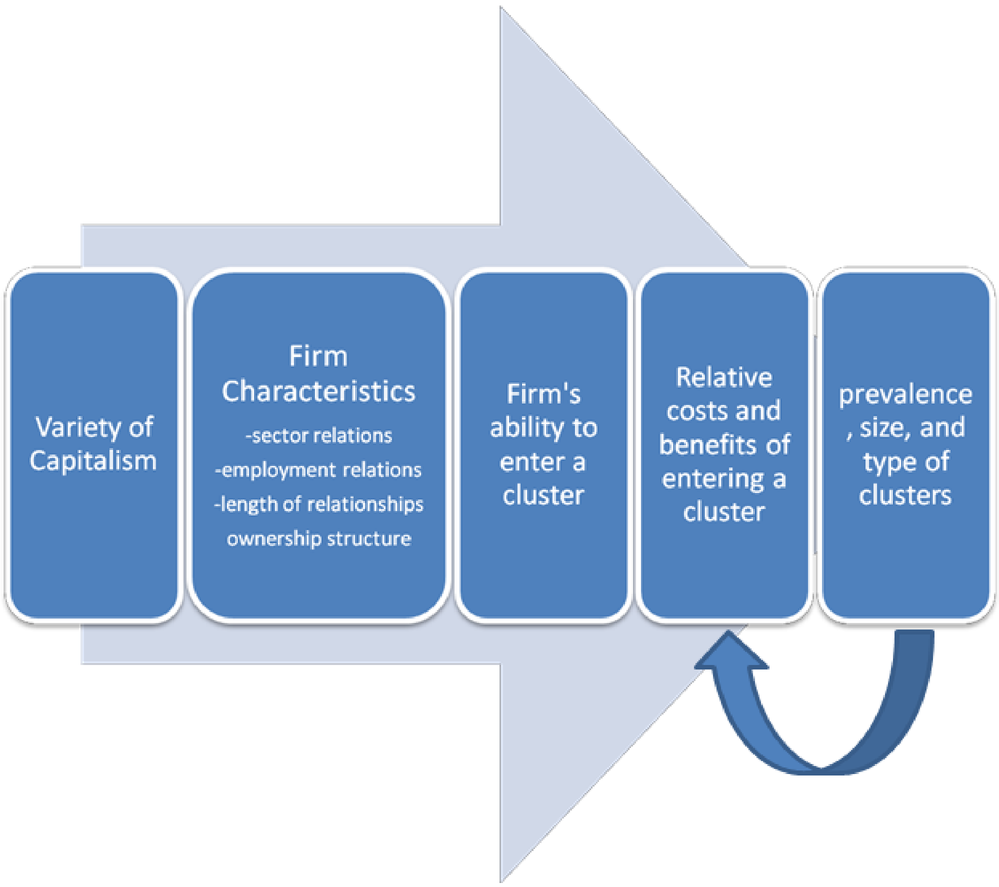
LMEs would benefit more than CMEs from clustering in this scenario for two reasons. First, since employees have skills that are more portable, firms in LMEs can join into clusters to mitigate the effects of knowledge leakages. Second, clusters tend to attract universities and other training institutions that by working closer to the cluster can encourage the formation of more industry specific skills.

2.3 Causal Mechanism

Clusters can naturally emerge and grow due to the relative advantages they confer to their members. Our theory argues that the emergence and trajectory of cluster growth is affected by the political-economic institutional environment in which cluster activity is nested. The VOC typology is useful in describing this environment and in exposing the relative benefits of clustering activities across the VOC types.

Figure 3 represents a formalization of the mechanism through which the environment influences clustering activity. In the first stage, the political arrangements of a country affect the degree to which the country relies on market mechanisms to structure relationships between economic actors. This constitutes the primary dimension along which a country is placed on the VOC spectrum. The VOC type is associated with a myriad of institutional complementarities that affect important dimensions of the industrial environment and firm characteristics. As we have seen LMEs rely more heavily on markets to resolve coordination problems and, as a result, firm relations are competitive, relationships with suppliers and employees are short term, ownership is dispersed, skills are general, and firm coordination through associations is much harder to come by. At the other end of the spectrum, CMEs rely more heavily on coordination and negotiation than market mechanisms to structure relationships. As a result, relationships between micro-level actors in CMEs are long term, firms are owned through blockholding structures, skills are sector-specific, and business associations are widespread and encompassing.

Figure 2: Diagram of Causal Mechanism



We assume that the decision to enter or remain in a cluster environment is made at the firm level. The differing characteristics that firms display at the opposite poles of the VOC spectrum affect a firm's decision to enter a cluster by altering the relative benefits of a cluster environment. Part of the decision-making process involves the ability of a firm to enter a cluster. The more mobile/liquid a firm's capital, the more easily they will be able to act upon perceived benefits to relocating to the cluster environment. LMEs have the advantage here. As Hall and Soskice (2001) observe: *"The more fluid markets of LMEs provide economic actors with greater opportunities to move their resources* *around in search of higher returns, encouraging them to acquire switchable assets, such as general skills or multi-purpose technologies."*

Finally, the prevalence, size, and types of clusters should feed-back into the cycle. If there exists an established cluster in a firm's industry (or complementary industry), then that firm is more likely to relocate to a cluster than if no cluster exists. Furthermore, larger clusters mean that more firms are experiencing competitive advantages and more positive externalities are generated in the cluster environment. Firms located outside of a large and growing cluster in their industry risk losing competitive advantage by remaining outside the cluster and therefore perceive greater benefits to entering the cluster environment.

2.4 Hypotheses

Based on our theory, we derive three testable hypotheses. First, we expect that LMEs will display greater overall clustering levels than CMEs. The greater compatibility of the cluster model with LMEs means that cluster-like externalities are more likely to be realized where agglomerations of firms exist. As these positive externalities begin to take hold, firms outside the cluster environment will be induced to enter a cluster in order to enhance their competitive advantages. The greater relative benefits of entering a cluster in LMEs as compared to CMEs will aggregate to greater overall clustering levels.

Our second hypothesis states that clusters in LMEs will be larger and more diverse. By larger, we mean that the region in which they are located will account for a greater share of the country's innovation. By more diverse, we mean that there will be more firms from a greater range of industries. We believe this to be the case because the cluster model is more compatible in LMEs. As a result, cluster growth in LMEs should benefit from returns to scale. The more the cluster grows, the more the market mechanisms are intensified, and the greater the positive externalities. Furthermore, the greater diversity of firms that enter the cluster, the more inter-sector linkages can be strengthened through geographical proximity. It is important to note that just because these benefits should accrue, does not mean that they must. However, we believe that, on balance, they are more likely to accrue in LMEs than in CMEs.

Our third hypothesis states that firms in LMEs are drawn to clusters because they act as functional equivalents for industrial benefits that they lack relative to their CME counterparts. Based on the VOC typology, these benefits include increased coordination among firms, longer relationships, access to skilled labor, access to risk capital, and deeper supplier linkages.

This hypothesis also implicitly holds that the factors driving firms to clusters are different for LMEs and CMEs. For example, clusters give firms in LMEs the opportunity to enjoy longer relationships with suppliers, and thus improve their access to high quality inputs. In CMEs, where they already tend to have long term relationships with suppliers, the benefit of entering into the cluster is not as great. Therefore, in this case, firms in LMEs that see access to high quality inputs as a pressing concern are more likely to be drawn to the cluster environment whereas CME firms may be reluctant to forgo their long term relationship with their supplier. This same scenario plays out across a number of the relevant dimensions to our analysis, and will be discussed in further detail later on in the paper.

Chapter Three: Research Design and Expectations

Having laid out a theory and hypotheses regarding cross-national differences resulting from VOC type, we will now construct a quantitative research design test our predictions. A quantitative research design is suitable for our purposes because it allows us to assess the degree to which certain environmental factors effect clustering. Since a host of factors influence the incentives of firms to cluster, a qualitative design would make it difficult to assess the relative importance of some factors as compared to others. Assuming homogeneity of our units through random selection, Large-n quantitative studies are high on external validity and can be invoked more readily across cases and time.

3.1 Unit of Analysis

Our unit of analysis is country-year. This is a fitting unit of analysis because we are interested in aggregate level, cross-national differences in clustering activity. Ideally, country-year would allow us to observe dynamic effects. Unfortunately, the data only spans 3-8 years, depending on the country. However, we use country-year in order to give us a larger sample size to draw from. Since we only have six representative cases of LMEs, this would make it difficult to achieve results that approach statistical significance if we just used a snapshot of clustering over one year. Thus, the country-year unit of analysis allows us to compare national level variation while providing a large enough sample to state our case with certainty.

3.2 Independent Variable: Variety of Capitalism

All tests of our hypotheses will incorporate VOC type as an independent variable. While the fit of a particular country in a VOC category can be argued - indeed there are shades of LME and CME in every economy - the existing VOC classifications are well researched and corroborated. The LMEs include Australia, Canada, Ireland, New Zealand, the United Kingdom and the United States. The CMEs include Austria, Belgium, Denmark, Finland, Germany, Netherlands, Norway Sweden, and Switzerland. Japan, considered in some studies to be a CME, is classified as an NME along with Korea based on Schneider (2008). The country of Estonia is not included in the LME set because it is not in the innovation-driven phase of development as determined by the World Economic Forum in their 2010-2011 Global Competitiveness Report. In between the LME and CME ideal types are the Mediterranean market economies (MMEs) of France and Italy as well as the Network Market Economies (NMEs) of Japan and Korea. Since MMEs and NMEs have mixed CME and LME characteristics, the application of our theory does not produce clear predictions as to clustering activity. Therefore, these types are not directly studied, but they are included in tabulations of OECD averages in order to help determine the baseline measurements from which the LME and CME distinction can be observed.

In leaning on this typology to test differences in cross-country cluster formation, the usefulness of the typology is also tested. VOC theory delineates a myriad of important industrial environment and firm characteristics that differ across the VOC spectrum. In order to assert that the characteristics of each type of VOC affect the incentives of firms to cluster, we must first check that these differences do, in fact, occur and are significant. If this is, indeed the case, the usefulness of these differing dimensions for predicting behaviors can either be corroborated or brought into doubt.

3.3 Dependent Variable: Measuring Clusterness

Each of our hypotheses involves some measurement of clustering activity as the dependent variable. The complication here is that clusters are notoriously difficult to measure. The process of identifying, defining, and describing a cluster is not standardized.[11] Operational definitions of clusters abound as researchers and practitioners develop their own measurement criteria and methodologies.

For our purposes, a cluster is the regional agglomeration of innovative activity that accounts for a disproportionate share of a country's total innovative activity.[12] This definition is intentionally outcome-centric. In constructing a country-level measurement of clustering activity, researchers have often relied on indicators or enablers of clustering activity that hint at innovation. For example, the World Economic Forum's Global Competitiveness Report asks a random sample of executives from every nation "In your country's economy, how prevalent are well-developed and deep clusters?" where 1 = nonexistent and 7 = widespread in many fields. Other than relying on firms' perceptions

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[11] "Regional Innovation Scoreboard | PRO INNO Europe®."*Home | PRO INNO Europe*®.Web.<http://www.proinno-europe.eu/page/regional-innovation-scoreboard>.

[12] A region contains a disproportion share of innovative activity if its share of patents in a country is greater than one divided by the total number of regions in a country. For example, a region that accounts for 5% of its country's total innovation, and is one out of 100 total regions, accounts for a disproportionate share of innovative activity because 5% > (1/100)

rather than hard data, this indicator tells us nothing about the types of clusters or any other cluster dimension that might be of interest.

The European Cluster Observatory provides researchers with a laundry list of indicators to select from when attempting to quantify the cluster phenomena. These include employees per region, employee growth per region, employees per enterprise per region, enterprises per region, wages per employee per region, business R&D share of GDP, public R&D share of GDP, population density, and a “stars” measurement of clusters based on a combination of region’s size (employment as total share of European employment), specialization (greater focus in certain industries), and focus (share of regional employment). In Table 5, these indicators are grouped by their relation to clusters.

