NATIONAL GRADUATE INSTITUTE FOR POLICY STUDIES
POLICY ANALYSIS PROGRAM

Dissertation

AGGLOMERATION ECONOMIES, LOCAL INDUSTRIAL STRUCTURE, AND DISTRIBUTION OF ECONOMIC ACTIVITIES: EMPIRICAL EVIDENCE FROM INDONESIA

KHOIRUNURROFIK

Submitted in partial fulfillment of the requirement for the degree of Ph.D. in Public Economics

October 2014

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to all those who have helped me to finish this dissertation. First, I am indebted to Professor Yoshitsugu Kanemoto, my committee chair and advisor, for the support he has extended to me. I am extremely grateful for his patience, persistence and motivational advice, and encouragement in all stages of my dissertation development. He gave me a chance to study and research this topic and has guided me all those years at GRIPS. I will always be thankful for his important contribution to my academic development.

I would also like to express my gratitude to committee members and an external examiner of my dissertation. Professors Roberto Leon-Gonzalez, Chikako Yamauchi, Makoto Hasegawa, all of them from GRIPS, and Professor Takaaki Takahashi of Tokyo University have shared their expertise and provided some useful advice to improve this dissertation.

I also extend my thanks to institutions that gave me important supports. First, the Mitsubishi Corporation has granted me a generous scholarship for five years to study in GRIPS. Second, my home institution, Institute for Economic and Social Research at School of Economics and Business of University of Indonesia, has gave me opportunity to continue my study and provide an access to all required data from LPEM Database. Third, the faculty, staff, and students of GRIPS have provided me with excellent academic environments over the years. Last, the Asia SEED has provided assistance during the five-years of my life in Tokyo, especially to Mr. Buji Ando and Ms. Yuki Matsuyama.

I have been very blessed to have such wonderful friends and would like to thank for our friendship along five years journey. I am indebted to my colleagues: Budi, Irfan, Chaikal, Yudhis, Rima and Prani, who I would regard as my extended family. Special thanks is due to Irfan who shared the GIS Euclidean-Distance between cities in Indonesia for this study.

Finally, I am very grateful to my family. I thank my parent, Amza and Siti Maisum, for all their love and constant prayer. I have always felt their support and it gave me strength in times of hardship. I also thank my younger brothers and sisters, Fathur, Ida, Eva, and Toni, for their love and support. Last but not least, I would love to thank my wife, Titik Sofiana, and our son and daughters, Taslim, Sakinah, Masyitoh, and Safira for their love, patience and unconditional support. I will never forget my family's sacrificed to support my doctoral study and kept cheering me whole time.

ABSTRACT OF THE DISSERTATION

Agglomeration Economies, Local Industrial Structure and Distribution of Economic Activities: Empirical Evidence from Indonesia

By
Khoirunurrofik

Dissertation Chair,
Prof. Yoshitsugu Kanemoto

The objectives of this dissertation are to examine empirically the effects of agglomeration economies on plant-level productivity and local productivity growth and to determine the trends and determinant factors of the spatial distribution of manufacturing industries. The first paper identifies the source of agglomeration economies and estimates their magnitude and spatial agglomeration externalities from neighboring districts or cities. The results suggest that economies of localization and urbanization do exist, but the former appears stronger than the latter. The types of agglomeration externalities are strongly associated with different sizes of plants and industrial sectors, and these factors provide clear-cut evidence of the nature of agglomeration economies. The analysis also shows that the sources of agglomeration changed over the economic cycles toward localization economies. Certain structural changes of industry are also identified in the post-economic crisis period; small-sized plants in the traditional and heavy industries drive these changes. This first paper also demonstrates strong evidence of the influence of agglomeration effects from neighboring districts.

The second paper examines the effects of dynamic agglomeration economies on the productivity growth of the industries in Indonesia's regions. The study

introduces employment market potential into the city-industry growth estimation for controlling local size and preventing overestimation of the agglomeration effects. The results suggest that both specialization and diversity are important for city-industry growth and that some externalities are stronger in different periods. A detailed analysis across industries reveals a strong relationship between local industrial structure and performance—productivity and employment growth—which is associated with industry maturity within its lifecycle stages.

The third paper analyzes the trends and determinant factors vis-à-vis spatial distribution in Indonesian manufacturing during the period of 1990–2010. There is a long-term increasing trend of regional specialization driven by core regions within Java and by affluent regions outside of Java. Among resource-based and labor-intensive industries, there is a smoothly declining trend of geographic concentration. An increasing trend in regional specialization and geographic concentration during the economic crisis is identified, which turns into a decreasing trend at the onset of setting up a decentralization policy. Finally, skills, export activities, and wage rates strongly determine the degree of agglomeration among Indonesian manufacturing industries.

The three papers contribute to a better understanding of the relation between agglomeration economies and productivity and the reasons for clustering of economic activities. The empirical findings suggest some policy implications to stimulate the agglomeration process and improve economic distribution across the country.

TABLE OF CONTENTS

Page

ACKNOWLEDGEMENTS……………………………………………………………….	i
ABSTRACT OF THE DISSERTATION……………………………………………	iii
TABLE OF CONTENTS…………………………………………………………….	v
LIST OF TABLES………………………………………………………………...	viii
LIST OF FIGURES………………………………………………………………	x
LIST OF ABBREVIATION AND ACRONYM…………………………………….	xi
CHAPTER 1. INTRODUCTION……………………………………………………	1
1.1 Background of the Research……………………………………………………..	1
1.2 Research Objectives……………………………………………………………...	5
1.3 Research Contribution……………………………………………………………	6
1.4 Structure of the Dissertation..……………………………………………………..	7
CHAPTER 2. ESTIMATING AGGLOMERATION ECONOMIES ALONG ECONOMIC CYCLES AND ACROSS GEOGRAPHICAL DISTANCES…...........	8
2.1 Introduction…………………………………………………………………………	8
2.2 Literature Review………………………………………………………………...	11
2.3 Data and Variables……………………………………………………………….	14
2.3.1 Manufacturing Plant Data…………………………………………………...	14
2.3.2 Price Deflator………………………………………………………………..	16
2.3.3 Capital Stock Data…………………………………………………………..	16
2.3.3 Regional Data………………………………………………………………..	17
2.4 Methods……………………………………………………………………………..	18

2.4.1 Empirical Estimation………………………………………………………… 18

2.4.2 Estimation Issues……………………………………………………….. 28

2.5 Results and Discussions………………………………………………………. 29

2.5.1 Aggregate Estimate……………………………………………………….. 29

2.5.2 Robustness Check………………………………………………………… 34

2.5.3 Estimates by Plant Size Classifications and Industrial Groups……………… 36

2.5.4 Agglomeration Externalities over Economic Cycle…………………………. 40

2.5.5 Agglomeration Externalities across Geographical Distance………………… 45

2.6 Conclusions…………………………………………………………………… 51

CHAPTER 3. MARKET POTENTIAL, LOCAL INDUSTRIAL STRUCTURE AND PRODUCTIVITY GROWTH ………………………………………………. 54

3.1 Introduction…………………………………………………………………… 54

3.2 Literature Review……………………………………………………………... 58

3.3 Data…………………………………………………………………………… 61

3.4 Model Specification: TFP and Employment Growth Model…....………………. 62

3.5 Estimation Issues and Instrumental Variables…………………………………... 69

3.6 Results and Discussions………………………………………………………. 71

3.6.1 Analysis of the TFP Growth Model………..……………………..…… 72

3.6.2 Productivity Growth by Time Periods: Long-Term and Medium-Term……. 77

3.6.3 Productivity Growth by Industry……………………………………………. 80

3.7 Conclusions…………………………………………………………………… 83

CHAPTER 4. TRENDS AND DETERMINANTS OF THE GEOGRAPHIC DISTRIBUTION OF ECONOMIC ACTIVITIES: EVIDENCE FROM INDONESIAN MANUFACTURING …………………………………………….. 85

4.1 Introduction…………………………………………………………………… 85

4.2 Literature Review……………………………………………………………... 88

4.3 Empirical Methods ………………………………………………………....... 92
4.3.1 Data and measurement……………… ……………………………………....... 92
4.3.2 Empirical Model for the Determinant of Geographic Concentration............. 96
4.4 Results and Discussions………………………………………………………. 97
4.4.1 Trend of Regional Specialization in Manufacturing………………………… 97
4.4.2 Trend of Geographic Concentration in Manufacturing……………………… 102
4.4.3 Determinant of Geographic Concentration………………………………….. 110
4.5 Conclusions…………………………………………………………….… 115

CHAPTER 5. CONCLUSION AND POLICY IMPLICATIONS………………….. 117
5.1 Major Findings……………………………………………………………... 117
5.2 Policy Implications……………………………………………………… 120
5.3 Limitations and Future Research……………………………….................. 121
APPENDIXES……………………………………………………………………. 122
Appendix to Chapter 2…………………………………………………………….. 122
Appendix to Chapter 3…………………………………………………………….. 133
Appendix to Chapter 4…………………………………………………………….. 135
BIBLIOGRAPHY………………………………………………………………… 136

LIST OF TABLES

Table		Page
2.1	Descriptive Statistics of Variables……………………………………..	30
2.2	Agglomeration Externalities: Main Result……………………………..	32
2.3	Agglomeration Externalities: Robustness Test…………………………	35
2.4	Agglomeration Externalities by Plant Size……………………………..	36
2.5	Agglomeration Externalities by Industry……………………………….	38
2.6	Agglomeration Externalities by Plant Size over Economic Cycles…….	41
2.7	Agglomeration Externalities by Industry over Economic Cycles………	42
2.8	Agglomeration Externalities by Plant Size over Economic Cycles for Traditional and Heavy Industries……………………………………….	43
2.9	Moran's Index of Spatial Autocorrelation………………………………	4
2.10	Agglomeration Externalities by Plant Size over Geographical Distance.	47
2.11	Agglomeration Externalities by Industry over Geographical Distance…	48
3.1	Partial Correlation of Instruments and Employment market potential…	71
3.2	Descriptive Statistics of Variables…………………………………….......	72
3.3	First Stage Regression……………………… ………………………….	73
3.3	City-Industry Productivity Growth : TFP Growth Model……..…………	75
3.5	City-Industry Productivity Growth: Robustness Test……………………..	77
3.6	Long- and Medium-Term City-Industry Productivity and Employment Growth………………………………………………………………………..	79
3.7	Long-term City-Industry Productivity and Employment Growth by Industry……………………………………………………………………….	81
3.8	Medium-term City-Industry Productivity and Employment Growth by Industry………………………………………………………….	83

4.1	Specialization Patterns in Indonesia, across Provinces.…………….......	100
4.2	Concentration (EGS) Pattern in Indonesia across Sectors, at the City Level.…………………………………………………………………	106
4.3	Concentration (EGS) Pattern in Indonesia across Sectors, at Province Level ……...…………………………………………………………….	107
4.4	Ranking of Agglomerated Industries ……...………………………………	108
4.5	Testing for Model Selection….………………………………………….	110
4.6	Determinants of Geographic Concentration, at City Level………………..	113
4.7	Determinants of Geographic Concentration using Robust SE, at City Level…………………………………………..…..………………….	114
A.2.1	Plants' Observation by Size, Economic Cycles and Industry Groups….	129
A.2.2	Variable Definition and Data Source………………………………...	130
A.2.3	Plant-Level Production Function Estimation…………………………...	131
A.3.1	Variable Definitions and Data Sources…………………………………	133
A.4.1	List of Three-Digit ISIC Codes based on OECD (1987) Classification……………………………………………………………	135

LIST OF FIGURES

Figure		Page
1.1	Indonesia's Economic and Manufacturing Sector Growth: The Manufacturing Sector's Contribution and its Productivity.…………….	3
1.2	The Distribution of Manufacturing Value Added………………….......	4
2.1	Distribution of Agglomeration Elasticities by Plant Size and Industry………………………………………………………….	39
2.2	Distribution of Agglomeration Elasticities by Plant Size and Industry over Economic Cycles…………………………………….	45
2.3	Localization Elasticities across Distance by Plant Sizes and Industry………………………………………………………….	50
2.4	Urbanization Elasticities across Distance by Plant Sizes and Industry…	51
4.1	RSI Patterns in Indonesia, 1990–2010…………………..……………...	98
4.2	RSI Patterns in Indonesia, Using Employment ………………………....	101
4.3	RSI Patterns in Indonesia, Using Value Added…..…………..…………	101
4.4	Geographic Concentration Pattern in Indonesia: EG Index, 1990–2010.	105
4.5	Geographic Concentration Pattern in Indonesia: EGS Index, 1990–2010	105
4.6	Geographic Concentration Pattern in Indonesia (Employment-Based), at City Level ..……………………………………………………….	109
4.7	Geographic Concentration Pattern in Indonesia (Employment-Based), at Province Level ……………………………………………………….	109
A.3.1	Distribution of City Size………………………………………………...	134
A.3.2	The Relationship Between TFP Growth and Agglomeration Externalities………………………………………………………......	134

LIST OF ABBREVIATION AND ACRONYM

BPS	Central Bureau of Statistics (*Badan Pusat Statistik*)
EG	Ellison-Glaeser Index
FDI	Foreign direct investment
GDP	Gross Domestic Product
GIS	Geographic information system
ICVAR	Incremental capital value added ratio
ISIC	International Standard of Industrial Classifications
IV	Instrumental variables
KLUI	Indonesian Field Business Classification (*Klasifikasi Lapangan Usaha Indonesia*)
LP	Levihnsohn–Petrin estimator
MAR	Marshall-Arrow-Romer
MAUP	Modifiable areal unit problem
MS	Maurel and Sédillot Index
NKIP	Plant identity codes (*Nomor Kode Induk Perusahaan*)
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary least square
OP	Olley–Pakes estimator
PIM	Perpetual investment method
PODES	Village potential survey (*Survei Potensi Desa*)
PSID	Plant identity codes
RSI	Regional Specialization Index
SI	Annual survey of large and medium firms (*Statistik Industri*)
SIC	Standard of Industrial Classifications
TFP	Total factor productivity
TSLS	Two-stage least squares
WPI	Wholesale price indices

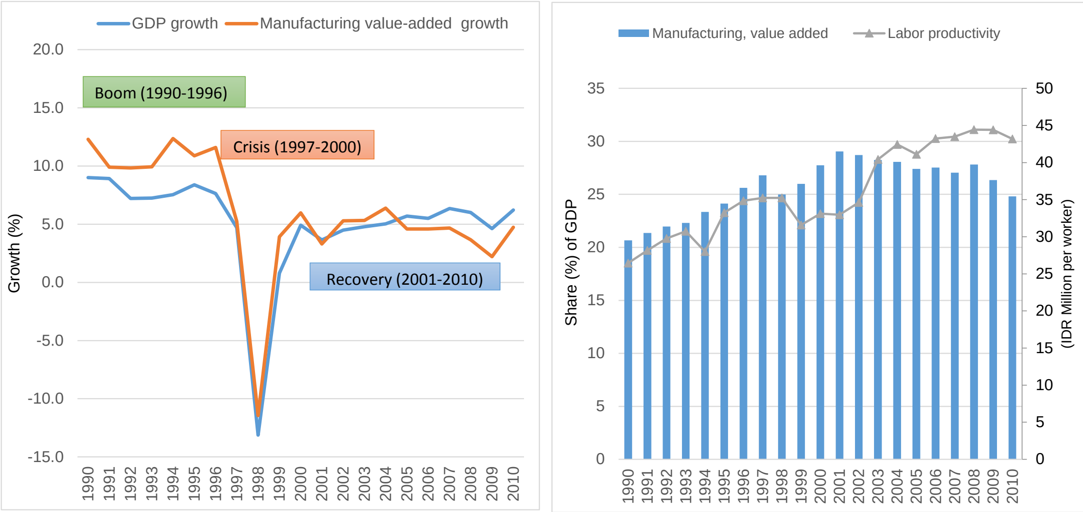
CHAPTER 1. INTRODUCTION

1.1. Background of the Research

Two general characteristics of the Indonesian economy are that it depends too much on manufacturing activities, and there is a geographical imbalance in favor of Java Island. Historically, the manufacturing sector registered remarkable growth and transformed the Indonesian economy from an agrarian to a semi-industrialized economy (World Bank, 2012). However, this sector is centered in Indonesia's major cities, particularly in Java, which contributed more than three-fourths of the national value added from 1990 to 2010 (BPS). This situation exerts pressure on the government to provide more infrastructure and amenities in the major cities. It also creates a disparity of incomes among regions since a few of the largest metro-megapolitan cities have dominated the economy. Therefore, there is increasing concern about the distribution of growth across the regions besides the achievement of economic growth of the whole country. Moreover, the regional development policies became key policies to create balanced growth across the regions through industrial decentralization. The regional policies usually attempt to promote non-major cities as new centers of economic activity. However, such policies pose a dilemma of choosing between lost efficiency from the higher factor productivity of increasing returns to scale in large urban areas and equity gains by achieving higher growth in select specialized regions. By comparing both effects through empirical modeling, we can identify what type of externality is actually related to the distribution of economic activities and also important for productivity and economic growth.