Table 5: Cluster indicator types

Indicators	Enablers	Firm activities	Outputs
Survey data, Stars, employee growth per region, employees per enterprise per region, enterprises per region, wages per employee per region	Tertiary education, Life-long learning, Public R&D, Broadband;	Business R&D, Non-R&D expenditures, SMEs innovating in-house, Innovative SMEs cooperating with others	Patents, New to firm products, Sales new to market

While all of the indicators are certainly relevant to the cluster-specific environment, we focus on the outputs only. We do this for a few reasons. First, we care about innovative outcomes. We expect that various combinations of enablers and firm activities help result in increased knowledge and innovation production. We can measure enablers all we want and speculate that they should lead to innovative outcomes, but if the innovative outcomes are not present, why add them to the measurement? Second, the VOC approach anticipates important differences in many of these indicators. Making the mistake of including overlapping attributes of our independent variable with our dependent variable can lead to unreliable results. Finally, by separating the enablers from the innovative activity, we can examine which enablers correlate most strongly with innovative outcomes.

The GINI Coefficient

How do we measure and compare cross-national differences in clustering activity? We are interested not just in the number of success of clusters, but in aggregate level "clusterness" itself, specifically with regards to clusters as ecosystems of innovation. What we want to know is how much of a country's innovative activity takes place disproportionately in certain regional hotbeds. Ideally, we want a measure that can aggregate clustering activity, that intrinsically conveys useful information, and that facilitates cross-country comparison. Our solution is to use a GINI coefficient of the inequality in the distribution of patenting activity. We dub this measure "GINI innovation."

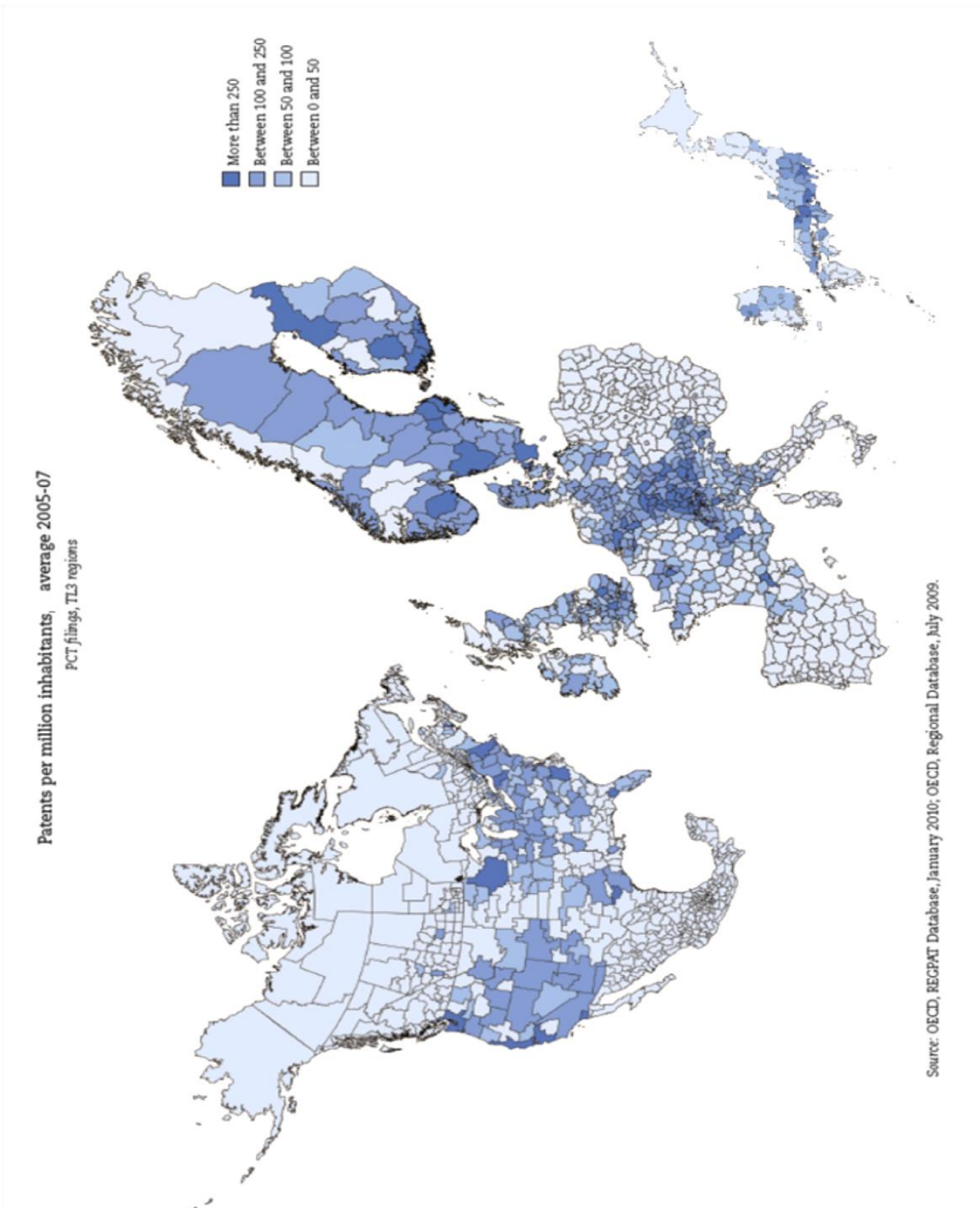
The GINI coefficient is a measure of inequality of a distribution that is commonly used at the country level with regards to income or wealth. . For this case, the Gini coefficient leverages disparities in the spatial distribution of innovative outcomes. It allows us to present a measure of the inequality of the distribution of patenting activity, where 0 expresses total equality and a value of 1 expresses maximal inequality. In constructing GINI innovation, we use patent counts to represent innovative outcomes. The greater share a region has of the total patent counts, the greater our measure statistical dispersion. For countries looking to bolster regional competitiveness, GINI coefficients of innovative activity closer to 1 are more desirable than scores closer to 0.

The OECD has classified regions within each member country. The classification is based on two territorial levels. The higher level(Territorial Level 2 – TL2) consists of 335 large regions; the lower level (Territorial Level 3 – TL3) is composed of 1 681 small regions. All regions are defined within national borders and in most cases correspond to administrative regions. Each TL3 region is contained within a TL2 region (except in Germany and the United States). This classification – which, for European countries, is largely consistent with the Eurostat classification – facilitates comparability between regions at the same territorial level. Using data from OECD Stat Extracts,[13] measures of patenting activity across TL3 regions can be assembled.

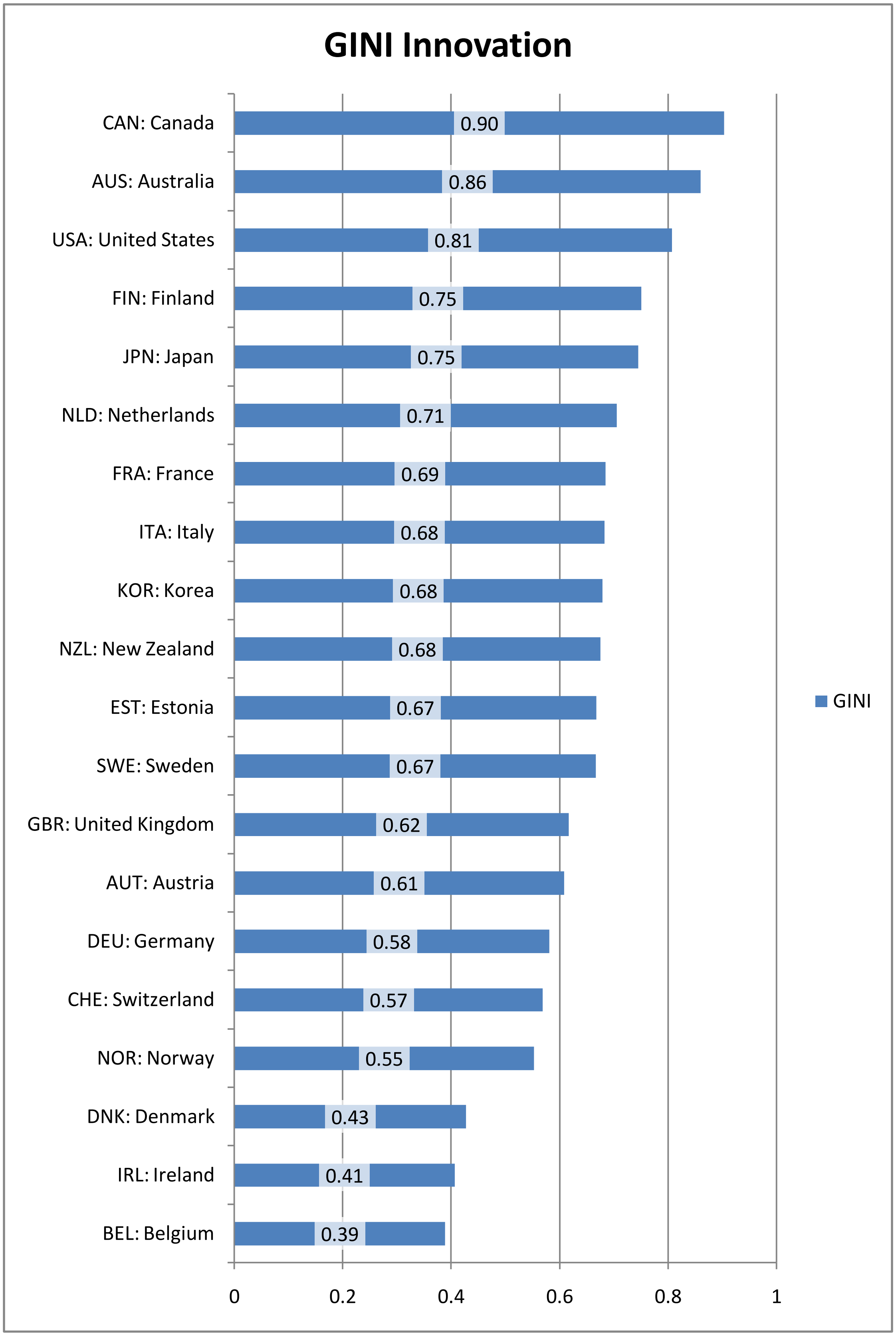
Figure 4 demonstrates that innovative activity is not "flat" (i.e. evenly distributed) across regions. Using the GINI innovation measure allows us to convey just how flat or "clustered" the innovative activity in a country is. Furthermore, it enables quick

[13] *OECD Statistics (GDP, Unemployment, Income, Population, Labour, Education, Trade, Finance, Prices...).* Web. 22 Mar. 2011. <http://stats.oecd.org>.

comparisons of country-level “clusterness.” The GINI coefficients reported in Graph 1 and Table 6 provide the average GINI coefficient for the years 2000-2008.



Graph 1: GINI Innovation by Country



Graph 2: GINI innovation by VOC type

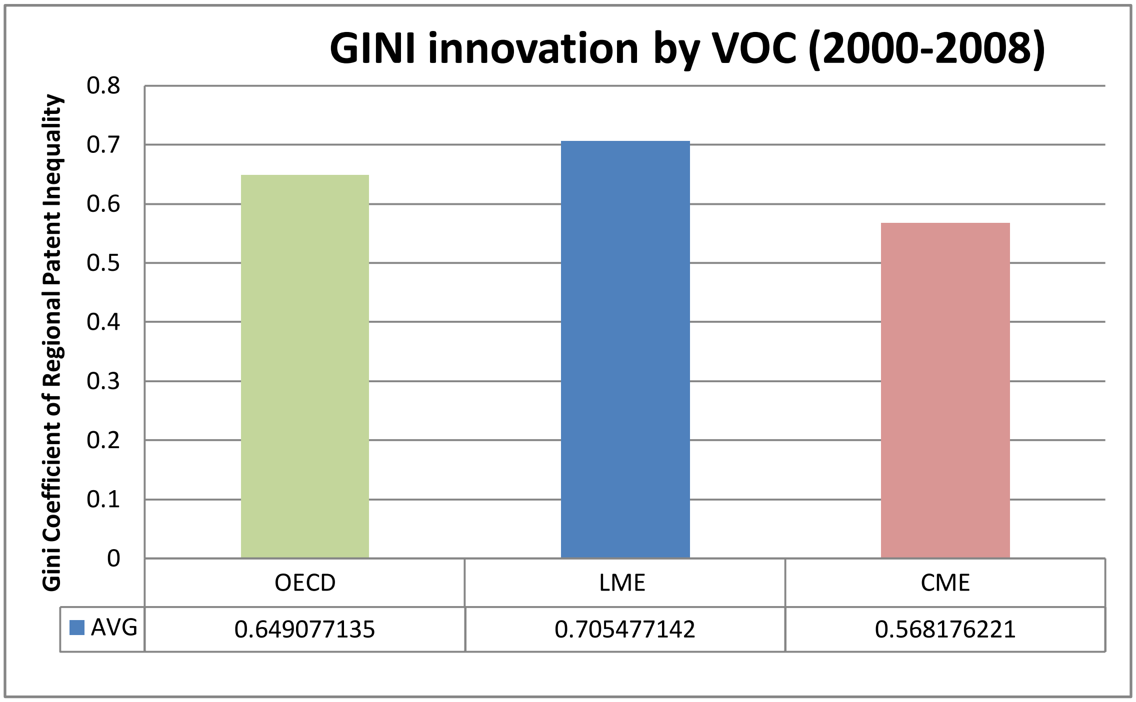


Table 6: Average GINI coefficients of innovation by VOC type

Summary statistics	**AVG**	**OBS**	**STD DEV**	**95% Confidence Interval**
OECD	0.6490	180	0.1361	0.63 – 0.67
LME	0.7054	70	0.1606	0.66 – 0.74
CME	0.5681	80	0.1120	0.54 – 0.58
LME - CME	0.1373	*unpaired*	0.0398	0.04 - .202

3.4Measuring Innovation: Patents

The most frequently used measurement of innovation is patents.[14] Proponents of this type of measurement argue that it is an acceptable measure at the aggregate level and is an adequate barometer of the total innovation in society. Use of patent data as a measurement is appealing because patent data are widely available, are perhaps the only

[14] Taylor, Mark Zachary. Empirical Evidence Against Varieties of Capitalism's Theory of Technological Innovation. *Cambridge University Press* 01 Jul 2004.

observable form of innovation over different industries at the macro level, and conform to strict definitional criteria.

When researchers elect to use patent data as their measurement, they are essentially accepting the patent criteria as their operational definition of innovation. According to the USPTO, a patent is a specific property right that is granted only after formal examination of the invention has revealed it to be nontrivial (that is, would not appear obvious to a skilled user of the relevant technology), useful (that is, has potential commercial value), and novel (that is, it is significantly different than existing technology).

Since the GINI measure of aggregate level clustering relies on patent data, it inherits many of pitfalls associated with the usage of patents as a proxy for innovation. The most obvious knock on the use of patents is that they only cover a moderate portion of innovative activity. Not every innovation has been patented, and not every patented innovation is produced and developed. Indeed, it has been estimated that less than 10 percent of patents drive 90 percent of the value.[15] R&D spenders often gauge their returns by the number of patents produced, giving innovators perverse incentives to generate as many patents as possible, irrespective of the quality. For one new product released, hundreds of its component parts may have received patents. Additionally, the use of patents to gauge the quality (radical vs incremental) and type of innovation (process or product) is difficult to impossible.

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[15]Dubner, Stephen J. "How Can We Measure Innovation?.". Web. 19 Oct. 2010. <http://freakonomics.blogs.nytimes.com/2008/04/25/how-can-we-measure-innovation-a-freakonomics-quorum/>.

Patents are acceptable for the purposes of the GINI coefficient because we are not attempting to account for and measure all innovative activity or even compare levels of innovative activity. What we are concerned about is the distribution. However, it can be argued that the patent measure fails to uncover certain clusters, perhaps those in service industries. This is indeed a concern and raises the possibility of controlling for patent-oriented industries.

3.5 Control Variable: Population Density

The population density of a country is used as a control variable in regressions using the GINI coefficient. Since we are measuring the inequality in the spatial distribution of innovative activity, one might want to use area as a control variable. However, the area of the country is not as important as how densely or sparsely that area is populated. Since we assume an initial random distribution where clusters emerging spontaneously due to geographical co-location, the more densely a country is populated, the more likely we are to have high levels of geographical co-location in certain areas. We do not control for urbanization because, in many instances, clusters and urban areas are one and the same. In contrast, a sparsely populated country, regardless of its area, may have higher GINI coefficient scores because a certain degree of factor accumulation is necessary in order to drive development. Again, it is not the absolute size of the country or the number of firms, but the proportion that is relevant for our purposes.

We use population density rather than firm density (number of firms divided by area) for a few reasons. First, it is the distribution of resources and how they are used that we care about. Second, there are differences in firm size across VOC type. If we controlled for numbers of firms, we would be biasing our results in favor VOCs with more small and mid-sized firms. Finally, the data for firm density is sketchy and unreliable at best.

3.6 Data Sources

To test our hypotheses, we rely on data from three sources, The OECD Stat Extracts database provides data for the OECD countries and selected non-member countries. As mentioned earlier, this data allows us to disaggregate important measures such as patent counts and population density by TL3 regions. It is used to construct the GINI innovation measurement and also provides us with regional indicators of cluster activity.

An alternative cluster measurement is assembled from a joint report from McKinsey & Company and the World Economic Forum. The “McKinsey data” tracks the number, growth, and diversity of patents issued by the USPTO from 1997-2006, defining clusters based on the location of each of the inventors. Momentum is defined as the average growth of patents in a cluster from 1997 to 2006. Diversity is a metric based on the number of separate companies and patent sectors in a cluster in 2006, while the cluster size is the number of patents granted in 2006. We use this data because it gives us a disaggregated view of clustering activity and also provides us with 3 interesting dimensions along which to analyze differences in cluster type.

Finally, in order to analyze the mechanism that draws firms into clusters, we use a combination of survey data and hard data provided by the World Economic Global Competitiveness Reports for the years 2008-2011. The survey data represents an average of 98 respondents per country. Most questions in the Survey ask respondents to evaluate, on a scale of 1 to 7, one particular aspect of their operating environment. At one end of the scale, 1 represents the worst possible situation; at the other end of the scale, 7 represents the best possible situation. Survey data is an appropriate measurement of the incentives of firms to enter a cluster because their cost-benefit analysis is based on their *perception* of the relative benefits the cluster endows.

3.7 Hypothesis Tests

Hypothesis 1: LMEs should display greater overall clustering levels than CMEs.

To test this claim, we rely on both the GINI coefficient measurement for the inequality in the distribution of innovative activity and the McKinsey cluster measurement. We will also examine this claim based on an indicator – an indexed score of the geographic concentration of population – to see if it holds up. Since there is no standardized measurement for clustering activity, we test it against our own measurement, an alternative measurement, and an indicator. We will use an unpaired, difference of means t-test for all the above measurements. If our hypothesis is confirmed when tested against all measurements, it will bolster the case for differences in clustering activity across VOC type.

If we find that there is no difference in overall clustering between LMEs or CMEs, or if we find that CMEs actually have greater overall clustering, this does not, necessarily disprove our hypothesis. We may obtain negative findings because CME countries are much older than LME countries. It is conceivable that they began clustering hundreds to thousands of years ago. We could look for the growth of clusters over time to see if expected clustering levels in LMEs are greater than CMEs. If this proves to be false, we would then revisit our theory. For example, we might expect that CMEs have different, but equally powerful motivations for clustering. The fact that they already have associations to coordinate actions, stronger relationships with suppliers, and skilled labor might reduce the barriers to clustering and any initial adjustment curve to the new form of relationship that LMEs experience when entering the cluster environment.

If this does, in fact, turn out to be the case, this is a fascinating finding in and of itself. Part of generating better policy prescriptions for clustering in innovation-driven economies involves understanding the context-specific factors that facilitate such a phenomena. If VOC does provide us with an important dimension for understanding the differing incentives to cluster, than future clustering initiatives should take this dimension into account before giving blanketed directives for improving regional competitiveness.

This hypothesis does not directly test the mechanism that spurs firms to enter the cluster environment. However, if we find differences across VOC type, it will spur us to believe that some combination of the political-economic institutional environment affects clustering activity.

Hypothesis 2: Clusters in LMEs should be larger and more diverse than clusters in CMEs

We rely exclusively on the McKinsey data to test this claim. Using the McKinsey "size" dimension, we will be able to conduct a difference of means t-test on LME clusters vs CME clusters. We will also conduct a difference of means t-test for the McKinsey diversity measurement. We will supplement these tests with charts in order to visualize the separation of clusters along the VOC dimension. This hypothesis will be falsified if we find no meaningful differences between LMEs and CMEs, or if CMEs display larger and more diverse clusters, on average, than LMEs.

Hypothesis 3: Firms in LMEs are drawn to clusters because they act as functional equivalents for industrial benefits that they lack relative to their CME counterparts

This hypothesis examines the mechanism through which firms in LMEs are drawn to clusters. Even if our first two hypotheses are disconfirmed, our theory anticipates that LME firms are attracted to clusters for the relative benefits they confer to their members. Based on the VOC typology, these benefits include increased coordination among firms, longer relationships, access to skilled labor, access to risk capital, and deeper supplier linkages.

Using executive responses to survey questions posed by the Global Competitiveness Report, we will test the mechanism across each dimension. We anticipate that more competitive LME environments will facilitate clustering. We also believe that higher clustering scores will be associated with higher responses to supplier quality, skilled labor and access to risk capital. We anticipate that the degree of these correlations will be higher in LMEs than in CMEs.

Chapter Four: Empirical Tests

In the previous chapters, we constructed a theoretical model that makes predictions about the nature of clustering activity across VOC types. In this chapter, we use empirical evidence to build our case for the accuracy of these predictions. We find a wide array of support for our claims. Furthermore, our evidence withstands sensitivity tests and the substitution of alternative measurements for key concepts such as country-level clusterness. We check the veracity of our evidence by substituting competing measures for clustering activity.

4.1 Hypothesis 1: *LMEs should display greater overall clustering levels than CMEs.*

Our first hypothesis makes the claim that LMEs should display greater overall clustering levels than CMEs. Using our GINI measurement of the inequality in the spatial distribution of innovative activity, we find that LMEs score consistently higher than their CME counterparts. Graph 2 shows a comparison of the GINI innovation score across VOC type for the years 2000-2008. The LME countries have an average GINI innovation measurement of .70 whereas CMEs are below the OECD average of 0.65 at a GINI score of 0.56.

When we conduct an unpaired difference of means t-test on our findings, we find significance at the α=.05 with a p-value of .004. This means that the observed difference between LMEs and CMEs is unlikely to have been caused by chance, but is indicative of true underlying differences between the two types. Substantively, we can interpret this to mean that innovative activity tends to be more concentrated in a few areas in LMEs whereas innovative activity in CMEs in more dispersed.