From the beginning of Indonesia's industrial development, the government has made a huge investment in Java to build many industrial zones. This policy led to the spatial concentration of manufacturing in a few of the largest metropolitan cities. The industrial zones offered firms access to the labor pool and inputs, allowed them to learn from other plants in the same industry, and finally achieve increasing returns to scale. Because a city consists of many types of industries and tends to become bigger over the years, many major cities in Java such as Jakarta, Surabaya, and Bandung have problems of congestion and overutilization of infrastructure. This implies a need for better identification of the sources of agglomeration economies, whether due to the localization or concentration of the industry or because the urbanization process affects city size (Rosenthal & Strange, 2004). Thus, this dissertation addresses the challenge to determine which type of agglomeration externality is actually stronger to influence plant-level productivity and city-industry growth.

Since the mid 1960s—when industrialization began in earnest—the manufacturing industry has been a leading sector in the Indonesian economy. The manufacturing sector's role in the growth and vitality of the economy was remarkable during the boom years of the early 1990s (see Fig. 1.1). However, the financial crisis of 1997–1998 changed that pattern and resulted in slower growth of the manufacturing industry, although some deregulations such as foreign ownership and tariff reduction were introduced to stimulate investment in those sectors (Aswicahyono et al., 2010). The crisis also crippled Indonesia's manufacturing-driven economic growth (Poczter et al., 2013).



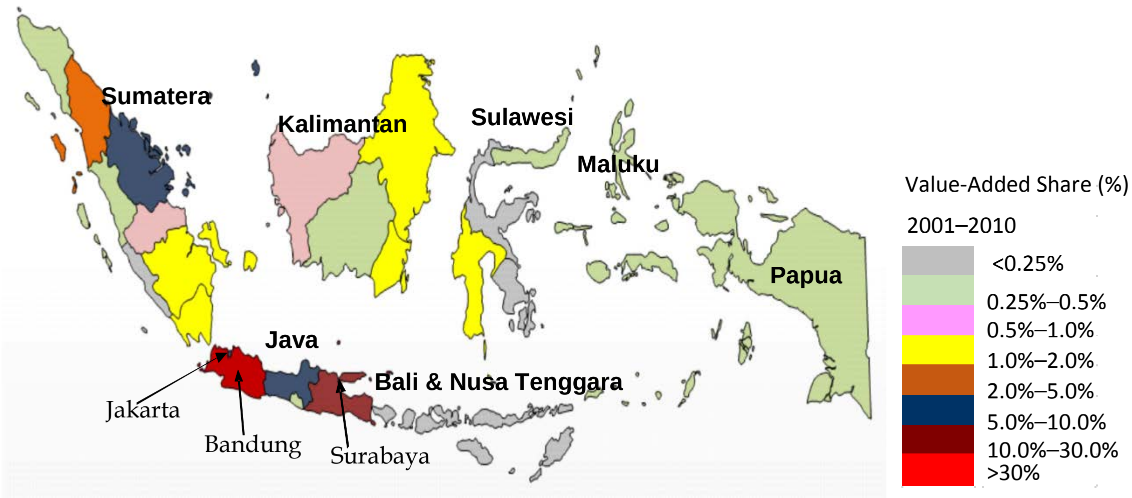
Source: Annual survey of large and medium firms 1990-2010, BPS and World Bank Development (WDI) data, author's calculation.

Figure 1.1. Indonesia's Economic and Manufacturing Sector Growth: The Manufacturing Sector's Contribution and Its Productivity

Although manufacturing's growth performance has been disappointing, only registering about 4% from 2001 to 2010 compared to 10% from 1990 to 1996, the sector still dominated the economy and contributed an average of 27.5% of the gross domestic product (GDP). Interestingly, the slower growth of the manufacturing sectors was not associated with the increase of labor productivity. It suggests there might be some external factors that also affected their productivity.

Accordingly, even though there is much literature explaining the relationship between agglomeration economies and productivity, as far as we know, no studies exist that compare the magnitude and sources of agglomeration economies throughout the economic cycle using micropanel data. This dissertation will attempt to examine the nature and scale of agglomeration economies for coping with external shocks in the face of the Asian financial crisis of 1997–1998 and the implementation of a decentralization policy. In the first paper, we address the question of how the external economies of scale or agglomeration economies affected productivity along the economic cycle before, during, and after the Asian financial crisis of 1997–1998. Subsequently, in the second paper, we address the question of how the dynamic agglomeration externalities affected city-industry growth at different times.

As we previously discussed, the development divide exists throughout Indonesia, whereas the population and economic activity are concentrated in Java and its surrounding areas. Indonesia's manufacturing activities are agglomerated mostly in Java in major cities such as Jakarta, Bandung, and Surabaya (see Fig. 2.2). From 1990 to 2000, it contributed 79.8% to the national value added of manufacturing and 77.6% from 2001 to 2010 (calculated from the annual survey of large and medium firms 1990–2010, BPS). Given the sector's unequal distribution, we are interested in examining the cross-regional externalities to determine if the geographic scope increases productivity and leads to spatial agglomeration formation in certain regions of the nation, particularly on Java Island.



Source: Annual survey of large and medium firms 1990-2010, BPS, author's calculation.

Figure 1.2. The Distribution of Manufacturing Value Added

The interest in the impact of geographic scopes has grown in light of the recent studies of this subject. Numerous studies were performed to examine the distance attenuation from individual plant externalities (for example, Graham, 2008; Rosenthal & Strange, 2003). Other studies attempted to investigate the spillover effects of agglomeration economies from neighboring counties or cities (for example, Henderson, 2003; Viladecans-Marsal, 2004). Another approach to identify geographic scopes is by looking at the spatial concentration of manufacturing firms. Kim (1995), He et al. (2008), and Lu and Tao (2009) studied the pattern of geographical concentration and examined the determinant factors of spatial distribution of manufacturing industries. However, most empirical studies of geographic scopes and geographical concentration largely focused on developed countries and provided limited evidence from developing countries except China. This dissertation addresses the effect of geographic scopes on plant-level productivity in the first paper, and in the third paper, we discuss the determinant factors of agglomeration economies.

1.2. Research Objectives

The main objective of this dissertation is to study the agglomeration effects on plant-level productivity, local productivity growth, and spatial distribution of manufacturing industries in Indonesia. To achieve this, we present three papers.

- The objectives of the first paper, "Estimating Agglomeration Economies along Economic Cycles and Across Geographical Distances," are to identify the source and estimate the magnitude of agglomeration economies, emphasizing how the economic crisis changed the nature of agglomeration economies, and identify the spatial agglomeration externalities from neighboring districts or cities.

- The second paper, "Market Potential, Local Industrial Structure, and Productivity Growth," examines the impact of the dynamic externalities of agglomeration economies on total factor productivity (TFP) and employment growth in both the long run (1990–2010) and the medium run (2000–2010).
- In the third paper, "Trends and Determinants of the Geographic Distribution of Economic Activities: Evidence from Indonesian Manufacturing," the distribution of economic activities in Indonesia is analyzed by looking at the trends of regional specialization and geographic concentration. Having the trends, this paper then empirically identifies the determinant factors of the geographical concentration of the manufacturing industry.

1.3. Research Contribution

This dissertation contributes to the empirical literature on agglomeration economies, particularly in the context of developing nations, in which the evidence is still limited. The contributions of this dissertation are as follows:

- The first paper contributes to the examinations of the effects of agglomeration economies on plant-level productivity in different economic situations. In the context of developing countries, this paper is also the first to study geographic scopes beyond single, local districts to determine plant-level productivity.

- Extending the previous literature, the second paper contributes by introducing employment market potential for controlling city size when estimating the impact of dynamic agglomeration externalities on city-industry growth.
- The last paper contributes by documenting the long-term regional specialization and concentration trends of the Indonesian manufacturing industry from 1990 to 2010; it also introduces a spatially weighted geographic concentration index in examining the determinant factors of the industry's spatial concentration.

1.4. Structure of the Dissertation

The dissertation is divided into five chapters. Chapter 1 gives a brief overview of the background, objectives, and contributions. Chapter 2 discusses the first paper to examine the effects of agglomeration economies along economic cycles and geographic scopes on plant-level productivity. In Chap. 3, the second paper is presented and studies the effects of dynamic agglomeration externalities on medium- and long-term TFP and employment growth. Chapter 4, the third paper, reports the trends and determinant factors vis-à-vis spatial distribution in Indonesian manufacturing. Finally, the conclusions, policy implications, and recommendation for further works are drawn in Chap. 5.

CHAPTER 2. ESTIMATING AGGLOMERATION ECONOMIES ALONG ECONOMIC CYCLES AND ACROSS GEOGRAPHICAL DISTANCES

2.1. Introduction

Although empirical literature exists, there are not many studies on the nature and source of agglomeration economies using micropanel data, with the exception of a few authors including Henderson (2003) and Martin et al. (2011). Furthermore, none of them discusses how the sources of agglomeration economies might change in response to economic situations, particularly during the financial crisis of 1997–1998. The previous studies may have ignored the effect of the crisis on the nature of agglomeration economies because the data were collected over a shorter period or the country researchers did not have enough knowledge about the crisis. However, we found literature that explained the financial crisis' effect on firm productivity. Unfortunately, those studies emphasized how the crisis affected productivity through the firm's internal economies of scale, such as ownership, labor cost, and export performance (for instance, Aswicahyono et al., 2010; Narjoko & Hill, 2007; Poczter et al., 2013). Therefore, we attempt to fill this gap in the literature by studying the effects of external economies from agglomeration economies—localization and urbanization economies—on productivity along the economic cycles covering the pre-crisis boom, deep crisis, and post-crisis recovery periods.

We define localization economies as the number of plants or employees of the same industry in the same region, while urbanization economies are defined as the number of employees in the same region. Having externalities from localization economies, firms benefit from spatial concentration, input sharing, labor pooling, intraindustry knowledge sharing, and innovative competition. On the other hand, urbanization economies offer higher productivity in diversified regions for firms because of interindustry exchanges of ideas, variety of business services, larger market size, and more product innovation (Gill & Goh, 2009).

As there is increased interest in the geographic scopes in light of recent studies on agglomeration economies, we also investigate the attenuation of agglomeration economies across geographic regions in the context of a developing nation, i.e., Indonesia. Since most of the empirical studies examining geographic scope focused on developed countries where network infrastructure is well developed and connected, this study provides evidence of geographic scopes from a country with less network infrastructure. Nevertheless, because of the lack of data on the distance between plants, we use the distance between districts or cities to account for spillover across regions. In examining geographic scopes, some researchers performed studies and examined the distance attenuation from individual plant externalities, including Rosenthal and Strange (2003) and Graham (2009) in the cases of the United States and Great Britain, respectively. Other studies attempted to investigate the spillover effects of agglomeration economies from neighboring counties or cities (for example, Henderson, 2003; Viladecans-Marsal, 2004).

The purposes of this paper are to estimate the source and magnitude of agglomeration economies, emphasizing how the economic crisis changed the nature of agglomeration economies and to identify the spatial agglomeration externalities from neighboring districts or cities, which are agglomeration effects beyond administrative boundaries. This paper contributes to the empirical literature on agglomeration economies studies in several ways. First, we provide new evidence of the effects of agglomeration economies on plant-level productivity in different economic situations. This paper reveals evidence of the relationship between plant size classification and industrial grouping with the type of agglomeration economies, which raises plant-level productivity. It also identifies the change of agglomeration sources in post-economic crisis periods. Second, in the context of developing countries, this paper is the first to study geographic scopes beyond single, local districts to determine plant-level productivity. It shows the presence of regional externalities and identifies the maximum distance of geographic scope that provides the highest agglomeration magnitudes to benefit plant-level productivity. Third, this paper uses a unique long-panel data set at the plant level that allows us to follow the plants' behaviors over years and over economic cycles. The use of microdata in agglomeration studies enhances the reliability of estimation results, as it allows the econometric model to contend with endogeneity concerns (Rosenthal & Strange, 2004).

The study applies a two-step empirical approach to the agglomeration model. In the first stage, we estimate plant-level TFP using a control function approach developed by Levinsohn and Petrin (2003). This method can address any simultaneity bias that would usually lead to coefficient overestimation in the production function. At the second stage, we regress the estimated TFP on the proxies of agglomeration economies and control variables. We control the time invariant of unobserved plant-level heterogeneity and industry characteristics by applying a panel fixed-effects estimation and adding industry-year dummies.

Furthermore, the cluster robust standard error for each industry region is imposed to account for spatial dependence among plants.

Having presented a brief overview of the importance and uniqueness of this research, the paper continues by providing a related literature survey. We then present our empirical modeling, and the data and variable construction are reported in the next section. Next, we describe the analyses and results, and, finally, we present our conclusions.

2.2. Literature Review

The debates on whether scale externalities are due to localization or urbanization economies have raised concerns about the validity of the sources of agglomeration economies. Intensive economic literature reviews that address this debate were clearly outlined by many authors. Those literature surveys collected empirical evidence and provided some guidelines on how to make better estimations and identifications (Beaudry & Schiffauerova, 2009; Melo et al., 2009; Rosenthal & Strange, 2004). Rosenthal and Strange (2004) assert the importance of three dimensions of economic scope, including industrial, temporal, and geographic scopes, in studying the nature and sources of agglomeration economies. A meta-study by Melo et al. (2009) points out that a difference in the data aggregation level and estimation techniques results in various sources and magnitude levels of agglomeration economies. Furthermore, Beaudry and Schiffauerova (2009) identify measurements and methodologies that can determine which types of externalities are supported. Gill and Goh (2009) discuss the distinction between localization and urbanization economies and emphasize the intra- or interindustry exchange of ideas and technology to derive productivity growth. Some studies attempt to answer the debate by focusing on empirical estimation.

In empirical works using plant-level data, the evidence points to location economies as the source of agglomeration economies; however, it might vary across different industries (Graham, 2009; Henderson, 2003; Martin et al, 2011). By using firm-level data of the machinery and high-tech industries from the United States, the findings of Henderson (2003) strongly emphasize that agglomeration is due to localization economies. Henderson was unsuccessful in uncovering evidence of urbanization economies. Likewise, the evidence from manufacturing and service industries in the United Kingdom reveals that localization and urbanization economies exist, but only localization economies report significant positive effects on productivity (Graham, 2009). Similarly, Martin et al. (2011) provide evidence that localization economies enhance plant-level productivity in France, but some limited evidence of urbanization economies is also identified. Overall, studies in developed countries indicate the dominance of localization economies over urbanization economies.