Graph 2: GINI innovation by VOC type

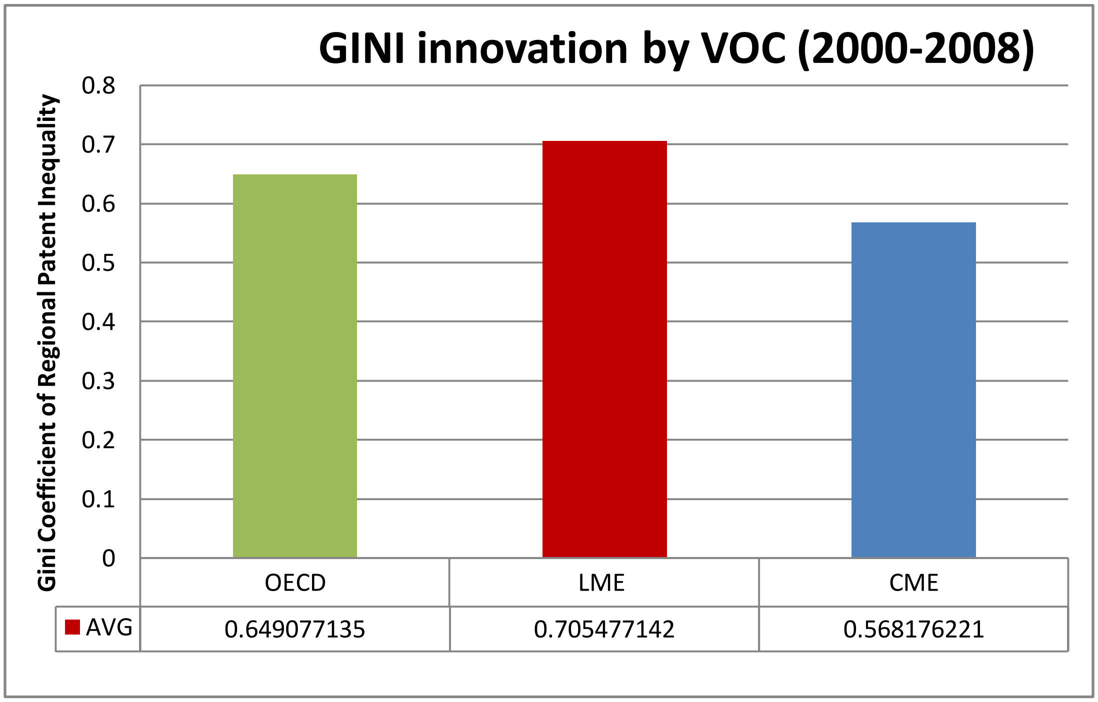


Table 7: Average GINI coefficients of innovation by VOC type

Summary statistics	**AVG**	**OBS**	**STD DEV**	**95% Confidence Interval**
OECD	0.6490	180	0.1361	0.63 – 0.67
LME	0.7054	70	0.1606	0.66 – 0.74
CME	0.5681	80	0.1120	0.54 – 0.58
LME - CME	0.1373	*unpaired*	0.0398	0.04 - .202

The VOC typology represents a package of political-economic institutions that our theory tells us impact the degree of clustering activity in a nation. A regression of our GINI innovation measurement versus a dummy variable for VOC (where LME = 1 and CME =0) can give us both the magnitude of the effect of VOC as well as an estimate of our degree of certainty. A regression without controls gives us a function for GINI innovation where GINI = .583 + .122(VOC). We expect that a move from CME, a value of 0, to LME, a value of 1, raises the GINI score by .122. A 95% confidence interval for our coefficient on VOC spans from .04 to .20. Since this interval does not contain the value 0, we are 95% confident that moving from CME to LME does increase the GINI coefficient. The magnitude of this effect is typically a 0.122 in the distribution of clustering activity.

Table 8: Regression of GINI innovation by VOC dummy (no controls)

GINI innovation	Coef.	Std. Err.	T	P > |t|	95% Conf. Int.
VOC	.122	.039	3.07	0.00	.04 - 0.20
constant	.583	.026	22.15	0.00	.53 - .63

In order to check if there are other factors driving our findings, we run the regression again controlling for population density. We use an interaction term for VOC and population density per square mile because our model anticipates that greater population density has different effects across VOC type. Whereas LME clusters should experience positive feedbacks and greater returns to scale, this does not necessarily have to be true in CMEs where intense local competition as a mechanism is not present. We thus conceptualize GINI as a function where:

$$GINI = \alpha + \beta(VOC) + \beta_1(Pop.\ Dens) + \beta_2(VOC*Pop.\ Dens)$$

Table 9: Regression of GINI innovation by VOC dummy and population density (interaction)

GINI innovation	Coef.	Std. Err.	T	P > |t|	95% Conf. Int.
VOC	.13	.05	2.56	0.014	.02 - .23
Pop. Dens	-.0001	.00	-.12	.238	-.0002 - 00
Interaction	-.0002	.001	-.15	.140	-.0005 – 0.0
constant	.618	.038	15.98	0.00	.54 - .69

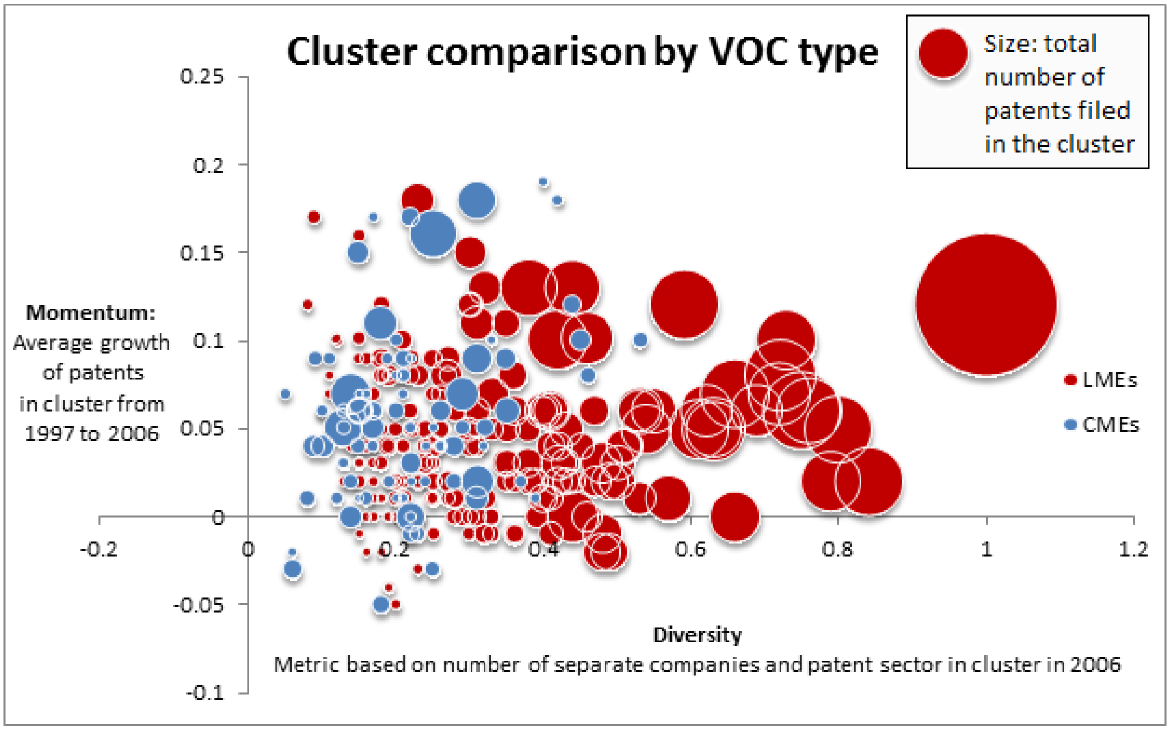
Table 9 shows the results of our regression of GINI innovation with interaction terms. A move from CME to LME is still statistically significant at the α=0.05 level. The magnitude of the effect of VOC is relatively unaffected from the original regression, maintaining a coefficient of 0.13. As anticipated, increased population density is negatively associated with the GINI coefficient. The more densely populated a certain country, the more evenly distributed their innovative activity is likely to be. Even though the magnitude of this effect seems small (at -0.0001), since the GINI measurement is from 0 to 1, and since population density ranges from 1 to 1261, this factor can still have a noticeable influence. Our interaction term shows us that the effect of population density is more pronounced in LMEs than in CMEs, with an increase of -.0002 in magnitude. However, neither population density nor our interaction term meets our threshold for statistical significance. Our relatively high constant of 0.618 seems to indicate that countries in the innovation-driven stage of development have already achieved a good degree of clustering levels.

Test 2: McKinsey Data

The GINI measure gives us an interesting insight into the concentration versus dispersion of innovative activity in a country. However, it does not tell us about the number or size of individual clusters in a nation. In order to judge the cross-national differences in terms of cluster numbers and performance, we turn to the McKinsey data.

The McKinsey data uses the location a patent was filed in as an indicator for the presence of a cluster. It measures clusters across three dimensions: momentum, diversity, and size. As discussed earlier, momentum is the average growth of patents in a cluster from 1997 to 2006, diversity is a metric based on the number of separate firms and patent sectors in the cluster in 2006, and size is the total number of patents granted in 2006. Normatively, a country should strive to have clusters that score higher on all three of these dimensions. For purposes of this test, we will say that a country has greater clustering levels the more total clusters it has and the greater the size of these clusters.

Graph 3: Cluster Mapping Comparison by VOC type



Graph 3 provides a revealing visual comparison of the clusters across the three dimensions of interest. The red clusters are located in LMEs while the blue clusters are located in CMEs. Simply scanning the graph shows us that LMEs tend to be both larger, in terms of the total number of patents filed, and more diverse, in terms of the number of separate firms and patent sectors in the cluster. It also appears that there are far more LME clusters than CME clusters. Table 10 provides summary statistics of the McKinsey data and confirms this trend. We find that there are statistically significant differences between LMEs and CMEs on the four different dimensions of interest. LMEs have more clusters per country, their clusters are more diverse, and they produce more total patents. CMEs have a slight advantage in patent growth (a momentum of .05 compared to .04), possibly because the smaller clusters are able to grow more rapidly relative to their overall size.

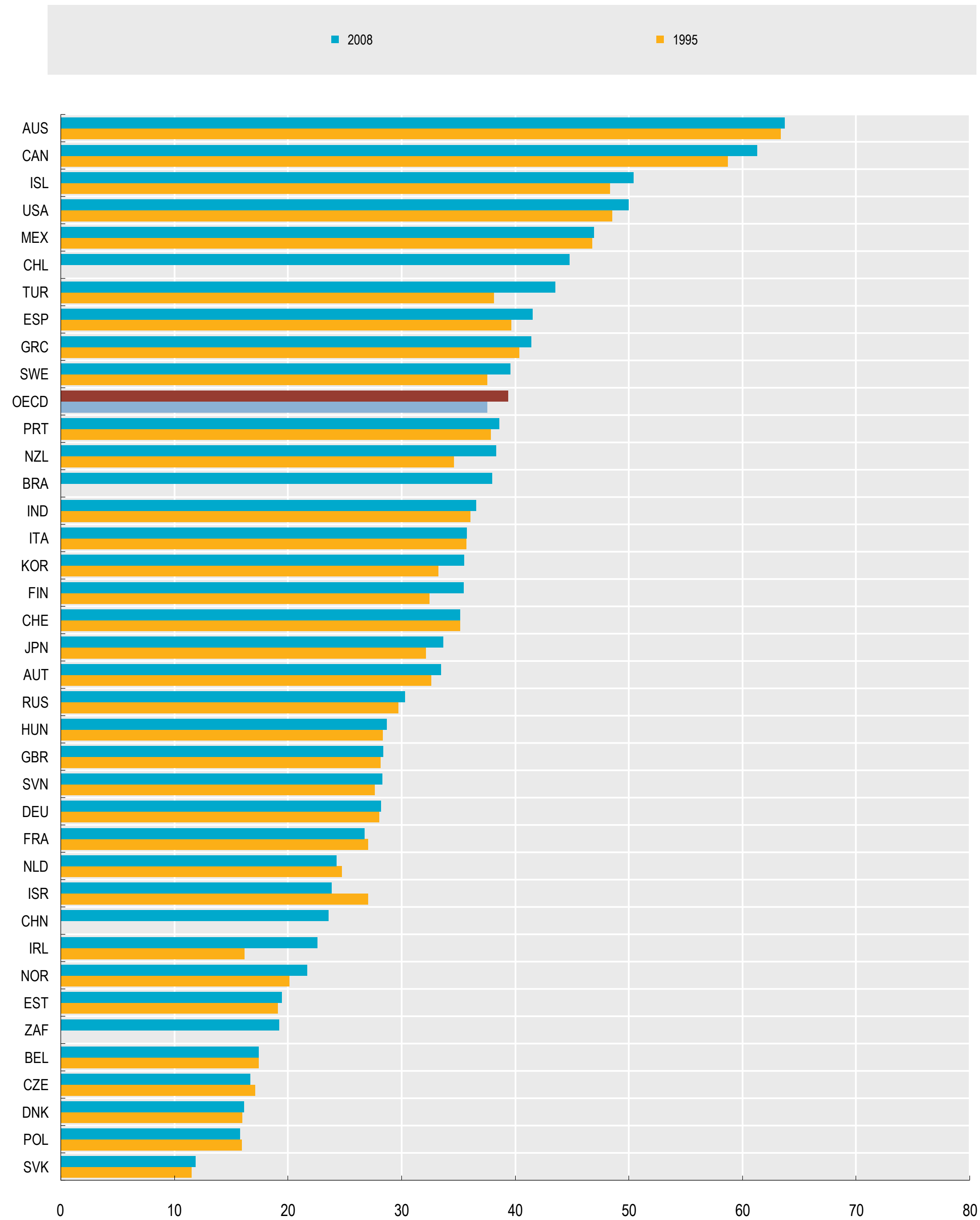
Table 10: McKinsey data summary statistics and t-test

	LME's		CMEs		T-test
	Mean	**Std. Dev**	**Mean**	**Std. Dev**	**p-value**
clusters per country	36.16	62.3	9.9	12.75	0.01
diversity	0.31	0.17	0.22	0.10	0.00
momentum	0.04	0.002	0.005	0.05	0.05
size	675.38	1345.18	316.11	382.43	0.01

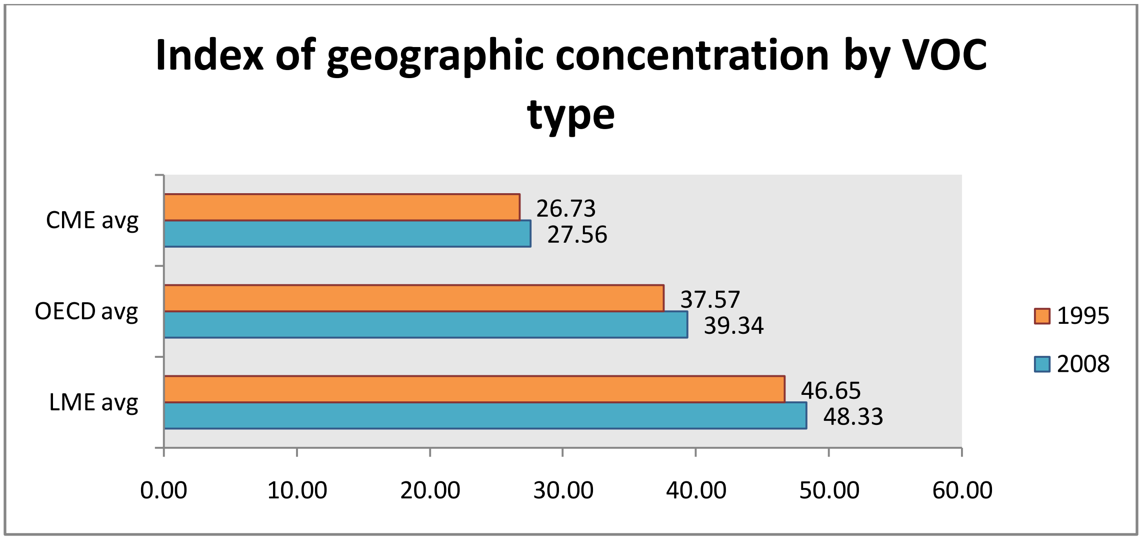
Finally, our theory has an important element of dynamic effects over time. We anticipate that increases in the size and prevalence of clusters should contribute to sustained and increased growth of these very same clusters because their presence raises the costs of not being the cluster and also raises the benefits of geographical proximity.Since the limitations of our data on clusters do not provide us with a long time frame with which to witness these effects, we opt to use a common indicator instead: the share of the national population in the ten percent of regions with the largest population. This measure is a widely used indicator for clusters because higher concentrations of population are associated with higher share of national employment rates, an element of cluster activity that comprises numerous operational definitions of clusters.

Graphs 4 and 5 show us that LMEs tend to concentrate their population in the ten percent of regions with the largest populations far more than their CME counterparts. Three of our six LMEs -Australia, Canada, and the USA - are in the top 5 of all countries.

Graph 4: Share of population in the ten per cent of regions with the largest population



Graph 5: Index of geographic concentration by VOC type

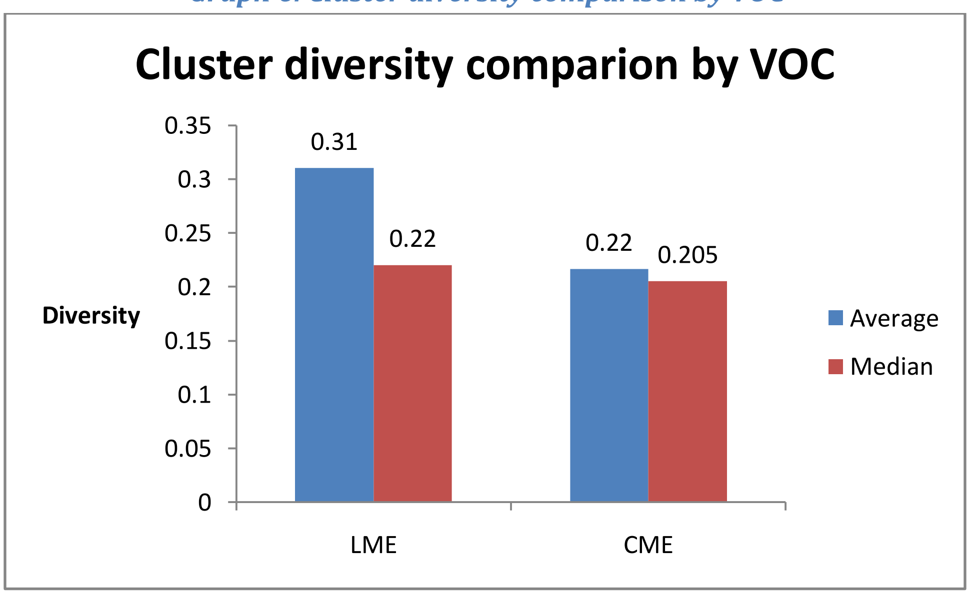


As Graph 5 demonstrates, the population of LMEs is far more concentrated in their ten most populous regions than CMEs. Even though we are measuring population and not firms or innovation, the fact that individuals gravitate towards the major population centers more readily in LMEs reveals that there are greater benefits to doing so. Furthermore, we see that the trend from 1995 to 2008 is towards*even greater population concentration* in the major population centers. This trend is also slightly greater in LMEs, an increase of 1.68, than in CMEs, an increase of 0.83. The significance of this trend is amplified when one takes into account that advances in transportation and communications technology should make geographical co-location less likely. Taken together, it seems to indicate that the benefits of geographical co-location are substantial, with a slight advantage to LMEs over CMEs in the long run.

4.2 Hypothesis 2: Clusters in LMEs should be larger and more diverse than clusters in CMEs

As seen in the test of our first hypothesis, the McKinsey data reveal that LMEs enjoy a statistically significant advantage in diversity and size of cluster compared to their CME counterparts. We take a more in-depth look at the McKinsey data to substantiate our second hypothesis. We show a comparison of clusters size and diversity using both the average and median scores across VOC type. The median is used because it is not as sensitive to outliers as the average. We expect that our measurements may be biased by the US, which is typically an "outlier by almost any measure," especially in regards to patent counts.[16]

Graph 6: Cluster diversity comparison by VOC



Graphs 6 and 7 show that cluster diversity and cluster size is much greater on average in LMEs than in CMEs but that the magnitude of this difference is mitigated

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[16] Taylor 2004

substantially when we look at the medians. The median diversity for a cluster in LMEs is 0.22 whereas the median for CMEs is 0.205. Since our difference of means t-test for diversity in Table 10 showed us that the difference is statistically significant, we do not discount that finding. Rather, the fact that the difference between the medians so much smaller than the divergence between the averages indicates that inclusion of the U.S. is indeed biasing our results.

Graph 7: Cluster size comparison by VOC

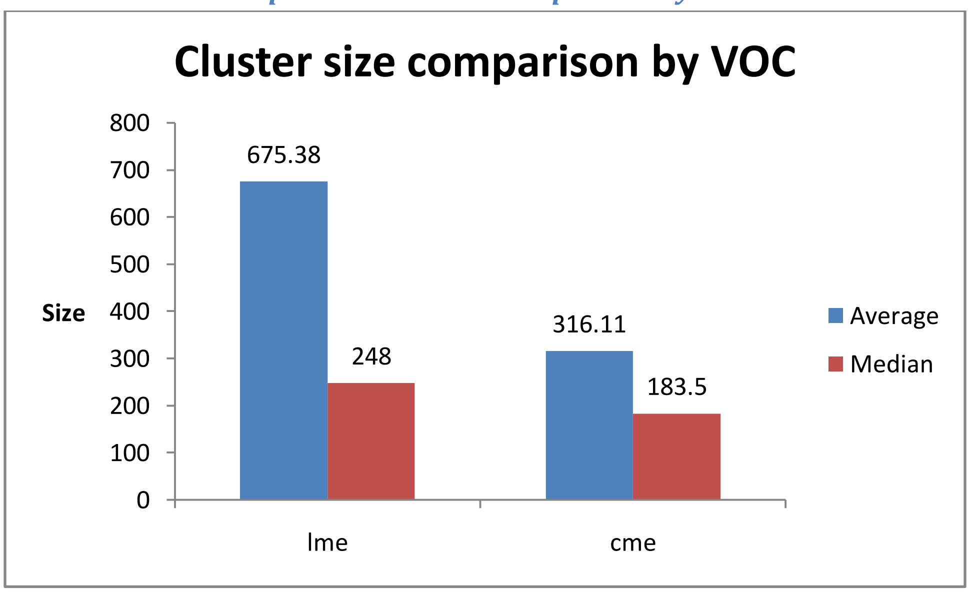
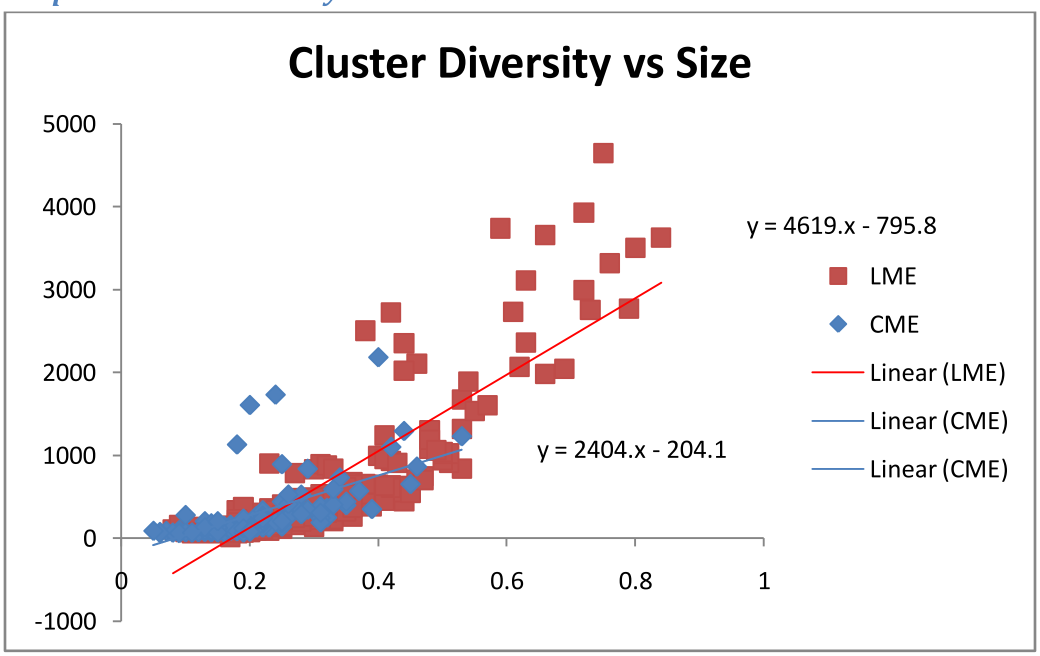


Table 11: Cluster size and diversity comparison

	diversity		size	
	AVG	median	AVG	median
LME	0.31	0.22	675.38	248
CME	0.22	0.205	316.11	183.5

If clusters in LMEs are indeed more diverse and produce more patents than in CMEs, what might be the effect of this over time? Cluster theory tells us that the inclusion of more firms from a diverse number of industries should produce increasing returns to scale. This should occur as a result to increasing local competition, the ability to quickly source new materials, and the ability to perceive new opportunities for innovation. Since the driving mechanism is vigorous local competition, and since our theory tells us that this affect should be more pronounced in LMEs than in CMEs, we would expect to find that our observed differences are in part driven by this effect. In other words, increased diversity should produce more innovative activity (increases in size) in LMEs than in CMEs. Graph 8 shows a comparison of cluster diversity vs cluster size by VOC type.