Kuncoro (2009) also suggests the domination of localization economies as agglomeration sources in Indonesia. Kuncoro investigated four selected industries and found that the benefits from agglomeration in the form of localization were stronger than from urbanization effects. The latest study related to agglomeration economies in Indonesia by Day and Ellis (2013) also asserts that the identified benefit comes from localization economies contributing to manufacturing growth, rather than from urbanization. The last two papers are relatively close to the work in this paper, seen in the separation of agglomeration effects into localization and urbanization economies. However, the current research benefits from having longer panel data at the plant level, as well as better empirical techniques to deal with problems arising from endogeneity.

The attenuation of agglomeration economies at greater distances is the main objective in examining geographic scope. In early research on agglomeration, many researchers did not address the spatial aspects of neighborhood effects. Henderson (2003) and Rosenthal and Strange (2003) first carried out research on the distance effects in agglomeration studies. By using zip codes as geographic boundaries, Rosenthal and Strange found that localization effects appear within five miles, while Henderson worked on county-level boundaries and found no significant effects from neighbors. Likewise, Graham (2009) claims 10 km is the maximum distance of localization spillovers among British manufacturing plants.

Because of data availability, this study could not measure the attenuated effects among plants, but we approximated using the distances between the capitals of districts or cities. We assume equal agglomeration effects of plants in similar districts or cities. Some previous papers applied a similar approach to examine the agglomeration effects of neighboring regions. Using city-level data from Spain, Viladecans-Marsal (2004) shows the presence of an agglomeration benefit from neighboring cities. Research that is more recent occurred in the field of geography and trade, looking at the impact of regional and supra-regional endowment on firm export performance (Rodríguez-Pose et al., 2013). By incorporating external factors from neighboring provinces in Indonesia, the authors concluded that not only pure agglomeration within one's own region contributed to export intensity, but also that regional externalities from neighboring provinces affected the likelihood of exporting. Accordingly, this study focuses on the neighboring effects of a lower administrative boundary level, i.e., district or city, to provide evidence of neighboring agglomeration effects and their impact on plant-level productivity.

2.3. Data and Variables

We gathered time series data from 1990 to 2010 and covered three distinct periods of the Indonesian economy relating to the Indonesian crisis of 1997–1998: the pre-crisis boom period (1990–1996), the deep crisis period (1997–2000), and the post-crisis recovery period (2001–2010). In addition, considering the oil price hike and the 2008 global financial crisis, the recovery period was divided further into two phases: the phase-1 recovery period (2001–2005) and the phase-2 recovery period (2006–2010). These rich panel data series permitted us to identify which types of scale externalities existed in Indonesia under different economic circumstances, given plant size and industry grouping.

2.3.1. Manufacturing Plant Data

We used an unpublished electronic data set on the annual survey of large and medium firms (*Statistik Industri*) conducted by BPS from 1990 to 2010. The data covered all manufacturing industries, which allowed us to conduct cross-industry and cross-region analyses. According to BPS, the survey respondents were companies with 20 or more employees, including new industrial companies that just began commercial production. In our work, each individual unit of observation was an establishment or a plant, since the information did not distinguish between a stand-alone establishment and a firm with many establishments.

The data spanned from 1990 to 2010 and included 459,677 plants. After cleaning and adjusting (see Appendix 2.1.), we constructed an unbalanced panel of cleaned observations with 442,842 unique observations, which represented 96.34% of the original observations. From these observations, we used only 442,157 observations that had estimated capital stock values. The detailed lists include the number of plants classified by size, economic cycles, and industry groups, and they are reported in Table A.2.1 in the Appendix.

To identify a plant in different periods of the survey, BPS classified each plant as one of two types: Plant Identity Code (PSID) and *Nomor Kode Induk Perusahaan* (NKIP), terms the BPS uses interchangeably. Having the data series of some years in both codes, we developed a concordance table that bridged PSID and NKIP. We used PSID codes for the remaining years that did not have PSID codes. A plant was also classified per the Indonesian Field Business Classification (KLUI), which is published by BPS and follows the International Standard Industrial Classification (ISIC). The codes changed over the years since their first production in 1968. This study included three periods of ISIC. From 1990 to 1997, our data were from ISIC Revision 2. For the period 1998–2009, we used data from ISIC Revision 3 (ISICrev3). Since 2010, BPS followed the United Nation's standards and updated the code to ISIC Revision 4 (ISICrev4).[1] Fortunately, BPS provides a bridge table of the five-digit ISIC, which allowed us to build a complete time series data set from 1990 to 2010.

[1]The information is provided by BPS in Manual Manufacturing Survey (Survei Industri Besar dan Sedang Bulanan) from http://sirusa.bps.go.id/index.php?r=sd/view&kd=2610&th=2012 accessed June 1, 2013.

2.3.2. Price Deflator

All values in a given year were expressed in 2000 constant prices. We used wholesale price indices (WPIs) published monthly in BPS's bulletin, *Statistik Bulanan Indikator Ekonomi*. We compiled these data from the CEIC database and annual publication of *Statistik Indonesia* from BPS. We deflated output, value added, intermediate input, and materials using the manufacturing WPI in five-digit ISIC. Meanwhile, wage was deflated using a GDP deflator and a weighted price of oil for the industry sector was used to deflate the values of energy and electricity.

2.3.3. Capital Stock Data

There are measurement issues regarding the true assessment of capital stock. The survey reported many missing numbers on investment since many respondents were intentionally reluctant to report because of tax considerations (Blalock & Gertler, 2008). We applied the perpetual investment method (PIM) to estimate the capital stock of firms in Indonesia (Jacob & Meister, 2005; Matthias & Javorcik, 2009; Rodríguez-Pose et al., 2013; Timmer, 1999). We calculated the investment values of a plant as the sum of five types of investments: land, building, machinery, vehicles, and other. Each type of investment was converted to real values by several types of price indices according to its type. We considered that there was no depreciation on land since land value tends to increase continuously. Following Jacob and Meister (2005), we deflated building investment with a non-residential and residential WPI. The imported machinery WPI and imported transport equipment WPI were used to deflate machinery and equipment and vehicles. Finally, we converted other investments to real values using construction WPI. For 1996, when investment values were not reported in the survey, we used linear extrapolation based on the investment values reported for the earlier years as suggested by Matthias and Javorcik (2009).

We employed the earliest available information on the replacement values of each capital category as a benchmark of capital stock, following Matthias and Javorcik (2009). If the replacement values were not available in the earliest year, we derived a benchmark capital stock by multiplying the average of the incremental capital value-added ratio for five consecutive years with the gross value added of the earliest year (Timmer, 1999; Jacob & Meister, 2005). We then constructed capital stock for the remaining years using the PIM and applied the following depreciation rates: 3.3% for building, 10% for machinery and equipment, and 20% for vehicles and other types of capital (Jacob & Meister, 2005; Matthias & Javorcik, 2009; Rodríguez-Pose et al., 2013; Timmer, 1999).

2.3.4. Regional Data

We used regional district data reflecting regional characteristics and natural endowments. We collected data on road lengths from BPS, while data on the land area were gathered from the Ministry of Home Affairs.[2] Furthermore, we generated data on the share of households with electricity and the share of coastal areas using the Village Potential Survey (PODES) of BPS. Since the number of districts in

---

[2] http://www.kemendagri.go.id/media/filemanager/2013/05/28/b/u/buku_induk_kode_data_dan_wilayah_2013.pdf accessed September 9, 2013.

Indonesia changed over time, particularly since 2001 (after the implementation of regional autonomy), we regrouped newly created districts back into their parent districts, keeping the 1990 configuration of 284 districts. This regrouping allowed us to compare across districts over the years from 1990 to 2010. Detailed information about the definition of the variables and data sources is given in the Appendix (Table A.2.2).

2.4. Methods

2.4.1. Empirical Estimation

A standard Cobb-Douglas production function in the form of translog linear techniques was applied extensively to study the determinant factors of agglomeration—and the ordinary least-squares (OLS) method was frequently used to estimate it. However, this approach usually suffers from endogeneity problems that may require techniques that are more advanced. The standard OLS estimation of plant-level productivity is possibly affected by a simultaneity bias stemming from an endogenous input choice. The correlation between error terms and explanatory variables in the estimation causes a bias, and, consequently, the least-squares estimation produces biased estimates on the coefficients. To deal with this issue, various methods have emerged in the literature.

The semiparametric estimators such as Olley-Pakes (OP, 1996) and Levinsonh and Petrin (LP, 2003) are increasingly becoming major tools to control the endogeneity problem when firm- or plant-level data are used.[3] Essentially, both

[3] van Beveren (2012) extensively reviewed and compared several estimation methods for total productivity at the plant level to deal with simultaneity and selection bias.

OP and LP methods propose a control function approach using a proxy variable to estimate the production function. This proxy variable should not be correlated at all with the unobserved productivity shock that is represented by a firm's investment decision or capital stock (van Beveren, 2012). These two methods proposed different variables to proxy capital stock: OP suggested investment as a proxy for capital stock, while LP proposed intermediate inputs such as materials, or energy or electricity consumption as a proxy variable. We preferred using the LP method rather than the OP method because of the lack of reliable investment data in the manufacturing data from Indonesia. As is common in the data from developing countries, there is a significant number of zero investments reported that could affect the estimation result if we use OP. Fortunately, that is not the case when using intermediate inputs such as materials, or energy or electricity consumption as a proxy variable for capital stock because such information is available from Indonesian manufacturing data (Vial, 2006).

We applied a two-step empirical approach in modeling agglomeration economies. First, we employed the semiparametric estimation of TFP introduced by Levinsohn and Petrin (2003) for each three-digit ISIC. This technique was useful to address possible simultaneity bias by using intermediate inputs as a proxy variable for unobserved shocks. We followed Levinsohn and Petrin (2003) by using the capital and electricity consumption of each plant as a proxy for unobserved productivity shock.[4] This method assumes that the capital level is the only

[4]We apply the Stata command "levpet" to estimate the plant-level production function. The command was created by Petrin et al. (2004).

endogenous variable. A detailed algorithm can be found in Levinsohn and Petrin (2003).

A standard Cobb-Douglas function to estimate the plant production function is represented as

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 k_{it} + \omega_{it} + \varepsilon_{it}, \tag{2.1}$$

where *y* represents the log of real value added by plant *i* at time *t*, *l* is the log of plant-level employment, and *k* is the log of real capital stock. The last two components are the productivity component of production function ω, and the error component ε, which should be uncorrelated with input choices. If $\xi_{it} = \omega_{it} + \varepsilon_{it}$ and Cov $(\xi_{it}, k_{it}) \neq 0$, then the estimation will be biased.

Levinsohn and Petrin (2003) consider employment (*l*) as a freely input variable and assume capital (k) as a state variable together with productivity shock (ω). Therefore, the demand for intermediate input (m) is written as

$$m_{it} = m_{it}(\omega_{it}, k_{it}). \tag{2.2}$$

By proving this demand function is monotonically increasing, LP inverted this function and obtained

$$\omega_{it} = \omega_{it}(k_{it}, m_{it}). \tag{2.3}$$

By substituting (2.3) with (2.1), we can write the plant production function as follows:

$$y_{it} = \beta_1 l_{it} + \Phi(k_{it}, m_{it}) + \varepsilon_{it,} \tag{2.4}$$

where

$$\Phi(k_{it}, m_{it}) = \beta_0 + \beta_2 k_{it} + \omega_{it}(k_{it}, m_{it}), \tag{2.5}$$

and $\Phi(k_{it}, m_{it})$ is a function of capital and materials.

Following Levinsohn and Petrin (2003), the productivity (ω) is assumed to follow a first-order Markov process

$$\beta_0 + \omega_{it} = \beta_0 + E[\omega_{it}|\omega_{it-1}] + \eta_{it} = h(\omega_{it}) + \eta_{it}, \qquad (2.6)$$

where η_{it} stand for an innovation shock. Plugging the last equation into the plant production function (2.1), we obtain

$$\begin{aligned} y_{it} &= \beta_1 l_{it} + \beta_2 k_{it} + h(\omega_{it}) + \eta_{it} + \varepsilon_{it} \\ &= \beta_1 l_{it} + \beta_2 k_{it} + h(\omega_{it}) + \varepsilon_{it}^{*}, \end{aligned} \qquad (2.7)$$

and we assume that there is no correlation between capital k_{it} and its error component ε_{it}^{*}, but it may have correlation with labor l_{it}. By imposing a third-order polynomial approximation in k_{it} and m_{it}, the consistent β_1, the estimated coefficient for labor using OLS can be done in the first step (Petrin et al., 2004). Equation (2.4) can then be written as

$$y_{it} = \delta_0 + \beta_1 l_{it} + \sum_{p=0}^{3}\sum_{q=0}^{3-i}\delta_{pq} m_{it}^{p} k_{it}^{q} + \varepsilon_{it}. \ (2.8)$$

The OLS estimation yields $\widehat{\beta_1}$ and $\widehat{\Phi}$, but it cannot distinguish the intercept of β_0 and $\Phi(k_{it}, m_{it})$. To estimate β_k, the estimated coefficient for capital, we rewrite Eq. (2.8) in the second step as follows:

$$\begin{aligned} \widehat{\Phi}(.) &= \widehat{y_{it}} - \widehat{\beta_2} l_{it} \\ &= \delta_0 + \sum_{p=0}^{3}\sum_{q=0}^{3-i}\widehat{\delta_{pq}} m_{it}^{p} k_{it}^{q} - \widehat{\beta_2} l_{it} \ . \end{aligned} \qquad (2.9)$$

This equation provides the initial β_k^{*}, and productivity shock ω_{it} is predicted by rewriting Eq. (2.5) as follows:

$$\widehat{\omega_{it}} = \widehat{\Phi_{it}} - \beta_k^{*} k_{it}. \qquad (2.10)$$

From Eq. (2.6), we know that $\omega_{it} = E[\omega_{it}|\omega_{it-1}] + \eta_{it}$, so the estimated plant production function becomes

$$\widehat{y_{it}} = \widehat{\beta_0} + \widehat{\beta_1} l_{it} + \widehat{\beta_2} k_{it} + E\left[\omega_{it}\widehat{|\omega_{it-1}}\right] + \eta_{it}\widehat{+\varepsilon_{it}}$$

$$\widehat{y_{it}} = \widehat{\beta_1} l_{it} + \beta_k^* k_{it} + E\left[\omega_{it}\widehat{|\omega_{it-1}}\right] + \eta_{it} \widehat{+ \varepsilon}_{it}, \tag{2.11}$$

where $\widehat{\beta_0} + \widehat{\beta_2} k_{it} = \beta_k^* k_{it}$.

The estimated residual of the production function is

$$\eta_{it} \widehat{+ \varepsilon}_{it} = \widehat{y_{it}} - \widehat{\beta_1} l_{it} - \beta_k^* k_{it} - E\left[\omega_{it}\widehat{|\omega_{it-1}}\right]. \tag{2.12}$$

By minimizing that residual of the production function, $\widehat{\beta_k}$ for capital is estimated as

$$\min_{\beta_k^*} \sum_t \sum_i \eta_{it} \widehat{+ \varepsilon}_{it} = \min_{\beta_k^*} \sum_t \sum_i \widehat{y_{it}} - \widehat{\beta_1} l_{it} - \beta_k^* k_{it} - E\left[\omega_{it}\widehat{|\omega_{it-1}}\right]. \tag{2.13}$$

To produce the standard error for all estimated coefficients, the algorithm uses a bootstrap approach.

After applying a semiparametric Levin-Petrin approach (Petrin et al., 2004), the TFP for each plant is estimated as

$$\begin{aligned} \text{TFP}_{it} &= \exp(\widehat{\omega}_{ijt}) \\ &= \exp(y_{it} - \widehat{\beta_0} - \widehat{\beta_1} l_{it} - \widehat{\beta_2} k_{it}), \end{aligned} \tag{2.14}$$

where TFP_{ijt} is the estimated TFP of plant *i* in industry *j* at time *t*. This estimated TFP would then be regressed on spatial environment variables and agglomeration measures in the next stage.