Graph 8: Cluster diversity vs cluster size



While there appears to be returns to scale for both LMEs and CMEs, our OLS lines reveal that these effects are greater for LMEs. The OLS for LMEs is size = 4619.1(diversity) – 795.85 while the OLS for CMEs is size=2404.9(diversity)-204.13.

This finding is of great substantive importance. As hypothesized, not only do LMEs display greater diversity and size than CMEs, we can anticipate that the returns to these advantages will be greater in the future. LMEs have a greater incentive to attract different firms from different sectors because the amount of patenting activity increases noticeably. The incentive for CMEs to engage in the same practice is there, but the *relative advantage* for LMEs is undoubtedly greater.

4.3 Hypothesis 3: *Firms in LMEs are drawn to clusters because they act as functional equivalents for industrial benefits that they lack relative to their CME counterparts*

Part of the goal of this paper is to assess the utility of a VOC approach to clustering activity. In testing this hypothesis, we are comparing the effect of certain dimensions of the political-economic environment on clustering activity. We expect that firms in LMEs are drawn to clusters because of relative benefits in the form of CME functional equivalents such as inter-firm coordination, longer term relations, deep supplier linkages, and access to highly skilled labor. We separate countries by the VOC dimension in order to look for differing effects of institutional components on a firm's decision to enter a cluster environment.

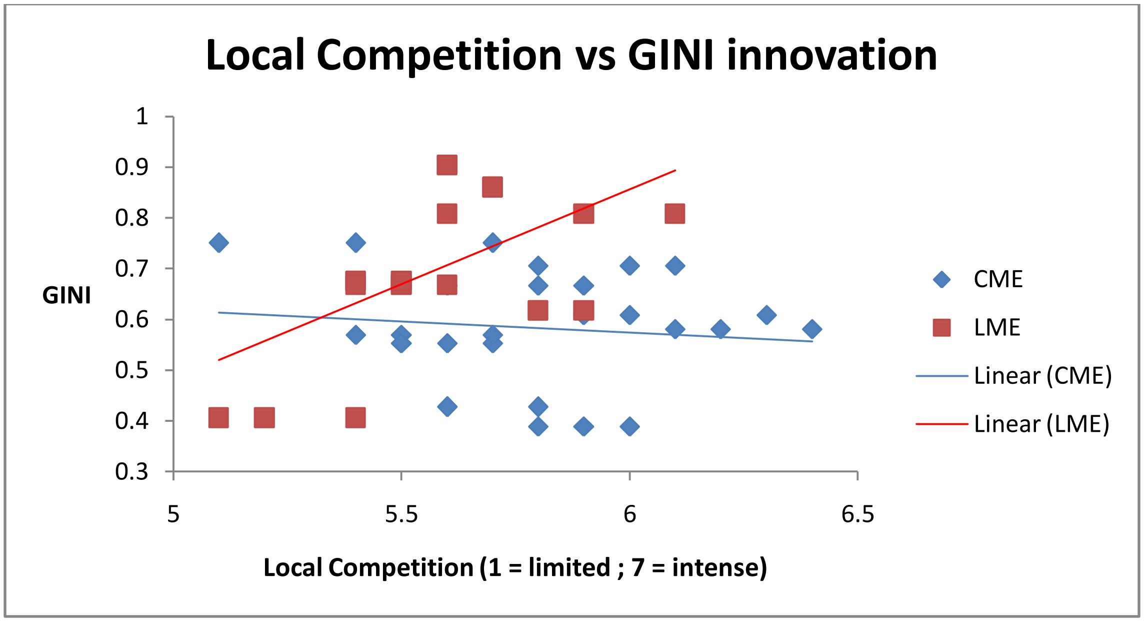
Allocative principle: Competitive environment:

Vigorous local competition is the mechanism through which the benefits of geographical proximity are generated. Our theory tells us that LMEs are more likely to conform to this Porterian model of cluster development. In order to test this claim, we look at survey responses of executives from the World Economic Forum's Global

Competitiveness Report. We expect that higher rates of competitiveness should produce better clustering activity in LMEs while the same does not have to be necessarily true for CMEs.

The WEF asks firms: "How would you assess the intensity of competition in the local markets in your country? [1 = limited in most industries; 7 = intense in most industries]." Graph 9 shows a scatter plot of aggregate firm responses versus the country's GINI innovation measurement. Interestingly, we find that CMEs tend to view the intensity of competition in local markets to be higher on average than how firm's perceive local competition in LMEs. While this finding certainly raises questions about the established belief that LMEs operate through competition, it must be kept in mind that the responses to these questions reflect a firm's perceptions and not what the objective reality is. Just because a respondent believes that conditions are a certain way, doesn't necessarily mean that they are that way. It could be the case that firms in LMEs are more accustomed to local competition, and that they consider it such a fundamental part of the environment, that their responses are not as strong to this question.

Graph 9: Local Competition vs GINI innovation



More importantly than the absolute response to the question of local competition is the relation between the local competition and the GINI measurement across VOC type. The results of our scatterplot in Graph 9 show us that for LMEs, more competitive environments are associated with higher clustering scores whereas in CMEs, there appears to be no relation, or perhaps even a negative relationship between local competition and GINI scores. A regression of intensity of local competition vs GINI innovation for LMEs (see Table 12) reaffirms a statistically significant positive effect. This suggests that there are perhaps different incentives that cause clustering in both environments. As per our theory, it is local competiton that drives the positive externalities of geographical co-location. However, for CMEs, it may in fact be better coordination and cooperation between firms that drives them to co-locate. As Estevez-Abe, Iversen, and Soskice note, firms in CMEs tend to focus on product differentiation and niche production because inter-firm collaboration would be harder to sustain if they adopted the intense product competition that characterize LMEs.

Table 12: Regression of GINI innovation by local competition

GINI innovation	Coef.	Std. Err.	T	P > |t|	95% Conf. Int.
Local competition	.37	.13	2.87	0.01	.101-.646
constant	-1.38	.72	-1.9	0.07	-2.91 - .138

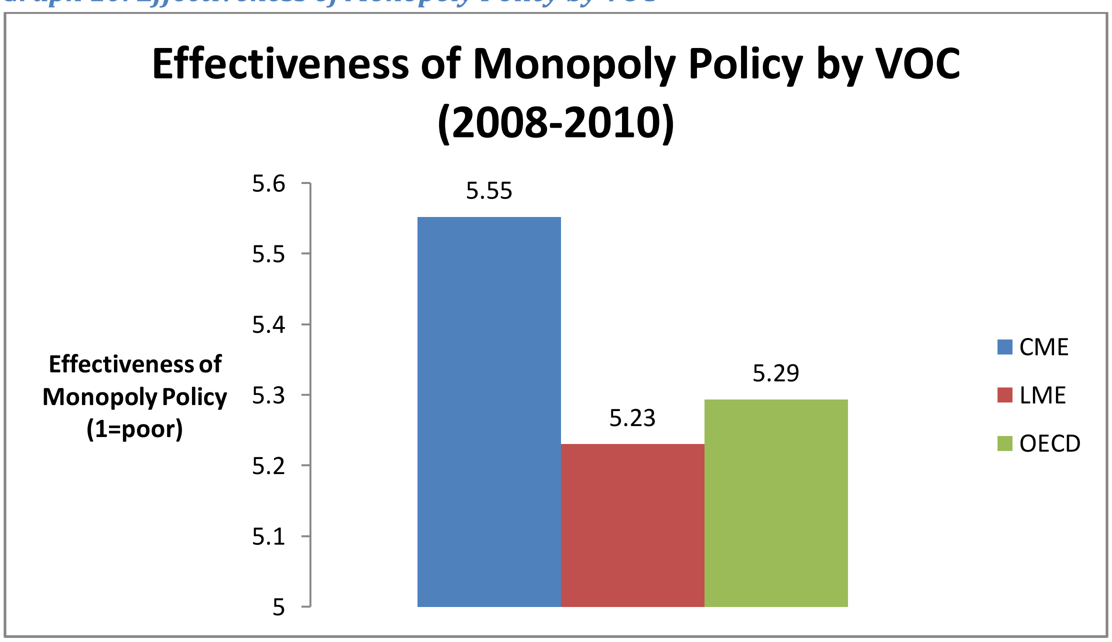
There is the potential of an edogeneity problem in this analysis. It could be argued that clustering is driving the perception of local competition rather than local competition driving clustering. This is an insight that our theory would probably argue is accurate, as there is a positive feedback loop. Since VOC is a theory of political-economic institutions, we will want to look at an element of the policy environment that affects local competition. Looking at an element of the institutional environment is one way to cut through the endogenity problem, assuming that the feature was present before the clustering activity took place.

Antitrust or Anti-monopoly policy is one aspect of the institutional environment that affects the ability of firms to coordinate on certain aspects and improves overall competitiveness in the industrial environment.We choose this dimension because some scholars are of the opinion that LMEs should impede cluster formation due, in part, to antitrust regulation which limits collusion.[17]However, when placed in the context of our theory, we believe the opposite would be true. We expect to find that more effective anti-monoply policy increased the competitiveness of the environment, and is therefore associated with higher GINI scores in LMEs, whereas this does not necessarily have to be the case for CMEs.

[17] Thanks to Professor Andrew Schrank for sharing this insight with me.

The WEF asks firms: To what extent does anti-monopoly policy promote competition in your country? [1 = does not promote competition; 7 = effectively promotes competition]? Interestingly, firms in CMEs survey an average of 5.55whereas firms in LMEs survey at 5.29. Whether this absolute difference is meaningful is not as relevant as the relation of anti-monopoly effectiveness to clustering scores. We find that there is a positive relationship between the effectiveness of anti-monopoly policy and higher GINI scores in both LMEs and CMEs but that the magnitude of the relationship is greater in LMEs (at a coefficient of .285) than in CMEs (a coefficient of .129). A regression for both VOC types in Tables 13 and 14 shows that the effect is statistically significant at the lower threshold of α=.10 for both and CMEs.