In the second step, we applied a fixed-effects panel data analysis to examine how agglomeration economies affect plant-level TFP, after controlling for plant and regional characteristics. We believed that assessing the agglomeration externalities at the plant level may help eliminate any aggregation bias and provide better estimation of agglomeration magnitude. The plant-level analysis highlights the need to control for plant-level, regional, and industry characteristics and to solve any firm selection bias. In general, Melo et al. (2009) find a slightly lower level of agglomeration magnitude when the study uses the firm level rather than the industry level or regional level.

The general framework for modeling agglomeration economies follows Rosenthal and Strange (2004). They defined the total benefit of agglomeration economies (A_i) as the result from spillover between plant *i* and plant *j*, $q\left(x_i, x_j\right)$, which depends on input levels, geographic proximity (*G*), industry type (*I*), and time dimension (*T*):

$$A_i = \sum_{j \in J} q\left(x_i, x_j\right) a(d_{ij}^G, d_{ij}^I, d_{ij}^T), \tag{2.15}$$

where $q\left(x_i, x_j\right)$ reflects benefits from interaction that depend on the scale of i's and j's activities. Meanwhile, d_{ij}^G stands for geographic distance, d_{ij}^I stands for industrial distance, and d_{ij}^T stands for temporal distance.

To cope with external economies, we adopted an augmented standard production function model as in Rosenthal and Strange (2004):

$$y_i = g(A_i) f(\boldsymbol{x_i}) \tag{2.16}$$

and, therefore,

$$\text{TFP}_{it} = g(A_{it}), \tag{2.17}$$

in which y_i is the plant's value added, x_i represents a vector of the plant's levels of traditional inputs such as labor and capital, and $g(A_I)$ denotes the production function shift from external economies. This framework assumes the neutrality of productivity or a status of balance between capital and labor. Thus, we can estimate agglomeration economies through $g(A_i)$ in which $g'^{(.)} \geq 0$.

From Eq. (2.17), we separated the econometric parameters for testing the effects of agglomeration economies on plant-level productivity into two specification models. All specifications were estimated using the fixed-effects model at the plant level and included industry-year (two-digit SIC) fixed effects. Model 1 is the baseline model, while model 2 is presented to deal with the geographical spillover from neighboring districts. Following Henderson (2003), we measured localization by decomposing the local industry's employment into that of the local industry plant and the average of employment by other local plants. Henderson argued that localization externalities are derived from spillover among plants, as he found stronger significance results when he used the plant number instead of the employment number. This approach solves the limitation of localization economies measured by local industry employment, which exhibits only a weakly significant impact on productivity. On the other hand, we measured urbanization economies using employment density. According to Melo et al. (2009), employment density is more robust against a district area, and it more accurately reflects productivity benefits or the potential congestion cost from urbanization economies in a region. In the second model, we measured the geographic scopes of localization and urbanization economies by adding neighbor agglomeration variables $\mathrm{WLocplant}_{jr't}$ and $\mathrm{WUrbanization}_{r't}$ to $\mathrm{Locplant}_{jrt}$ and $\mathrm{Urbanization}_{rt}$, respectively.

Model 1: Baseline Model.

$$\begin{aligned}\mathrm{lnTFP}_{irt} = {} & \alpha_0 + \beta_1 \mathrm{lnAge}_{irt} + \beta_2 \mathrm{lnSize}_{irt} + \beta_3 \mathrm{DFDI}_{irt} + \beta_4 \mathrm{DGov}_{irt} + \\ & \beta_5 \mathrm{DExport}_{irt} + \beta_6 \mathrm{Coastal}_{rt} + \beta_7 \mathrm{Electricity}_{rt} + \beta_8 \mathrm{Roaddens}_{rt} + \\ & \beta_9 \mathrm{lnDistport}_{rt} + \beta_{10} \mathrm{lnAvrindregemp}_{jrt} + \beta_{11} \mathrm{lnLocplant}_{jrt} + \\ & \beta_{12} \mathrm{lnUrbanization}_{rt} + e_{irt} \qquad (2.18)\end{aligned}$$

Model 2: Geographic Scope.

$$\begin{aligned}\mathrm{lnTFP}_{irt} = {} & \alpha_0 + \beta_1 \mathrm{lnAge}_{irt} + \beta_2 \mathrm{lnSize}_{irt} + \beta_3 \mathrm{DFDI}_{irt} + \beta_4 \mathrm{DGov}_{irt} + \\ & \beta_5 \mathrm{DExport}_{irt} + \beta_6 \mathrm{Coastal}_{rt} + \beta_7 \mathrm{Electricity}_{rt} + \beta_8 \mathrm{Roaddens}_{rt} + \\ & \beta_9 \mathrm{lnDistport}_{rt} + \beta_{10} \mathrm{lnAvrindregemp}_{jrt} + \\ & \beta_{11} \mathrm{ln}(\mathrm{Locplant}_{jrt} + \mathrm{WLocplant}_{jr't}) + \beta_{12} \mathrm{ln}(\mathrm{Urbanization}_{rt} + \\ & \mathrm{WUrbanization}_{r't}) + e_{irt} \qquad (2.19)\end{aligned}$$

The agglomeration economies variables were measured using the three-digit industrial classification, as suggested by Beaudry and Schiffauerova (2009). In this aggregation level, we expected to have better identification to separate agglomeration externalities from localization and urbanization economies. All non-dummies and share variables are in log form. lnTFP_{irt} represents the TFP of plant *i* in region *r* at year *t*. Plant characteristics control for their individual production function, whereas regional characteristics control for geographical advantages and spatial environments. $\mathrm{Locplant}_{j,r}$ is the number of plants in industry *j* of region *r* at time *t*. Avrindregemp refers to the average number of employees within the same industry *j* and region *r* but with the exclusion of one's own plant *I*,

$$\mathrm{Avrindregemp}_{i,j,r} = \frac{(\sum_i \mathrm{emp}_{i,j,r}) - \mathrm{emp}_i}{\mathrm{Locplant}_{j,r} - 1}. \qquad (2.20)$$

Following Melo et al. (2009), we preferred to measure urbanization economies using employment density. Urbanization represents employment density in region *r* at time *t* instead of the total number of employees in a region,

$$\mathrm{Urbanization}_r = \frac{\mathrm{emp}_r}{\mathrm{area}_r}. \qquad (2.21)$$

Age and Size are the age of the plant and the number of plant employees, respectively, while DFDI, DGov, and DExport stand for the dummy variables of foreign ownership, government ownership, and export activity. DFDI is equal to 1 if the plant is at least 10% foreign owned, Dgov is equal to 1 if the government's share is greater than 50%, and DExport is equal to 1 if the plants export during that year. Moreover, geographical advantages and spatial environments that reflect regional characteristics are specified in the model. Coastal represents the percentage of villages that have a littoral area, while Electricity stands for the percentage of households that have electricity. Roaddens indicates the ratio of the total length of three types of roads: national, provincial, and district to provincial.[5]

We used the geographic information system (GIS) Euclidean distance to map spatial aspects and interaction among districts. The GIS distance among districts is inherently weighted because of its interaction with the measurements of cross-regional effects. While Rodríguez-Pose et al. (2013) used that method to capture external effects among provinces in Indonesia, we took a lower level of administrative boundaries: so-called "districts." This choice is more relevant to the current regional situation in Indonesia since the country has been implementing a regional autonomy system and transferred many authorities to district governments. By using GIS data, we also constructed the distance to the nearest main port in Indonesia (Distport); those ports include Belawan, Tanjung Priok, Tanjung Perak, Balikpapan, and Makassar.

[5]We only had access to road data for the provincial level, since road data in the district level are neither properly recorded nor publicly available.

To capture regional externalities using a spatial weights matrix, we followed the distance-decay process associated with agglomeration, weighted by the inverse of distance (Graham, 2009; Rodríguez-Pose et al., 2013). By assumption, the district capital is located at the center of the district's area. The matrix of the neighboring spatial distance is

$$\boldsymbol{D}(\boldsymbol{\delta})\begin{cases} d_{ij}^{*}(\delta) = 0 \text{ if } i = j \\ d_{ij}^{*}(\delta) = d_{ij} \text{ if } d_{ij} \leq \delta \\ d_{ij}^{*}(\delta) = \sim \text{ if } d_{ij} > \delta \end{cases}, \tag{2.22}$$

where δ denotes a distance threshold between the capitals of neighboring districts in which we assumed that regional externalities still appeared. If the Euclidean distance d_{ij} from capital district *i* to capital district *j* is smaller than δ, then the spatial distance $d_{ij}^{*}(\delta)$ is equal to d_{ij}. Now that we have a distance matrix, we computed W_{ij}, the weighted neighbor distance matrix for region *i* with respect to neighbor *j*:

$$W_{ij} = \frac{1/d_{ij}^{*}(\delta)}{\sum_j 1/d_{ij}^{*}(\delta)}. \tag{2.23}$$

The fixed cutoff criteria, or distance threshold, is a radius of 5–50 km between the districts' capitals, in light of the finding that localization takes place below 50 km (Duranton & Overman, 2005).

We applied the classic index, Moran's I statistics of spatial association, to test if the geographical distribution of the manufacturing sectors was spatially dependent and not random, following Rigby and Essletzbichler (2002) and Viladecans-Marsal (2004). This index can be interpreted as the correlation between variables—such as productivity of a certain industry in a region—and its surrounding regions. The index is defined as

$$IM_k = \frac{\sum_i \sum_j W_{ij}(\text{TFP}_{ki} - \overline{\text{TFP}}_k)(\text{TFP}_{kj} - \overline{TFP}_k)}{\sum_i (\text{TFP}_{ki} - \overline{\text{TFP}}_k)}, \qquad (2.24)$$

where IM_k is Moran's I test for sector *k*, TFP is the two-digit ISIC total factor productivity, *i* and *j* are the districts, and $\overline{\text{TFP}}$ is the average of TFP.

2.4.2. Estimation Issues

The most challenging issues in examining the relationship between agglomeration and productivity are endogeneity, or simultaneity, and firm selectivity (Hanson 2001; Rosenthal & Strange, 2004). Several techniques address this problem. To solve the problem of simultaneity bias caused by input endogeneity in plant-level production function, our first step was to apply a control function approach developed by Levinsohn and Petrin (2003). In the second step, we estimated our empirical models using the fixed-effects model at the plant level. By incorporating plant fixed effects, we were able to control the plant's unobservable characteristics that affected the plant's location selection (Henderson, 2003). With these treatments, we were also able to solve the endogeneity problem and plant selection. Theoretically, we eliminated the bias of plant behavior, which was likely to locate the plant in the most productive and agglomerate regions. However, there was still a potential bias due to unobservable characteristics of regions and industries that may have affected plant productivity. Therefore, we decomposed the error term as follows:

$$e_{irt} = \delta\lambda_{jt} + \varepsilon_{it}, \qquad (2.25)$$

where $\delta\lambda_{jt}$ stands for industry time-period fixed effects (SIC two-year dummies) and ε_{it} is the remaining white noise error. Thus, in addition to plant fixed effects, we also imposed industry-year fixed effects to control the remaining shocks that were not absorbed by plant fixed effects (Henderson, 2003; Maré & Graham, 2013).

The last concern regarding estimation issues was the spatial dependence among plants within an industry in specific regions. We were aware of the possible correlation among plants within an industry sector in a region but not across an industry. This means that plants within the same cluster are not independent, but plants in different clusters of industry districts are independent. This may cause errors by being correlated within a cluster. To deal with this, we allowed the standard errors to be clustered by industry district. By imposing cluster errors, we avoided the underestimated standard errors that tend to lead to rejection of the null hypothesis (Cameron et al., 2011; Moulton, 1990; Nichols & Schaffer, 2007).

2.5. Results and Discussion

2.5.1 Aggregate Estimate

We used the TFP level that was calculated from the plant-level production function estimation as a dependent variable. The estimation results of the plant-level production function for each three-digit SIC are reported in the Appendix (Table A.2.3). It indicates that in 66% of the sectors, constant returns to scale could not be rejected.

Moreover, we classified the independent variables into four groups: plant characteristics, regional characteristics, agglomeration economies, and neighbors' agglomeration economies. Table 2.1 presents summary statistics of the variables used in our empirical model. At first glance, Table 1 shows there is large heterogeneity concerning plant size and a high variation of road density, indicating an imbalance in the amount of transport infrastructure across regions. It also demonstrates that urbanization economies' measurement is slightly more dispersed than that of localization economies'.

Table 2.1. Descriptive Statistics of Variables.

Variable	Mean	SD	CV
Dependent Variable (# of observations = 442,157)			
TFP	217.69	949.34	4.36
Firm Characteristics (# = 442,157)			
Size	186.65	646.36	3.46
Age	14.66	13.60	0.93
Regional Characteristics (# = 5,660)			
Coastal (%)	7.44	12.88	1.73
Electricity (%)	94.51	10.48	0.11
Roaddens	1.67	3.06	1.83
Distport	722.83	273.87	0.38
Agglomeration Economies (# = 65,691)			
Locplant	6.74	17.38	2.58
Avrindregemp	121.56	406.20	3.34
Urbanizations [a]	38.22	115.23	3.01
Distance Agglomeration Economies (# = 5,660)			
Locplant-5	27.65	35.18	1.27
Locplant-25	28.89	32.63	1.13
Locplant-50	28.91	32.58	1.13
Urbanization-5	82.19	143.20	1.74
Urbanization-25	85.46	133.94	1.57
Urbanization-50	85.55	133.75	1.56

Note: SD = standard deviation. CV = coefficient of variance.
δ = 5,25, and 50 km. [a] Number of observations = 5,660.

The main results of the empirical model estimation are shown in Table 2.2. The estimation results of the baseline model are presented in columns (1) and (2), examining the existence of agglomeration externalities in Indonesia; columns (3)–(5) show different results from the modified model, which considers geographic scopes. The OLS estimation results reported the estimated coefficients in column (1), showing significance effects of both localization and urbanization economies.[6] However, these results might overestimate true values because of a possible reversed causality between agglomeration variables and productivity.

By applying fixed-effects methods and industry-year dummies, the results in column (2) show that localization economies strongly determine productivity, with significance coefficient values of 0.060. This implies that a 1% increase in the number of plants within an industry for each district will enhance plant productivity by 0.060. Our estimation of localization economies is less than half of the findings by Kuncoro (2009), which showed significant coefficients within the range of 0.13 to 0.24 for all specifications. These differences can be explained by the fact that we improved the estimation method by eliminating the possible biases of input endogeneity and plant self-selection and absorbing the unobserved plant fixed effects. However, our result indicated a relatively similar magnitude with localization economies from other countries, including 0.02 to 0.08 for manufacturing in the United States (Henderson, 2003), 0.03 for British manufacturing (Graham, 2008),

[6] The pairwise correlation coefficients between the level and first difference of lnlocplant and lnavrindregemp are 0.254 and -0.009, respectively, suggesting no multicollinearity between variables representing localization.

0.032–0.063 for Korean manufacturing (Lee et al., 2010), and 0.05–0.06 for French manufacturing (Martin et al., 2011).