Graph 10: Effectiveness of Monopoly Policy by VOC



Graph 11: Effectiveness of Anti-Monopoly Policy vs GINI Innovation

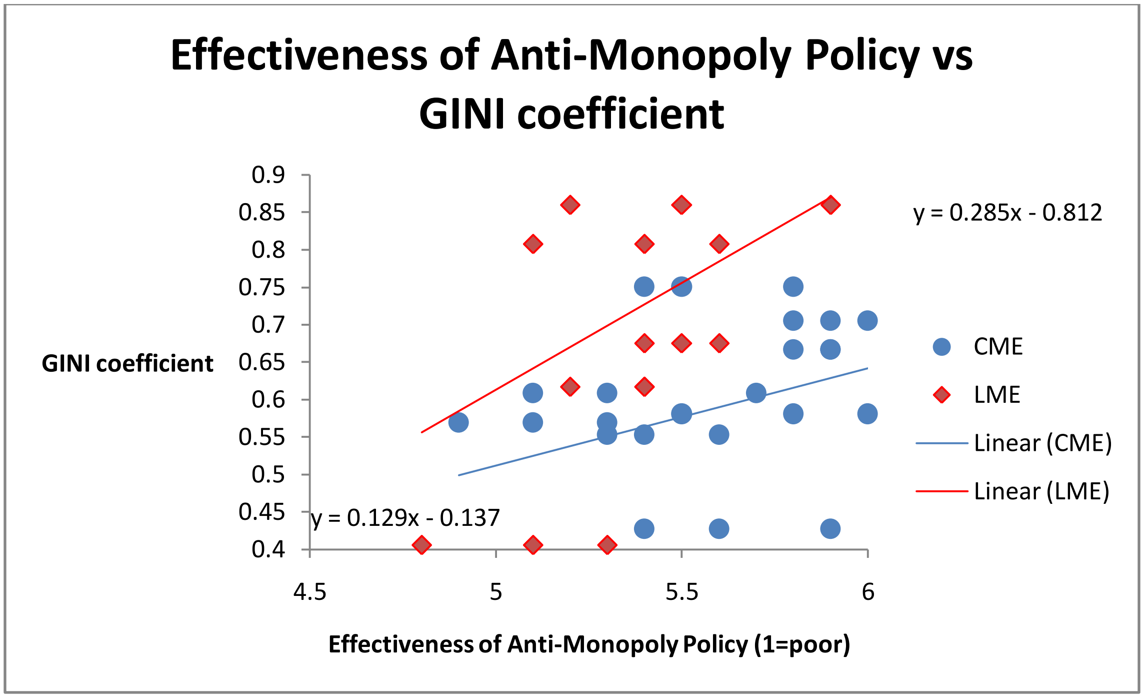


Table 13: Regression of GINI innovation by LME Anti-Monopoly Effectiveness

GINI innovation	Coef.	Std. Err.	T	P > |t|	95% Conf. Int.
LME Anti-Monopoly	.285	.164	1.74	0.10	-.063 - .633
constant	-.812	.879	-0.92	.369	-2.67 – 1.05

Table 14: Regression of GINI innovation by CME Anti-Monopoly Effectiveness

GINI innovation	Coef.	Std. Err.	T	P > |t|	95% Conf. Int.
CME Anti-Monopoly	.129	.069	1.86	.075	-.014 - .273
constant	-.137	.389	-.35	.727	-.938 - .663

These results seem to lend support to our theory that institutional features that increase industrial competitiveness are conducive to improving clusters. Furthermore, these institutional features appear to have a stronger impact in LMEs than in CMEs. However, a critical distinction between LMEs and CMEs should be drawn. Whereas increased competition seemed to always be associated with higher clustering scores in LMEs, this was not the case for CMEs. Since we saw that CME countries with higher reported levels of local competition tended to have lower GINI scores it may be the case that competition is not necessary, nor perhaps desirable, for the formation of certain kinds of clusters in CME environments

Capital mobility/liquidity:

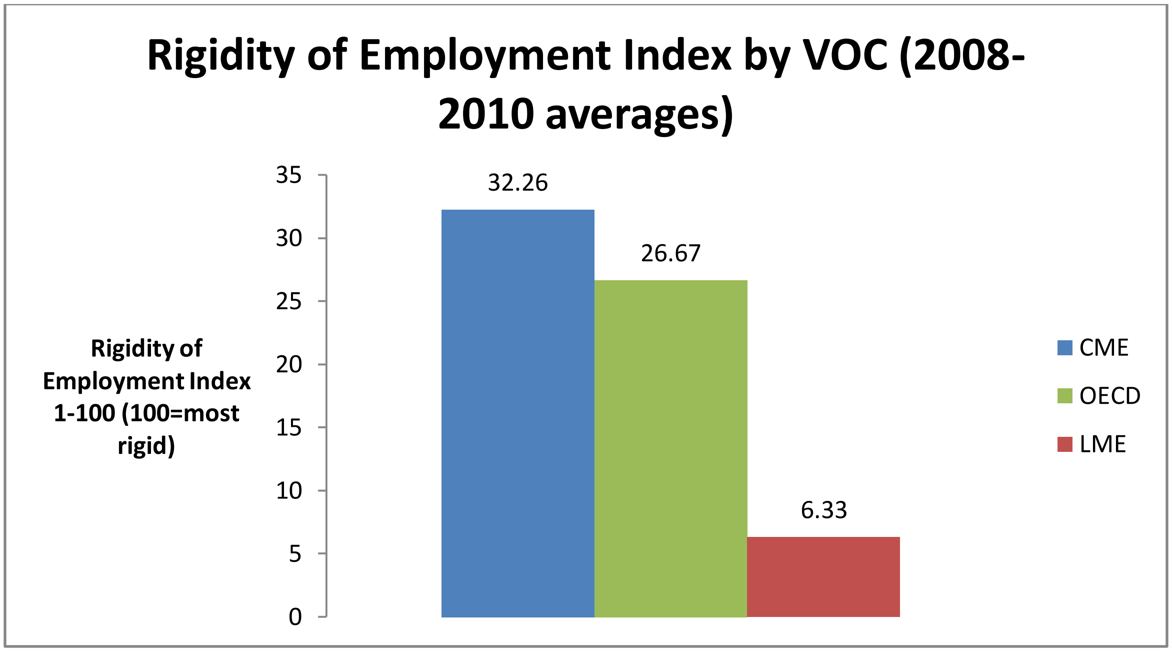
Another component of our theory relates to the ability of a firm to move into the cluster environment. The more barriers a firm faces to relocate, the less likely they are to move into a cluster environment. We expect that firms in LMEs are more able to move into clusters because of better capital mobility and the availability of risk capital. We test two components of the institutional environment: the rigidity of employment and the availability of venture capital.

The rigidity of employment index measures the regulation of employment, specifically the hiring and firing of workers and the rigidity of working hours. This index is the average of three sub indexes: a difficulty of hiring index, a rigidity of hours index, and a difficulty of firing index. The index ranges from 0 to 100, with higher values indicating more rigid regulations.

The rigidity of employment is relevant to cluster analysis for multiple reasons. First, the more difficult it is to hire or fire employees, the more difficult it will be for a firm outside of a cluster to relocate into the cluster environment. We would therefore expect that higher scores on the rigidity of employment scale would be associated with lower clustering levels. Second, rigidity of employment is an aspect of the political institutional arrangements of the country that should differ across VOC type and should impact clustering activity.

According to Saxenian (2004), the fluidity of personnel can play a critical role in sustained cluster health. In comparing the success of the Silicon Valley to the stagnation of Route 128, Saxenian found that the freedom to change firms or quit jobs was much greater, and in fact, encouraged in Silicon Valley. By comparison, leaving one firm for another was infrequent and considered an act of disloyalty in Route 128. Along these lines, we expect that where employment practices are less rigid, the increased fluidity of personnel will enable knowledge leakages and thus contribute to improved clustering. Furthermore, we anticipate that LMEs will have less rigid employment conditions. As Hall and Soskice (2001) note: "top management has unilateral control over the firm, including the substantial freedom to hire and fire…in these markets, it is relatively easy for firms to release or hire labor in order to take advantage of new opportunities."

Graph 12: Rigidity of Employment Index by VOC



Graph 12 shows us that LMEs have far less rigid employment practices than CMEs. The difference in the LME indexed score of 6.33 and the CME indexed score is staggering when compared to the OECD average of 26.67. A t-test reveals statistically significant differences at the α=0.01 level. The differences here are more compelling since this index is measured with hard data as compared to the WEF survey data.

Graph 13: Rigidity of Employment vs GINI innovation

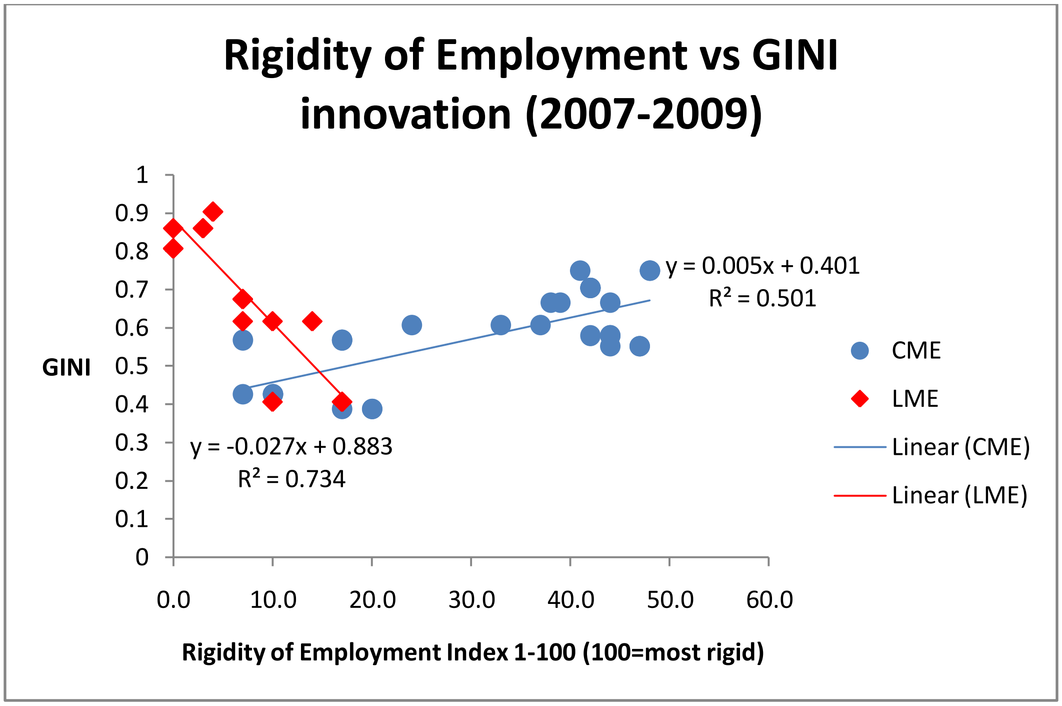


Table 15: Regression of GINI innovation by LME Rigidity of Employment

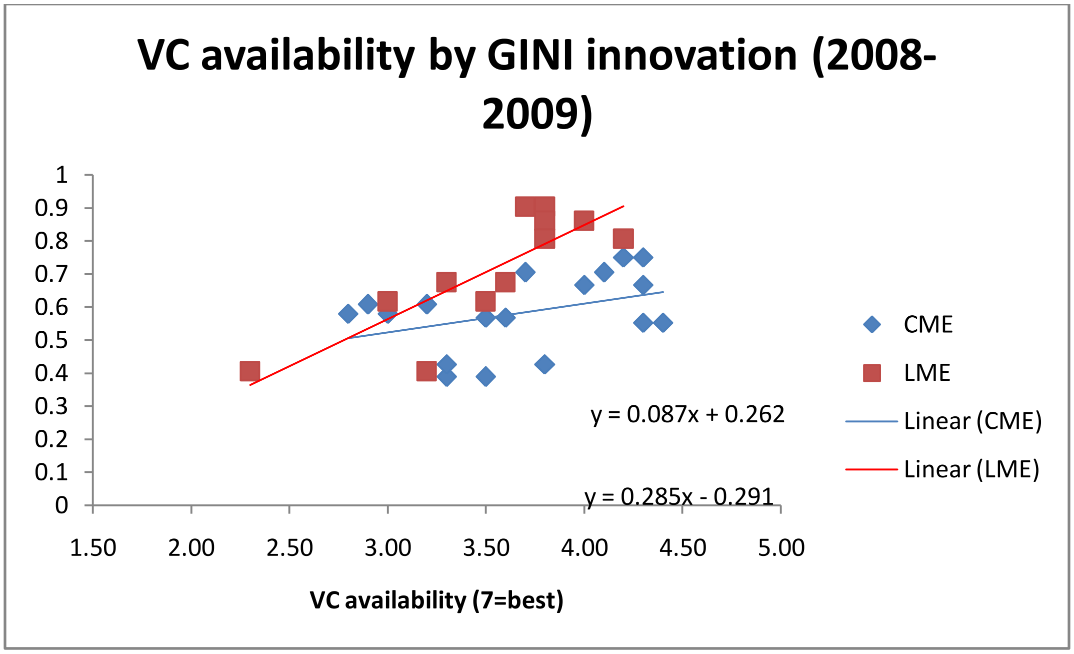
GINI innovation	Coef.	Std. Err.	T	P > |t|	95% Conf. Int.
LME employment	-.027	-004	-6.6+5	0.00	-.035 - -.018
constant	.88	..033	26.11	0.00	.811 - .955
CME employment	.005	.001	5.02	0.00	.003 - .007
constant	.401	.03	10.14	0.00	.319 - .483

Given that rigidity of employment differs substantially across VOC type, how does it affect clustering activity? Graph 13 demonstrates that more rigid employment practices hurt clustering ability in LMEs. A regression produces a statistically significant coefficient for employment rigidity of -0.0271. This tells us that for every 1 unit increase across the rigidity of employment index, the GINI innovation score decreases by -0.0271. This finding is consistent with our expectations. We anticipated that an element of the political environment, in this case employment practices, hinders both the capital mobility of a company and its ability to be competitive, and thus decreases the relative benefits of clustering for firms in LMEs.