Table 2.2.Agglomeration Externalities: Main Result

Dependent Variable:	**Total Factor Productivity (LnTFP)**				
Specification	**Model 1**		**Model 2**		
Empirical Method :	**OLS**	**FE**	**5 km**	**25 km**	**50 km**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Age (Ln)	-0.065***	0.109***	0.111***	0.110***	0.110***
	[0.008]	[0.009]	[0.010]	[0.009]	[0.009]
Size (Ln)	0.282***	0.059***	0.059***	0.059***	0.059***
	[0.011]	[0.012]	[0.012]	[0.012]	[0.012]
DFDI (1=Foreign)	0.319***	0.118***	0.118***	0.118***	0.118***
	[0.037]	[0.017]	[0.017]	[0.017]	[0.017]
Dgov (1=Gov)	0.409***	0.238***	0.238***	0.238***	0.238***
	[0.036]	[0.026]	[0.026]	[0.026]	[0.026]
Dexp (1=Exp)	0.009	-0.004	-0.004	-0.004	-0.004
	[0.021]	[0.009]	[0.009]	[0.009]	[0.009]
Coastal (%)	0.001	0.004***	0.005***	0.005***	0.005***
	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]
Electricity (%)	-0.005***	0.001**	0.002**	0.002**	0.002**
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Roaddens (Ln)	-0.002	0.063***	0.063***	0.064***	0.064***
	[0.019]	[0.023]	[0.023]	[0.023]	[0.023]
Distport (Ln)	0.544***	-1.132**	-1.089**	-1.053**	-1.067**
	[0.069]	[0.459]	[0.463]	[0.461]	[0.459]
Avregindemp (Ln)	0.103***	0.004	0.006	0.005	0.005
	[0.009]	[0.004]	[0.004]	[0.004]	[0.004]
Locplant (Ln)	-0.024	0.060***	0.095***	0.101***	0.101***
	[0.025]	[0.016]	[0.030]	[0.033]	[0.033]
Urbanization (Ln)	0.043***	0.019	0.028	0.061**	0.061**
	[0.009]	[0.013]	[0.023]	[0.028]	[0.028]
_cons	-1.788***	10.617***	10.077***	9.651***	9.741***
	[0.628]	[3.003]	[3.052]	[3.031]	[3.020]
Industry-Year Dummies	Y	Y	Y	Y	Y
Plant Fixed Effects	N	Y	Y	Y	Y
N x T	442,157	442,157	442,157	442,157	442,157
R^2	0.378	0.073	0.073	0.073	0.073

Notes: Robust standard errors for correcting at the industry-district level are reported in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The importance of the geographical area in the analysis of agglomeration economies is highlighted in columns (2)–(4). By expanding the geographic reach beyond the local area, the estimation results of agglomeration economies have changed. The estimation captured not only location effects—as in column (2)—but also the identification of the neighboring effects. The longer distance of regional externalities is associated with the constant effects of localization, after reaching a peak at a certain level of distance.

In terms of control variables, all plant characteristic variables are significant in determining productivity—except a dummy variable for export. The plant's age shows a positive significant coefficient, indicating internalization of the accumulated knowledge of the plants over years of improving productivity. The size of the company is also positive and a statistically significant determinant of productivity, indicating the higher productivity of a larger plant size. Furthermore, foreign direct investment (FDI) and government plants show a positive and statistically significant effect, which implies that plants with higher productivity are more likely to have better access to sources of capital and overseas markets (Narjoko & Hill, 2007).

We further confirmed the importance of network externalities represented by road density. The estimated coefficients are moderately robust, between 0.063 and 0.064. This result suggests that the improvement of road infrastructure across districts or cities within a province not only leads to network connectivity between employments and plants with their counterparts outside of the region, but it also increases productivity. The positive effects of coastal location and electricity on productivity indicate the importance of regional competitiveness for enhancing plant-level productivity. Although we did not consider the availability and quality of the network, the GIS-Euclidean distance that measures the distance between districts' capital to seaport was remarkably appropriate as an approximation of travel time and transportation costs. The estimated coefficients are consistently negative and statistically significant; i.e., the greater the distance to an international seaport, the longer the travel time and the higher the cost.

2.5.2. Robustness Check

To confirm the robustness of our results, we performed robustness checks reported in Table 2.3. The table presents the different specifications. The estimates from the benchmark model are presented in column (1) for comparison; estimates using different subsamples are presented in columns (2)–(6). The respective subsamples are the plants that have existed for a minimum of 10 or 15 years within the period of study, excluding the food and beverage industry, low-technology industries, and natural-resources-based industries. Column (7) provides the results from alternative measures of productivity. When replacing TFP with value added per labor as a dependent variable, capital per labor is added to capture the capital intensity effects.

The table shows considerable consistency in both sign and significance level. In general, the only differences in the results appear in the magnitude of the estimated coefficients. From this table, we concluded that our empirical models were robust to a variety of specifications and alternative measures of productivity. The estimated coefficient in column (7) is slightly higher than the fixed-effects estimation results because of the upward bias caused by an input endogeneity problem. These results also suggest that the estimate of TFP using the Levin-Petrin method and the application of the fixed-effects estimation are the best choices in our study for estimating the magnitudes of agglomeration. It certainly solved our endogeneity concern. However, although the results indicate that localization economies seem to be more important than urbanization economies in the case of Indonesia, further investigation into the relationship between plant size heterogeneity and type of industry is warranted.

Table 2.3. Agglomeration Externalities: Robustness Test

Dependent Variable:	**Total Factor Productivity (Ln TFP)**						**Labor Productivity**
Robustness Strategy	**Full Sample**	**Smpl>= 15 Yrs**	**Smpl>= 10 Yrs**	**Excluding food & beverage**	**Excluding low-technology**	**Excluding resources-based**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Age (Ln)	0.109***	0.110***	0.108***	0.103***	0.098***	0.106***	0.106***
	[0.009]	[0.010]	[0.012]	[0.016]	[0.014]	[0.012]	[0.010]
Size(Ln)	0.059***	0.095***	0.113***	0.064***	0.051***	0.057***	-0.093***
	[0.012]	[0.010]	[0.012]	[0.014]	[0.015]	[0.014]	[0.011]
Capital Labor Ratio (Ln)							0.079***
							[0.006]
DFDI (1=Foreign)	0.118***	0.116***	0.119***	0.153***	0.126***	0.145***	0.131***
	[0.017]	[0.019]	[0.021]	[0.030]	[0.024]	[0.020]	[0.018]
Dgov (1=Gov)	0.238***	0.241***	0.254***	0.189***	0.230***	0.250***	0.238***
	[0.026]	[0.032]	[0.041]	[0.029]	[0.037]	[0.029]	[0.026]
Dexp (1=Exp)	-0.004	-0.008	-0.018	0.018	-0.004	-0.002	0.000
	[0.009]	[0.009]	[0.011]	[0.014]	[0.010]	[0.009]	[0.009]
Coastal (%)	0.004***	0.002	0.003	0.001	0.005**	0.006***	0.004**
	[0.002]	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]
Electricity (%)	0.001**	0.001	0.000	-0.001	0.001	0.001	0.001**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Roaddens(Ln)	0.063***	0.068***	0.073**	0.067**	0.112***	0.089***	0.061***
	[0.023]	[0.025]	[0.029]	[0.034]	[0.030]	[0.026]	[0.023]
Distport(Ln)	-1.132**	-0.740	-1.008	-1.397	-2.223***	-2.003***	-1.189**
	[0.459]	[0.487]	[0.712]	[0.897]	[0.754]	[0.705]	[0.471]
Avregindemp(Ln)	0.004	0.002	0.006	0.004	0.003	0.006	0.004
	[0.004]	[0.004]	[0.005]	[0.006]	[0.005]	[0.005]	[0.004]
Locplant(Ln)	0.060***	0.042**	0.051**	0.058*	0.059***	0.057***	0.062***
	[0.016]	[0.020]	[0.023]	[0.030]	[0.023]	[0.020]	[0.016]
Urbanization (Ln)	0.019	0.044***	0.042**	0.016	0.002	0.011	0.018
	[0.013]	[0.016]	[0.020]	[0.023]	[0.019]	[0.016]	[0.013]
_cons	10.62***	8.105**	9.712**	12.707**	17.711***	16.293***	11.741***
	[3.003]	[3.171]	[4.602]	[5.835]	[4.922]	[4.600]	[3.083]
N x T	442,157	328,847	259,104	142,192	195,276	277,311	442,157
R^2	0.073	0.081	0.086	0.088	0.088	0.084	0.076

Notes: Robust standard errors for correcting at the industry-district level are reported in brackets.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5.3. *Estimates by Plant Size Classifications and Industrial Groups*

We now turn to the analysis of disaggregated data to examine the agglomeration effects on the productivity of plants. We categorized the plants as follows: “small” (20–49 employees), “medium” (50–249), and “large” (250+). As far as plant size is concerned, a well-defined pattern among small, medium, and large plants is shown in Table 2.4. There are notable differences in the effects of agglomeration with respect to plant-size heterogeneity. The smaller plants experience more urbanization economies than the larger plants do, which indicates that the small plants enjoy the diversity of the environment across industries in the entire region. Consequently, those plants tend to have stronger productive advantages in large cities. On the other hand, medium and large manufacturing plants tend to accumulate more external economies from localization. Those plants are better situated in more localized economies in order to absorb the benefit from Marshallian externalities such as input sharing, labor pooling, and knowledge spillover.

Table 2.4. Agglomeration Externalities by Plant Size

Dependent Variable:	**Total Factor Productivity (Ln TFP)**		
Plant's Size	**Small (20-49)**	**Medium (50-249)**	**Large (>= 250)**
Avregindemp(Ln)	0.002	0.002	0.004
	[0.006]	[0.006]	[0.008]
Locplant(Ln)	0.034*	0.061**	0.080**
	[0.020]	[0.024]	[0.033]
Urbanization (Ln)	0.056***	0.031	-0.015
	[0.017]	[0.020]	[0.035]
_cons	11.857***	8.999*	10.713
	[3.536]	[5.429]	[6.785]
N x T	237,647	138,278	66,232
R^2	0.087	0.077	0.074

Notes: Estimations include fixed effects at the plant-level and dummies of industry-year. Each regression includes control for the plant's characteristics of age, size, dummies of ownership (DFDI, Dgov), and export activity, and regional characteristics of coastal area, access to electricity, road density, and distance to the closest international port. Robust standard errors for correcting at the industry-district level are reported in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We further analyzed the effects of agglomeration on productivity through industry groups. Following Henderson et al. (2001), we classified the 23 industries of the two-digit SIC into six groups: (a) traditional, (b) heavy, (c) transportation equipment, (d) machinery and electronics, (e) high-technology, and (f) other industries. We assumed that externalities of labor pooling occurred between plants in the same two-digit SIC in the same region. By aggregating into six industry groups, we allowed broader externalities among plants in different two-digit SICs but we maintained the similar broad industry group.

Table 2.5 compares the effects of agglomeration economies that benefit certain industries. It shows that the traditional and machinery and electronics industries received external benefits from localization economies and are more productive in a localized area. This finding confirms that a specialized environment can provide favorable conditions for these typical, resource-based, and labor-intensive industries (as they defined in the OECD classification scheme; OECD, 1987). This is supported by the fact that the location of mature firms is attractive to the new plants, as it implicitly informs them of the most suitable area compared to others with similar conditions (Henderson & Kuncoro, 1996). Another study by Deichmann et al. (2005) suggests that localization economies and infrastructure improvements are important factors in firms' decisions in plant location and other activities in Indonesia. Moreover, Amiti and Cameron (2007) also suggested that localization economies in Indonesia emerged by looking at the interaction between firms in supply and demand relationships. They found that the firms enjoyed at least two of the three sources of agglomeration, namely, input sharing and labor market pooling.

On the other hand, agglomeration externalities in the form of urbanization affect the transport equipment industries. This finding enabled us to explain the nature of those industries, which received greater external benefits from diversified environments and large areas. The productivity in these industries strongly depends on the target market, which is the main competitiveness factor for this type of consumer-driven good. However, these results differed from Henderson et al. (2001) and Lee et al. (2010), both of which concluded that the transport equipment industry in Korea received external benefits from localization, while the same sector in Indonesia received external benefits from urbanization economies. This implies that the Korean transport industry consists of producers who run their businesses in concentrated and specialized areas. In contrast to the Korean case, the Indonesian transport industry is made up mostly of the assemblers and traders that need a larger area and diverse market environment in order to sell their products. The results also reveal that other manufacturing industries, including publishing and recycling, benefit more from agglomeration economies.

Table 2.5. Agglomeration Externalities by Industry

Dependent Variable:	**Total Factor Productivity (Ln TFP)**					
Industry Group	**Traditional**	**Heavy**	**Transport**	**Machinery & Electronic**	**High Techno logy**	**Other Mnf**
Avregindemp(Ln)	0.004	-0.002	0.015	0.004	0.025	0.013
	[0.006]	[0.007]	[0.020]	[0.013]	[0.022]	[0.023]
Locplant(Ln)	0.056***	0.053	0.036	0.114**	0.056	0.190***
	[0.020]	[0.034]	[0.063]	[0.054]	[0.206]	[0.071]
Urbanization (Ln)	0.017	-0.017	0.276***	0.000	0.135	0.125***
	[0.017]	[0.025]	[0.073]	[0.063]	[0.208]	[0.046]
_cons	10.172***	15.917**	-9.590	12.137	-42.646**	-0.984
	[3.923]	[6.776]	[15.213]	[10.760]	[19.782]	[5.907]
N x T	286,116	107,875	11,728	18,014	4,642	13,782
R^2	0.064	0.082	0.099	0.117	0.095	0.109

Notes: Estimations include fixed effects at the plant-level and dummies of industry-year. Each regression includes control for the plant's characteristics of age, size, dummies of ownership (DFDI, Dgov), and export activity, and regional characteristics of coastal area, access to electricity, road density, and distance to the closest international port. Robust standard errors for correcting at the industry-district level are reported in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.1 shows the position of each plant size classification as well as industrial classification. The agglomeration magnitudes of plant sizes show the position at adjacent points of small, medium, and large plants, but small-sized plants could benefit from both localization and urbanization. The scatter plots also show that the other manufacturing industries, comprising publishing and recycling, are the most successful agglomerated industries. This sector is able to utilize inter- and extra-industrial external effects and take advantage of localization and urbanization externalities. Furthermore, the transport equipment industry received the highest level of urbanization externalities, while the machinery and electronics industry benefited the most from localization.

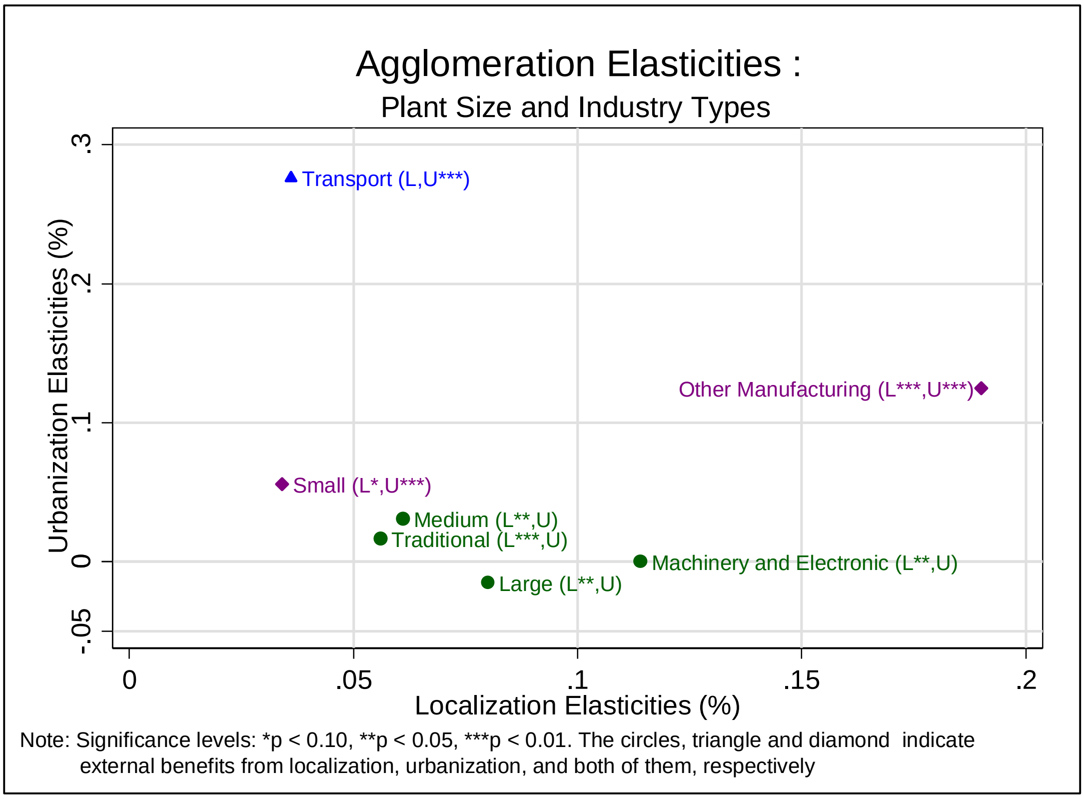


Figure 2.1. Distribution of Agglomeration Elasticities by Plant Size and Industry

2.5.4. Agglomeration Externalities over Economic Cycles

Table 2.6 shows that small plants are relatively flexible; they can adjust and behave dynamically in response to economic situations. The productivity of small plants strongly benefited from urbanization economies during the economic crisis, but in later stages, the agglomeration sources were adjusted into localization economies. There is evidence of industrial structural change, in which small plants hold localization externalities into the post-crisis periods. On the other hand, the large plants continued to receive externalities benefits from localization both during and after the economic crisis, while the medium-sized plants received external benefit from localization in the post-crisis period. Finally, the table indicates the strong existence of localization over all the plants in the post-crisis periods.