Our theory gains further validation when we compare the rigidity of employment in CMEs against GINI scores. Here we find a statistically significant positive correlation between more rigid employment practices and clustering scores. Once again, this seems to indicate that clusters in CMEs form for different reasons than clusters in CMEs. Whereas policies that increase the intensity of market mechanisms for LMEs help improve clustering activity, they can hinder clustering activity in CMEs.

VOC theory also predicts that LMEs should have an abundance of risk capital compared to CMEs. The availability of risk capital is an important component in a firm's ability to enter a cluster environment. We compare the effects of the availability of venture capital by the GINI score.

Graph 14: VC availability by GINI innovation



A test of venture capital ("VC") availability by GINI innovation produces a few findings of interest. First, while VOC theory anticipates that VC, or risk capital, is more widely available in LMEs, we actually find higher VC scores for CMEs. This does not necessarily mean that VC is more widely available in CMEs, but rather that firms in perceive this to be the reality. More importantly, we see that as the perception of VC availability increases in LMEs, so does the GINI coefficient. While the direction of the effect is the same, the magnitude is far lower in CMEs (0.087 slope compared to 0.285 slope). This can be interpreted in a number of ways. First, there is probably a feedback loop effect wherein the availability of VC improves clustering activity, which, in turn, attracts more VC firms to a location. As seen in the case of Silicon Valley, sellers of finance (VC firms) were attracted to the investment opportunities in the valley. Buyers of finance (firms) were then incentivized to start their operations in the valley due to the availability of finance. The second major take-away from our results is that this feedback effect is not as strong in CMEs as it is in LMEs. Taken together, these results appear consistent with the expectations of our theory that firms in LMEs more readily embrace the cluster environment due, in part, to the increased opportunities for finance.

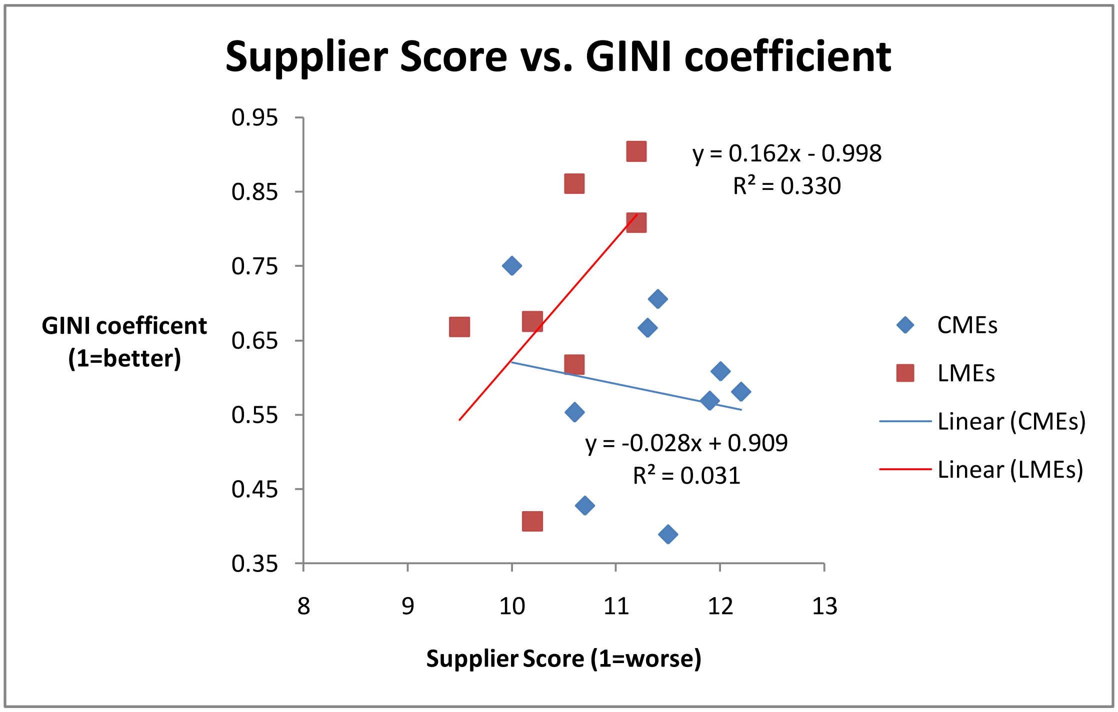
Supplier relationships:

The VOC literature states that the relationship between firms and suppliers varies considerably across VOC type. In LMEs, supplier relationships are competitive and conducted at arms-length, whereas in CMEs, they are long-term and negotiated. According to our theory, firms in LMEs should be more attracted to clusters because geographical proximity improves their access to suppliers, generates longer-term relationships with these suppliers, and, as a result, improves the ability of these suppliers to provide firms with the materials they need to implement innovative projects.

The WEF asks firms two questions relating to suppliers: "How numerous are local suppliers in your country? [1 = largely nonexistent; 7 = very numerous]" and "How would you assess the quality of local suppliers in your country? [1 = very poor; 7 = very good]"? Since responses to these questions correlate strongly with each other, we have added them together in a measure called supplier score that represents the satisfaction with both the quantity and quality of suppliers. As expected, firms in CMEs are generally more satisfied with suppliers than firms in LMEs. However, we find that an increase in supplier relationships is associated with higher GINI scores in LMEs whereas the reverse is true in CMEs. It is likely that the presence of clusters is improving the supplier relations in LMEs rather than supplier relations improving clustering activity. What is interesting is that geographical co-location does not seem to improve supplier relations in

CMEs but actually might hurt it. These findings seem to provide further confirmation of our theory. Firms likely gravitate towards clusters in LME because they enhance supplier relations, whereas this effect is not present in CMEs.

Graph 15: Supplier Score vs GINI coefficient



Chapter Five: Discussion

Clusters have emerged as an important component of numerous countries' national competitiveness agenda. As researchers and consultants begin to advise policy-makers on cluster initiatives, careful attention should be paid to the context-specific political-economic institutions of the region. This research has contributed to the existing literature in multiple ways. First, we introduced a new, outcome-oriented measure for aggregate-level clustering activity. Our GINI innovation measure provides an untapped perspective for looking at country-wide clustering patterns. Second, this research put forward an original theory of cross-national clustering differences that explored how the political-economic institutional environment affects firm's perceptions of the relative benefits of entering a cluster. The major contribution of this research was in substantiating the utility of a VOC approach to cluster analysis. Dividing countries along the LME to CME spectrum reveals important differences in aggregate level clustering patterns. We have shown that clusters are more prevalent, larger, and diverse in LMEs. Furthermore, we have shown that various elements of the political-institutional environment can have opposite effects for cluster formation with regards to LMEs and CMEs.

5.1 Policy Implications

To date, cluster initiatives have lacked a set of general guidelines that take into account political variables. Transferring successful cluster models have produced numerous failures, while efforts to build clusters from scratch have met a similar fate.

Our research demonstrates that the political-economic environment in which a cluster is situated matters. Specifically, the package of institutions associated with VOC type can provide a general guideline for cluster promotion. For LMEs, policy that improves local competition, such as antitrust regulations, can “grease the gears” of the market mechanism and thus provide better coordination of firms in the cluster environment. Furthermore, through an understanding of the benefits of clusters that attract firms, government actors at the regional level can promote clusters accordingly. This means widening the range of participating firms and industries, offering incentives for the provision of risk capital, easing employment regulations, upgrading institutions for collaboration, and promoting public-private collaboration.

While Porterian guidelines generally seem appropriate for LMEs, both our theory and our findings seem to indicate that they are problematic for CMEs. Where increases in local competition correlated with improved clusterness in LMEs, we actually found that this was deleterious to clusterness in CMEs. Furthermore, features of the institutional environment, such as employment rigidity, had the opposite effect in LMEs and CMEs. In a system that relies more heavily on coordination, negotiation, and long-term relationships, it appears that fostering labor-employer relations rather than leaving them to the whims of the market result in greater innovative outcomes. Findings like these should make policy-makers in CMEs wary to accept the Porterian strategy hook, line, and sinker. A set of new general guidelines for clusters in CMEs should be generated, while cluster initiatives should continue to inject context-specific considerations into their agenda.

In sum, policy-makers should not abandon a context-specific approach that takes into account the cultural and structural peculiarities of a region. However, for regions that generally exhibit greater dependency on market mechanisms for coordination and tend to structure relationships around these mechanisms, a Porterian strategy to cluster development serves as a good general guideline. Where market relationships are characterized by coordination through encompassing associations and long-standing relationships, a Porterian model can be detrimental to cluster development.

5.2 Future Research

Areas for future research can be found in the limitations of this study. First, like researchers before us, we do not provide a theory about the political origins of clusters. Clusters are not relatively new phenomena, but have been around for centuries. While our theory assumes an initial random distribution, it is highly likely that geography and country age played a major role in early clustering activity. Where comparative advantages in access to natural resources were present in a region, it seems likely that firms converged around that area. This clustering activity was not necessarily a result of positive spillovers from the intensification of market mechanisms, but it constitutes clustering activity nonetheless. Future research should address this question as it likely has implications for cluster initiatives in European CMEs.

Second, if the Porterian strategy seems appropriate as a general guideline for LMEs, what type of strategy can serve as a general guideline for cluster development in CMEs? Humphrey and Schmitz (2002) discuss 4 types of value-chain governance through which coordination occurs:1) *Arms-length transactions* or coordination through market relationships 2) *network* cooperation between firms of more or less equal power which share their competencies within the chain 3) *quasi-hierarchical* relationships between legally independent firms in which one is subordinate to the other, with a leader in the chain defining the rules to which the rest of the actors have to comply; and 4) *hierarchical relationships* where a firm is owned by an external firm. While they discuss value chain governance, it is probable that clusters display different governance structures that are microcosms for the greater sets of institutions in which they are nested. Just like the Porterian cluster model appears to be a microcosm of LME relationships and mechanisms, a CME cluster may parallel a "network" governed value chain.

Third, we have demonstrated how separating firms into LME and CME camps reveals important differences in clustering activity. LMEs and CMEs sit at opposite poles of the spectrum, and therefore, were likely to demonstrate the most pronounce differences. Future research should look at how other VOC arrangements, namely MMEs, NMEs, and HMEs, affect clustering activity.

Fourth, there are several issues of endogeneity with our analysis. As it stands right now, we cannot be certain if it is the greater clustering levels that are driving our survey results, or if it is our survey results that are driving our greater clustering levels. A survey conducted amongst firms in the cluster environment vs. those out of the cluster environment could help partially cut through this dilemma. If we see differing responses on key dimensions of our theory, we would be able to isolate the effect of the cluster on the firm's perception of their environment. We attempted to resolve this issue by looking at "hard data" of institutional features such as antitrust regulations and employment rigidity. Future research should combine this approach with the aforementioned survey in order to overcome the endogeneity problem.

Finally, this study also has implications for the VOC theory of innovation. The VOC theory of innovation holds that LMEs should display "radical" technological change whereas CMEs should exhibit "incremental" technological change. Taylor (2004) provides compelling evidence that dispels this theory. It is possible that clustering activity can help explain why the VOC theory of innovation does not hold. Since LME firms in clusters experience CME-like relationships with each other, it is possible that these industries become more typified by incremental innovation. Thus, the disparity in types of innovation is reduced. What we would want to know is, given the affinity of LME firms to enter innovation clusters, what type of innovative activity goes on there? Looking inside the black-box of clusters could provide us with interesting insights into this question.

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