The different effects of economic cycles among types of industries are presented in Table 2.7. The table shows that traditional industries (e.g., food and beverage, tobacco, and wood and furniture) persistently benefited from localization economies over the post-crisis periods. Meanwhile, the transport equipment industry continually benefited from urbanization economies in the pre- and post-crisis periods. We identified that the transport equipment industry was the only industry that received positive externalities from urbanization in the pre-crisis period; however, the crisis weakened the external benefits from the agglomeration economies of this industry. The only manufacturing industries that still benefitted from urbanization economies during the crisis were those in the “other” category such as printing, publishing, and recycling. It is also worth pointing out that the high-technology industry received negative externalities or experienced deagglomeration economies both before and after the crisis, although the industry received benefits from urbanization economies during a recent period. These results are contrary to Henderson (2003), who found positive effects of this sector on productivity in the United States. In general, the presence of localization economies dominates that of urbanization economies, particularly in the recovery phases.

Table 2.6. Agglomeration Externalities by Plant Size over Economic Cycles

Dependent Variable:		**Total Factor Productivity (Ln TFP)**			
Economic Cycles	**N x T**	**Boom (1990-96)**	**Crisis (1997-00)**	**Recovery (2001-05)**	**Recovery (2006-10)**
Small Firm (20-49 Workers)					
Locplant(Ln)	237,647	0.006	0.004	0.096*	0.145***
		[0.026]	[0.039]	[0.050]	[0.043]
Urbanization (Ln)	237,647	0.021	0.054*	0.039	0.037
		[0.022]	[0.028]	[0.040]	[0.034]
Medium Firm (50-249 Workers)					
Locplant(Ln)	138,278	-0.008	-0.061	0.095*	0.123***
		[0.031]	[0.064]	[0.056]	[0.043]
Urbanization (Ln)	138,278	0.014	0.061	-0.027	0.031
		[0.026]	[0.053]	[0.054]	[0.044]
Large Firm (≥ 250 Workers)					
Locplant(Ln)	66,232	0.003	0.231**	0.116*	0.257***
		[0.046]	[0.104]	[0.064]	[0.079]
Urbanization (Ln)	66,232	0.056	-0.004	-0.099	-0.157**
		[0.050]	[0.107]	[0.067]	[0.077]
All Firm					
Locplant(Ln)	442,157	0.019	0.034	0.091**	0.154***
		[0.021]	[0.035]	[0.036]	[0.030]
Urbanization (Ln)	442,157	0.010	0.014	-0.044	0.005
		[0.018]	[0.027]	[0.033]	[0.026]

Notes: Estimations include fixed effects at the plant-level and dummies of industry-year. Each regression includes control for the plant's characteristics of age, size, dummies of ownership (DFDI, Dgov), and export activity, and regional characteristics of coastal area, access to electricity, road density, and distance to the closest international port. Robust standard errors for correcting at the industry-district level are reported in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.7. Agglomeration Externalities by Industry over Economic Cycles

Dependent Variable: Economic Cycles	N x T	Total Factor Productivity (Ln TFP) Boom (1990-96)	Crisis (1997-00)	Recovery (2001-05)	Recovery (2006-10)
Traditional Industries					
Locplant(Ln)	286,116	0.025	0.068	0.108***	0.162***
		[0.026]	[0.044]	[0.042]	[0.037]
Urbanization (Ln)	286,116	-0.015	0.016	-0.019	-0.023
		[0.022]	[0.033]	[0.036]	[0.029]
Heavy Industries					
Locplant(Ln)	107,875	-0.003	-0.035	-0.029	0.201***
		[0.043]	[0.063]	[0.083]	[0.058]
Urbanization (Ln)	107,875	0.028	-0.019	-0.047	0.017
		[0.033]	[0.054]	[0.073]	[0.058]
Transport Industries					
Locplant(Ln)	11,728	0.066	-0.088	-0.051	-0.234
		[0.100]	[0.202]	[0.206]	[0.215]
Urbanization (Ln)	11,728	0.258***	0.122	-0.299	0.457**
		[0.080]	[0.157]	[0.264]	[0.200]
Machinery and Electronic Industries					
Locplant(Ln)	18,014	0.060	0.006	0.135	0.144
		[0.076]	[0.257]	[0.252]	[0.180]
Urbanization (Ln)	18,014	0.051	0.017	-0.568	0.211
		[0.055]	[0.141]	[0.446]	[0.216]
High-Technology Industries					
Locplant(Ln)	4,642	-0.505**	0.281	0.46	-0.484*
		[0.217]	[0.296]	[0.665]	[0.266]
Urbanization (Ln)	4,642	-0.059	0.127	-1.906***	0.663*
		[0.193]	[0.405]	[0.684]	[0.333]
Other Industries					
Locplant(Ln)	13,782	0.07	-0.028	0.511**	0.045
		[0.087]	[0.204]	[0.198]	[0.119]
Urbanization (Ln)	13,782	0.019	0.228*	0.004	0.044
		[0.063]	[0.119]	[0.130]	[0.116]

Notes: Estimations include fixed effects at the plant-level and dummies of industry-year. Each regression includes control for the plant's characteristics of age, size, dummies of ownership (DFDI, Dgov), and export activity, and regional characteristics of coastal area, access to electricity, road density, and distance to the closest international port. Robust standard errors for correcting at the industry-district level are reported in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To explore the industrial structural change of small-sized plants, we examined the agglomeration economies by plant sizes over an economic cycle for the traditional and heavy industries. These sectors are the two largest industry groups, which represent about 89.1% of the total number of observations within the study period. Table 2.8 shows that small plants in traditional and heavy industries drove the industrial structural changes from urbanization to localization economies in the post-crisis periods.

Table 2.8. Agglomeration Externalities by Plant Size over Economic Cycles for Traditional and Heavy Industries

Dependent Variable:	Total Factor Productivity (Ln TFP)				Total Factor Productivity (Ln TFP)			
Economic Cycles	Boom (1990-96)	Crisis (1997-00)	Recovery (2001-05)	Recovery (2006-10)	Boom (1990-96)	Crisis (1997-00)	Recovery (2001-05)	Recovery (2006-10)
Industry Groups	Traditional Industries				Heavy Industries			
Small size								
N x T	43,324	29,129	35,006	52,269	16427	11399	12299	14705
Locplant(Ln)	0.004	0.011	0.082	0.130**	-0.038	-0.01	0.089	0.279***
	[0.034]	[0.051]	[0.058]	[0.052]	[0.046]	[0.065]	[0.114]	[0.078]
Urbanization (Ln)	-0.010	0.070**	0.063	0.014	0.067**	0.011	0.024	0.041
	[0.028]	[0.034]	[0.043]	[0.036]	[0.031]	[0.056]	[0.085]	[0.072]
Medium size								
N x T	24,095	15,601	19,402	23,282	11300	7693	9188	10191
Locplant(Ln)	-0.035	0.010	0.139**	0.161***	0.025	-0.252**	-0.091	0.018
	[0.039]	[0.081]	[0.065]	[0.053]	[0.062]	[0.119]	[0.115]	[0.091]
Urbanization (Ln)	0.027	0.066	0.053	0.000	-0.019	-0.023	-0.11	0.083
	[0.031]	[0.068]	[0.058]	[0.051]	[0.057]	[0.105]	[0.141]	[0.103]
Large size								
N x T	13,343	8,882	11,026	10,757	4259	2900	3674	3840
Locplant(Ln)	0.042	0.213*	0.176**	0.306***	-0.028	0.357	-0.263*	0.295*
	[0.054]	[0.118]	[0.069]	[0.095]	[0.093]	[0.263]	[0.147]	[0.166]
Urbanization (Ln)	0.042	-0.032	-0.103	-0.175*	0.161	0.088	-0.078	-0.213
	[0.063]	[0.125]	[0.073]	[0.090]	[0.098]	[0.225]	[0.149]	[0.176]

Notes: Estimations include fixed effects at the plant-level and dummies of industry-year. Each regression includes control for the plant's characteristics of age, size, dummies of ownership (DFDI, Dgov), and export activity, and regional characteristics of coastal area, access to electricity, road density, and distance to the closest international port. Robust standard errors for correcting at the industry-district level are reported in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The shifting of small plant agglomeration sources in the traditional and heavy industries can be explained as follows. First, small plants had difficulty accessing financing after the credit rationing of the post-crisis periods (Aswicahyono et al., 2010); subsequently, a small plant might have changed its strategy from dependence on a variety of industries within a region to an approach that takes advantage of a specialized environment that stems from similar industries. It will help the plants lower the cost of production by having access to labor pooling, input sharing, and knowledge transfer within an industry. Second, referring to the industry lifecycle theory by Duranton and Puga (2001), urbanization economies are usually suitable for small and new entry plants that highly depend on external environments in their early stages. However, the crisis increased the barrier of entry, and the resulting exit rate was higher than the entry rate (Aswicahyono et al., 2010). Consequently, the smaller entry rate made urbanization economies seem weaker; the surviving plants matured during the post-crisis periods and tended to relocate to specialized areas, enjoying the benefits from localization economies.

In addition, Figure 2.2 clarifies the different behaviors between plant size categories and industry groups. The figure indicates the behavior of plants for adjustment in order to capture external benefits from agglomeration over economic cycles. It shows that small-sized plants and other manufacturing industries received external benefits from urbanization economies, while large-sized plants acquired external benefits from localization economies during the crisis. The strong existence of agglomeration effects on productivity for small plants during the crisis and post-crisis periods may support the finding of Aswicahyono et al. (2010) about the higher productivity of small plants. The study found that small plants were the only contributors to employment growth and registered a strong growth of about 8.8% from 1996 to 2006. Another important finding from the figure is a significant negative effect of urbanization economies on large plants. It indicates that the deagglomeration experience for large plants may be due to congestion, cost of labor, or institutional costs in large areas.

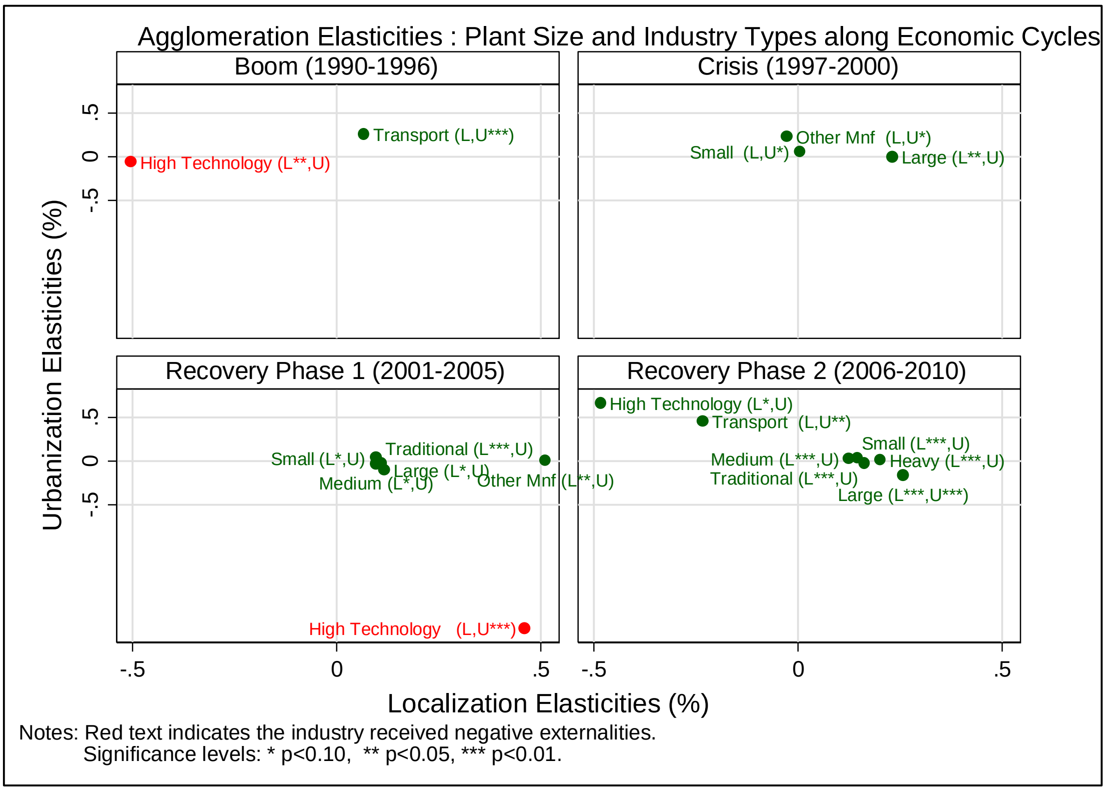


Figure 2.2.Distribution of Agglomeration Elasticities by Plant Size and Industry over Economic Cycles

2.5.5. Agglomeration Externalities across Geographical Distances

Having discussed the impact of agglomeration economies in different economic situations, in this section we address the possible regional externalities of agglomeration economies of neighboring cities. Before employing model 2 to examine the impact of agglomeration economies across distances, we applied Moran's Index for measuring spatial autocorrelation. The results in Table 2.9 provide strong evidence that the TFPs of the districts are spatially autocorrelated within individual two-digit SIC manufacturing sectors. Most industries have a strong positive significance at the 0.01 level, which indicates that the high productivity of the industrial sectors is dependent on similar sectors in nearby districts. These findings suggest that the neighboring effect exists, as shown by Viladecans-Marsal (2004).

Table 2.9. Moran's Index of Spatial Autocorrelation

Group	ISIC2- Industry	Moran's Index of Spatial Autocorrelation		
		1990 TFP	2000 TFP	2010 TFP
Traditional	15 - Food and beverage		0.085***	0.066***
	16 - Tobacco	0.017*	0.03**	0.022*
	17 – Textiles	0.055***	0.163***	0.063***
	18 – Apparel		0.015	0.166***
	19 - Tanning and leather	0.066**	0.105***	0.005*
	20 - Wood and its products, except furniture		0.043***	0.037***
	21 - Paper and paper products		0.054**	0.014
	36 - Furniture; manufacturing n.e.c.		0.007	0.026**
Heavy	23 - Coke, refined petroleum and fuel		0.017	0.062
	24 - Chemicals and chemical products	0.001	-0.007	0.000
	25 - Rubber and plastics		0.068***	0.142***
	26 - Other non-metallic minerals	0.045***	0.023**	0.047***
	27 - Basic metals	-0.028	-0.02	-0.016
	28 - Fabricated metal , except machinery		0.009	0.069***
Transportation	34 - Motor vehicles, trailers and semitrailers	-0.095	-0.003	-0.032
	35 - Other transport equipment		0.209***	0.051*
Machinery and Electronic	29 - Machinery and equipment n.e.c.		0.168***	0.008
	31 - Electrical machinery and apparatus n.e.c.		-0.123*	-0.053
High-technology	30 - Office, accounting, and computing machinery	-0.312	0.07	-0.068
	32 – Radio, TV, and communication equipment	0.14	-0.006	0.195
	33 - Medical, precision and optical , watches and clocks	0.106*	0.13**	0.064
Other	22 - Publishing, printing, and recording		-0.032	-0.07**
	37 – Recycling		0.024	-0.009

Note. Moran's Index is calculated with a 50-km threshold distance.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.10 shows that the agglomeration magnitudes arise from spatial proximity. The table shows the increasing values of localization and urbanization economies, which imply that industrial distribution can be concentrated in a few regions, and that a strong connection exists among plants across regions. The results provide clear evidence that all plant categories receive external benefits from neighboring districts. The small plants acquire neighboring agglomeration economies in both localization and urbanization economies. Meanwhile, the medium and large plants obtain agglomeration benefits of localization of neighboring regions. The different maximum distance of the greatest agglomeration effects between localization and urbanization is also identified. The localization economies of neighboring districts are detected within shorter distances than the urbanization economies of neighboring districts. The maximum distances are about 20 and 30 km, respectively.

With regard to geographical settings, it is apparent from the empirical evidence that industrial sectors are affected differently by agglomeration economies of neighboring districts. Table 2.11 presents the neighboring effects of agglomeration economies by industry, across geographical proximity. It shows the different responses of industries to their neighboring agglomeration effects; for example, the traditional industry and machinery and electronics industry are influenced by the neighbors' localization economies.

Table 2.10. Agglomeration Externalities by Plant size over Geographical Distance

Dependent Variable:		**Total Factor Productivity (Ln TFP)**								
	N x T	**Own District**	**Threshold Distance between Neighboring Districts Capitals**							
			5km	**10km**	**15km**	**20km**	**25km**	**30km**	**35km**	**50km**
Small Firm (20-49 Workers)										
Locplant(Ln)	237,647	0.034*	0.055	0.058*	0.059*	0.061*	0.061*	0.060*	0.060*	0.060*
		[0.020]	[0.034]	[0.035]	[0.036]	[0.036]	[0.036]	[0.036]	[0.036]	[0.036]
Urbanization (Ln)	238,028	237,647	0.056***	0.064**	0.079**	0.089**	0.092**	0.093**	0.097**	0.096**
		[0.017]	[0.031]	[0.036]	[0.038]	[0.038]	[0.039]	[0.039]	[0.039]	[0.039]
Medium Firm (50-249 Workers)										
Locplant(Ln)	138,278	0.061**	0.121***	0.117**	0.118**	0.119**	0.119**	0.119**	0.119**	0.119**
		[0.024]	[0.044]	[0.047]	[0.047]	[0.047]	[0.047]	[0.047]	[0.047]	[0.047]
Urbanization (Ln)	138,402	138,278	0.031	0.016	0.048	0.045	0.044	0.045	0.045	0.044
		[0.020]	[0.032]	[0.037]	[0.038]	[0.039]	[0.039]	[0.039]	[0.039]	[0.039]
Large Firm (≥ 250 Workers)										
Locplant(Ln)	66,232	0.080**	0.131**	0.160**	0.156**	0.160**	0.159**	0.160**	0.160**	0.160**
		[0.033]	[0.061]	[0.063]	[0.064]	[0.064]	[0.064]	[0.064]	[0.064]	[0.064]
Urbanization (Ln)	66,257	66,232	-0.015	-0.063	-0.041	-0.040	-0.045	-0.039	-0.043	-0.043
		[0.035]	[0.062]	[0.070]	[0.069]	[0.070]	[0.071]	[0.071]	[0.071]	[0.071]

Notes: Estimations include fixed effects at the plant-level and dummies of industry-year. Each regression includes control for the plant's characteristics of age, size, dummies of ownership (DFDI, Dgov), and export activity, and regional characteristics of coastal area, access to electricity, road density, and distance to the closest international port. Robust standard errors for correcting at the industry-district level are reported in brackets.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.11. Agglomeration Externalities by Industry over Geographical Distance

Dependent Variable:	N x T	Total Factor Productivity (Ln TFP)								
		Own District	Threshold Distance between Neighboring Districts Capitals							
			5km	10km	15km	20km	25km	30km	35km	50km
Traditional Industries										
Locplant(Ln)	286,116	0.056***	0.111***	0.112***	0.111***	0.112***	0.112***	0.112***	0.112***	0.112***
		[0.020]	[0.035]	[0.037]	[0.038]	[0.038]	[0.038]	[0.038]	[0.038]	[0.038]
Urbanization (Ln)	286,116	0.017	-0.01	0.009	0.015	0.017	0.020	0.019	0.018	0.018
		[0.017]	[0.029]	[0.032]	[0.032]	[0.033]	[0.033]	[0.033]	[0.033]	[0.033]
Heavy Industries										
Locplant(Ln)	107,875	0.053	0.019	0.025	0.028	0.031	0.032	0.032	0.032	0.032
		[0.034]	[0.062]	[0.065]	[0.066]	[0.066]	[0.066]	[0.066]	[0.066]	[0.066]
Urbanization (Ln)	107,875	-0.017	0.074	0.100*	0.103*	0.100*	0.100*	0.100*	0.099*	0.099*
		[0.025]	[0.050]	[0.059]	[0.060]	[0.060]	[0.060]	[0.060]	[0.060]	[0.060]
Transport Industries										
Locplant(Ln)	11,728	0.036	0.175	0.219*	0.192	0.182	0.183	0.178	0.174	0.175
		[0.063]	[0.115]	[0.129]	[0.132]	[0.133]	[0.133]	[0.133]	[0.134]	[0.133]
Urbanization (Ln)	11,728	0.276***	0.127	0.168	0.234**	0.260**	0.270**	0.285**	0.283**	0.283**
		[0.073]	[0.098]	[0.116]	[0.112]	[0.113]	[0.111]	[0.111]	[0.111]	[0.111]
Machinery and Electronic Industries										
Locplant(Ln)	18,014	0.114**	0.196***	0.194***	0.194***	0.194***	0.194***	0.193***	0.193***	0.193***
		[0.054]	[0.070]	[0.071]	[0.071]	[0.071]	[0.071]	[0.071]	[0.071]	[0.071]
Urbanization (Ln)	18,014	0.000	0.025	0.014	0.014	0.013	0.012	0.013	0.013	0.013
		[0.063]	[0.104]	[0.128]	[0.131]	[0.132]	[0.132]	[0.132]	[0.132]	[0.132]
High-Technology Industries										
Locplant(Ln)	4,642	0.056	0.092	0.140	0.158	0.160	0.158	0.158	0.158	0.157
		[0.206]	[0.320]	[0.328]	[0.330]	[0.331]	[0.330]	[0.330]	[0.330]	[0.330]
Urbanization (Ln)	4,642	0.135	0.204	0.259	0.249	0.229	0.229	0.229	0.229	0.229
		[0.208]	[0.266]	[0.352]	[0.365]	[0.366]	[0.365]	[0.365]	[0.364]	[0.364]
Other Industries										
Locplant(Ln)	13,782	0.190***	0.237**	0.300***	0.309***	0.316***	0.321***	0.311***	0.314***	0.315***
		[0.071]	[0.113]	[0.113]	[0.113]	[0.113]	[0.113]	[0.114]	[0.114]	[0.114]
Urbanization (Ln)	13,782	0.125***	0.231***	0.241***	0.246**	0.249**	0.254**	0.274***	0.268**	0.267**
		[0.046]	[0.079]	[0.092]	[0.095]	[0.101]	[0.103]	[0.105]	[0.104]	[0.104]

Notes: Estimations include fixed effects at the plant-level and dummies of industry-year. Each regression includes control for the plant's characteristics of age, size, dummies of ownership (DFDI, Dgov), and export activity, and regional characteristics of coastal area, access to electricity, road density, and distance to the closest international port. Robust standard errors for correcting at the industry-district level are reported in brackets.
Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Our result is similar to that of Graham (2009), who also identified the maximum effect of localization spillover from neighbors of the food and beverage industries within 5 km. On the other hand, the transport industries receive external benefits from neighbors' urbanization economies, while the other industry category receives both agglomeration benefits from its neighbors. This second set of results is contrary to the findings of Graham (2009), who found that the transport sectors' geographic externalities occurred in the form of localization. In fact, there is a sector that cannot capture agglomeration externalities beyond their own district or city—the high-technology industries.

Figures 2.3 and 2.4 show the change of agglomeration elasticity and marginal elasticity over the distance band for each plant size category and industry. We focus only on the coefficients that turned out to be statistically significant. Following Rosenthal and Strange (2003), marginal elasticity (average change of elasticity per kilometer) is determined by computing the gap between the two adjacent estimated localization or urbanization coefficients and dividing it by the distance between the midpoints. The figures show that the maximum impact of the neighbors' localization economies occurs at a smaller distance than that of the neighbors' urbanization economies.

Concerning plant size classifications, the small, medium, and large plants receive the maximum influence (the highest marginal elasticity) from localization economies of the neighboring districts when they are within 5 km. Additionally, small plants also receive the highest external benefits from urbanization economies of the neighboring districts effects when they are within 10 km. Comparing the estimated significant coefficients across distances, other manufacturing plants are the most connected to the similar industry in neighboring districts. Meanwhile, the transportation equipment industry receives the highest regional externalities of urbanization from neighboring districts. The machinery and electronics industry receives the maximum influence from localization economies of neighboring districts within 5 km, while the transportation industry receives the highest external benefits from urbanization economies of neighboring districts' effects within 20 km.

The average change elasticity of localization economies peaks at 5 km, which shows the maximum impact of agglomeration economies on plant-level productivity. After reaching the peak, the marginal elasticity is then likely to decrease sharply with distance. The result also shows that the highest marginal elasticity of urbanization economies across industries lies between about 5 and 20 km.

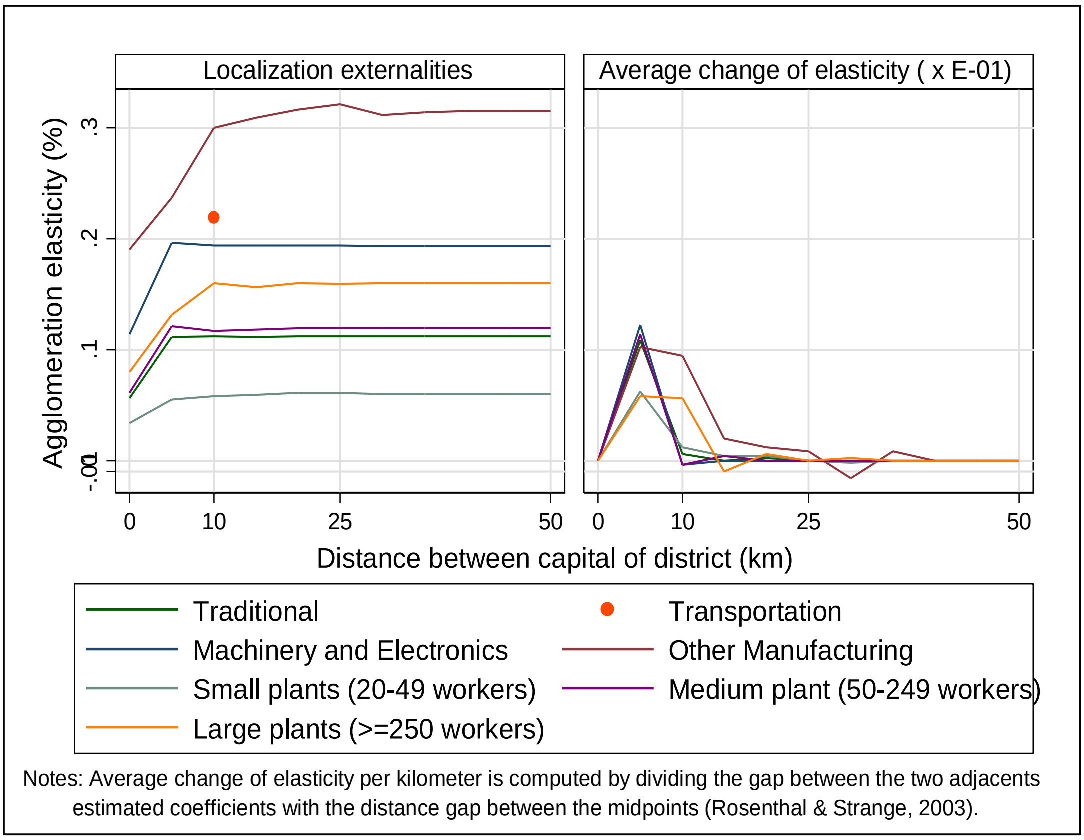
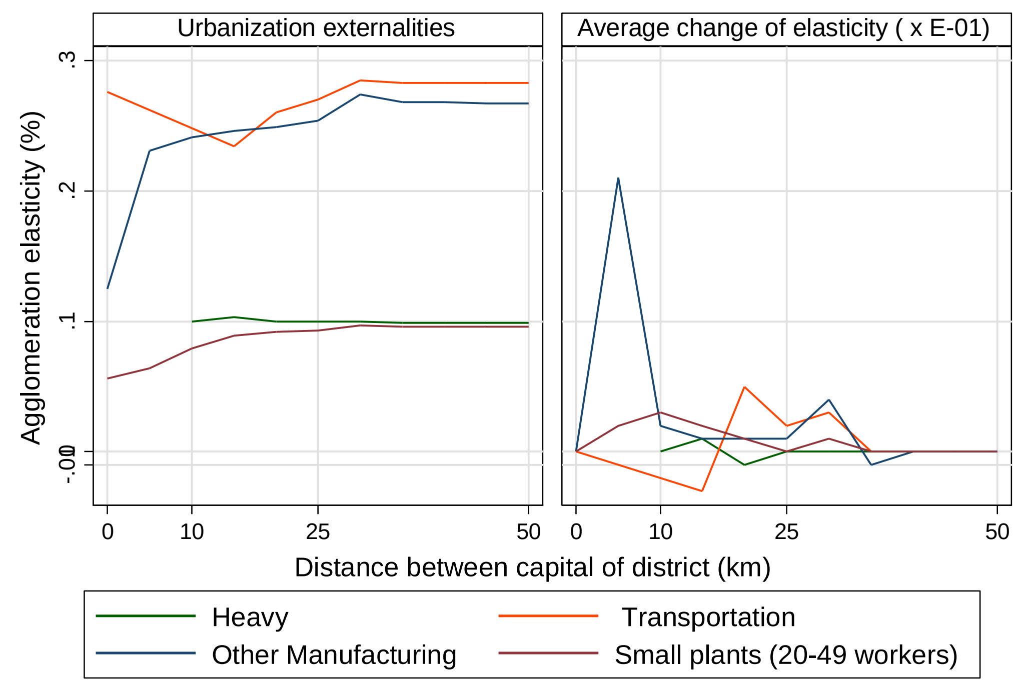


Figure 2.3. Localization Elasticities across Distance by Plant Sizes and Industry



Notes: Average change of elasticity per kilometer is computed by dividing the gap between the two adjacents estimated coefficients with the distance gap between the midpoints (Rosenthal & Strange, 2003).

Figure 2.4. Urbanization Elasticities across Distance by Plant Sizes and Industry

2.6. Conclusions

In this paper, we argued that both agglomeration sources, localization and urbanization economies, coexist. With regard to plant-size heterogeneity and industrial groups, the localization economies enhanced the productivity of medium- and large-sized plants, and the traditional industry, heavy industry, and machinery and electronics industry. On the other hand, urbanization economies increased productivity of the transportation industry. However, both sources of agglomeration increased the productivity of small-sized plants and other manufacturing sectors.

The breakdown estimation across economic cycles and geographical distances revealed shifting and adjustment of agglomeration sources and magnitudes. The research highlighted the adjustment of agglomeration externalities toward the importance of localization economies for productivity after the economic crisis of 1997–1998. This suggests that to some extent there was a structural change of the industry from urbanization economies to economies of localization, especially for small plants of traditional and heavy industries. It is only the small-sized plants that were relatively flexible enough to capture the economic benefits of agglomeration, by shifting from urbanization economies during the economic crisis and then altered to favor localization economies in the recovery phase. On the other hand, the medium and large plants continued to receive more external benefits from localization economies during the crisis and afterward. We suggested that the nature and source of agglomeration economies change under different economic circumstances.

The empirical analysis also demonstrated that the effects of agglomeration economies vary across industrial groups in regards to the changed economic situation. It provides important lessons to policymakers on how to provide appropriate policies, especially during times of economic crisis. The localization economies strongly and positively affected productivity of resource-based industries, such as traditional industries (e.g., food and beverage, tobacco, textile, apparel, leather, wood, paper, and furniture), and fairly increased productivity of heavy industries (e.g., coal coke, refined petrol and nuclear fuel, chemicals and their products, minerals, metal, and fabricated metal) in post-crisis periods. On the other hand, the transportation industry was more productive in the diversified environment caused by urbanization economies.

By extending the geographic scope beyond single, local districts, this research showcased the existence of agglomeration spillover from neighboring regions, which achieves maximum impact within a 5–20-km radius (in most specifications) before it begins to attenuate at 25–35 km. The results also showed clear evidence of the importance of geography and the presence of regional externalities in the analysis of plant-level productivity.

CHAPTER 3. MARKET POTENTIAL, LOCAL INDUSTRIAL STRUCTURE, AND PRODUCTIVITY GROWTH

3.1. Introduction

The manufacturing industry's role as an engine of sustained regional growth became an important topic in Indonesian development after the fiscal decentralization of 2001. However, a 2012 World Bank report asserted that the sector has been trapped in a "growth recession" and suffered "slow" or "weak" growth (p. 2); these drawbacks prevented the industry from returning to the level of performance it exhibited prior to the Asian financial crisis—that is, when it was significantly contributing to economic growth.

For that reason, empirical study, therefore, becomes very important to provide evidence as to what kinds of factors can increase the sector's productivity growth from the point of view of the local industrial structure. This local view is important because the decentralization policy introduced since 2001 should open the door for local government to promote policies inducing industry growth. As a result, the policy changed the population distribution of cities across the country. This implies that city size is not stable and would change due to the interaction between centripetal and centrifugal agglomeration forces (Abdel-Rahman & Anas, 2004). In Indonesia, the number of cities in respect to city size classification has changed over time.[7] It shows a declining trend in the number of small-medium cities and an increasing trend in the number of metro-megapolitan cities. For instance, there were

[7]City size is classified into three categories: "small-medium" (population under 500,000), "large" (population between 500,000 and 1,000,000), and "metro-megapolitan" (population over 1,000,000).

154 small-medium cities in 1990, 77 in 2000, and 53 in 2010. Figure A.3.1 in the Appendix shows a substantial change in the number of cities by size.

Accordingly, we are interested in examining the effect of agglomeration economies by period: long run (1990–2010) and medium run (2000–2010) given the change of city size distribution. According to Oates (1993), fiscal decentralization is the way to promote long-run economic growth because it leads to better resource allocation and a more productive, and possibly smaller, public sector. Thus, the stronger effects of externalities in medium-term growth can be associated with the effects of post-2001 decentralization policy.

Since the seminal paper by Glaeser et al. (1992), many empirical works attempted to explain the relationship between local industrial structure—namely, specialization, competition, and diversity—and growth patterns in cities. The studies usually specify these variables as representative of dynamic agglomeration externalities in employment growth regression and, later on, in TFP growth regression. One important variable in such kind of growth regression is city size. Given that city size significantly influences local economic growth,[8] a variable controlling city size becomes an important factor in determining the magnitudes of externalities.

In the early literature on this topic, the city-industry growth regression included initial employment in the city and sector, in addition to local industrial structure variables (Glaeser et al., 1992). However, Combes (2000) questioned the use of initial employment in the city and sector because it can lead to overestimation

[8] For instance, Rosenthal and Strange (2004) found that the impact of city size on productivity is between 3% and 8%.

of localization economies. Duranton and Puga (2014) provided a detailed explanation of the problem; because initial employment is also used to compute specialization, there are possible measurement errors when they are included in the regression due to mean-reversion effects of employment. Alternatively, Combes (2000) proposed the total employment in a city as a proxy for local size, a method followed in Cingano and Schivardi (2004) and Almeida (2007). However, this proxy still disregards the effects that employment in neighboring regions has on productivity growth. The discounting of neighboring agglomeration effects can lead to the underestimation of local size and, consequently, result in overestimation of the dynamic externalities on local productivity growth. By considering neighboring effects, this paper attempts to capture the regional employment of both a local, single city and its neighbor and then use these measurements as a variable that represents the employment market potential.

The objectives of this paper are to estimate the effects of dynamic externalities of agglomeration economies on TFP and employment growth in both the long run (1990–2010) and the medium run (2000–2010) and to introduce employment market potential to control city size within the relationship between local industrial structure and city growth. We expect to contribute to the empirical literature in two ways. First, we provide evidence of the importance of the employment market potential for controlling a local size and subsequently affecting the source type and the magnitude of dynamic agglomeration externalities. This corrects the overestimation of regional employment by controlling for local size growth instead of using regional employment (for example, Cingano & Schivardi, 2004; Almeida, 2007). Second, we provide evidence of a changing local industrial structure, identified in both the long-term and medium-term analyses, toward stronger diversity and the new role of competition in the medium term.

This study explores a unique long-panel plant-level data set for Indonesian manufacturing from 1990 to 2010. We measure local economic performance in TFP and employment growth. This paper calculates TFP using a control function approach to account carefully for input endogeneity. While Cingano and Schivardi (2004) employed an OP estimator, we prefer to use the LP method similar to Almeida and Fernades (2013), with respect to data availability, for estimating the firm's production function. The aggregate TFP at the industry-city level is weighted by plant output. Knowing the potential of reversed causality between the employment potential of a market and city-industry growth, we apply the OLS and instrumental-variables (IV) estimation methods. In more detail analyses, we also run regressions for each period: long term (1990–2010) and medium term (2000–2010). Furthermore, we conduct an empirical investigation across industries to examine whether the industry lifecycle theory can explain the impact of industrial structure on city growth.

This paper is organized as follows. The first section provides an overview of the importance of the research and its novelty. The second part offers an analysis of the theoretical background and empirical studies related on the subject literature. The third section describes the data and the construction of variables, and the empirical modeling and related estimation issues are reported in the fourth and fifth sections, respectively. Finally, the results and analysis are described in the sixth section. The seventh section provides our conclusions.

3.2. Literature Review

Rosenthal and Strange (2004) highlight the importance of geographic scope in studying agglomeration economies. To account for neighboring agglomeration effects, we introduce employment market potential for controlling a local size, by summing local employment and the employment of neighboring cities, weighted by distance. Melo et al. (2009) argue that market potential can absorb spatial spillover or regional externalities from neighboring regions over space and outside geographic boundaries. Combes et al. (2010) and Holl (2012), in France and Spain, respectively, are among the studies that explore the role of market potential in firm-level productivity. After instrumenting market potential with long-lag variables and local geographic characteristics, they found a positive impact of market potential on plant productivity levels. However, the current paper differs from those works since we focus on long-run TFP growth and city-industry level, rather than on yearly changes in the TFP plant level.

The importance of knowledge as a source of both firm dynamics and local growth calls into debate which type of economic activity facilitates knowledge spillover (De Groot et al., 2009). The spillover of knowledge can improve technological change, subsequently increasing economic growth. One of the first works to address the role of knowledge spillover on local economic growth, Glaeser et al. (1992) explains how urban areas and local economies develop over time through the contributions of three types of externalities: intraindustry knowledge spillover, interindustry knowledge spillover, and local competition.

By virtue of spatial proximity, firms and workers within a particular industry located near each other can enjoy knowledge spillover from similar or different technologies, access a pooled market of labor and employment skill, and benefit from intermediate input sharing, all of which enhances firm productivity (Gill & Goh, 2010). In a dynamic context, these external scale economies, or intraindustry knowledge spillover effects, are known as Marshal, Arrow, and Romer (MAR) externalities (Glaeser et al., 1992). On the other hand, interindustry exchanges of ideas and technology among different kinds of industries could create more variety in business services, enlarge market size on the supply and demand sides, and facilitate more product innovation and firm growth (Gill & Goh, 2009). In a dynamic context, these effects are known as Jacob externalities (Glaeser et al., 1992). The third type of externality known as Porter externalities stems from the recognition that local competition also plays a role in firms' development. Local competition is a main source of pressure on firms to create innovative products and adopt new technologies (Glaeser et al., 1992).

The empirical literature on dynamic externalities emerged to offer contradictory findings as the result of different approaches to measuring local growth. When growth is measured by employment, the results tend to support the existence of Jacob externalities (Glaeser et al., 1992; Combes, 2000). Using country-level data from the United States to analyze employment growth, Glaeser et al. (1992) highlight that local competition (Porter) and diversity (Jacobs) externalities are more likely to support growth performance but own-industry (MAR) externalities do not. Likewise, Combes (2000) finds that diversity has a positive impact on employment growth in the service sectors but adversely affected the manufacturing industry in France. However, Henderson et al. (1995) provide some evidence that both specialization and diversity can contribute to employment growth, depending on the maturity of the industry. Conversely, some authors prefer to measure local growth using TFP. They find that MAR externalities and, to some extent, Porter externalities are the important externalities leading to growth (Dekle, 2002; Cingano & Schivardi, 2004; Almeida, 2007). These authors argue that there is possibly an identification problem in the employment growth regression and pointed out that the subsequent interpretation of employment growth overlooked the positive link between productivity growth and employment growth.

The employment growth regression may suffer from some limitations, as noted by Dekle (2002), Cingano and Schivardi (2004), and Combes et al. (2004). These authors argue that the connection between employment growth and productivity growth is not necessarily, nor always, positive; therefore, it remains a problem of interpretation. Duranton and Puga (2014) argue that the results from employment growth regression might be valid in a sector with constant markup and an elastic price of demand. In such a sector, the increased productivity results in higher output, larger revenue, and increased employment. However, the results do not hold in a sector with an inelastic price of demand, such as the traditional manufacturing industry, in which increased productivity may lead to declining employment. To deal with this problem, Dekle (2002) and Cingano and Schivardi (2004) use TFP growth instead of employment growth as a proxy for local economic performance. Their results indicate that specialization effects often positively affect TFP growth in Japanese prefectures, while diversity does not significantly affect TFP in the Italian local labor system. Similar evidence in Almeida (2007) supports the existence of MAR externalities on aggregate productivity growth in most sectors in Portuguese regions.

Knowing the debate between the use of employment growth versus TFP growth, there is consensus that all of the results are still inconclusive regarding the existence of the various externalities and the roles they play in economic growth. The results of many empirical works conflict in their findings, with some evidence for the existence of some types of externalities with certain benefits and some evidence for the existence of others with other benefits. The findings in Henderson et al. (1995) provide evidence of both Jacob externalities, which play an important role in the employment growth of high-technology industries, and MAR externalities, which have a stronger effect on mature industries, in the United States. Other papers employing TFP growth as a dependent variable also result in inconclusive findings of externalities. Maroccu et al. (2013) find that higher specialization (MAR externalities) reduces TFP growth while larger diversity (Jacobs externalities) enhances TFP growth. The recent paper by Almeida and Fernandes (2013) investigate the impact of agglomeration externalities on long-run TFP growth in Chilean manufacturing; it reveals the importance of diversity for higher long-run TFP growth.

3.3. Data

This study employed data from the *Statistik Industri*, an unpublished electronic data set on the annual survey of large and medium firms conducted by Indonesia's Central Bureau of Statistics (BPS), from 1990 to 2010. All values in this research were expressed in 2000 real values. We used the WPI published monthly in BPS's bulletin, *Statistik Bulanan Indikator Ekonomi*. We gathered data on road length from BPS, while land area data were collected from the Ministry of Home

Affairs.[9] Furthermore, we used data from the Village Potential Statistics (PODES) of BPS to generate data on the share of households connected to electricity, the share of coastal area, and the land used by the non-agricultural sector. We used the GIS Euclidean distance to calculate market potential.

3.4. Model Specification: TFP and Employment Growth Model

This study applied a two-step empirical approach to agglomeration economies modeling: (1) plant-level production function estimation and (2) productivity and employment growth estimation. To address a possible bias due to input endogeneity in the production function, in the first step we used a semiparametric estimation of TFP introduced in Levinsohn and Petrin (2003) for each three-digit SIC. Following their method, we used capital and electricity consumption as a proxy for unobserved productivity shock.[10] The plant production function is specified as

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 k_{it} + \omega_{it} + \varepsilon_{it}, \tag{3.1}$$

where *y* represents the log of real value added by plant *i* at time *t*, *l* is the log of plant-level employment, and *k* is the log of real capital stock. We decomposed the residual into a productivity component ω, and the error component ε, which should be uncorrelated with input choices (see Sec. 2.4.1 for more detail). Furthermore, a

---

[9]Data accessible at http://www.kemendagri.go.id/media/filemanager/2013/05/28/b/u/buku_induk_kode_data_dan_wilayah_2013.pdf.

[10]Stata command “levpet” created by Petrin et al. (2004) was used to estimate the plant-level production function.

semiparametric Levin-Petrin approach (Petrin et al., 2004) estimates TFP for each plant as

$$\mathrm{TFP}_{it} = \exp(\widehat{\omega}_{ijt}) = \mathrm{e\,xp}(\, y_{it} - \widehat{\beta_0} - \widehat{\beta_1} l_{it} - \widehat{\beta_2} k_{it}), \tag{3.2}$$

where TFP_{ijt} is the estimated TFP of plant *i* in industry *j* at time *t*. From the estimated TFP and employment at the plant level, we calculated a weighted average of the industry-city TFP growth using plant output as the weight. Accordingly, we also calculated employment growth from plant-level data.

In the second step, we applied OLS and IV estimations to examine how dynamic agglomeration externalities affected TFP and employment growth, after controlling for the average age of the local industry and regional characteristics such as land area and share of non-agricultural land. We applied IV estimation to deal with the possible simultaneity bias between employment market potential and productivity growth, which is due to firm selectivity. That is, a plant might choose a location in the most productive and agglomerate regions and introduce reversed causality into the model.

The general framework for modeling the relationship between dynamic agglomeration externalities and city-industry growth was specified according to the framework of de Groot et al. (2009) following the seminal work of Glaeser et al. (1992) starting from a simple Cobb-Douglas function with a single input of labor. The basic assumption of the model was perfect competition, and there was no technological innovation of labor saving due to capital accumulation (Glaeser et al., 1992)

$$y_{irt} = A_{irt} l_{irt}^{1-\alpha}, \tag{3.3}$$

where y_{irt} denotes real value added of industry *i*, region *r*, and year *t*. *A* represents technology, and *l* refers labor as inputs,

$$\pi_{irt} = A_{irt} l_{irt}^{1-\alpha} - w_{irt} l_{irt}. \tag{3.4}$$

To maximize the firm's profit, we equate the marginal product of labor to its wage (w):

$$\alpha \frac{A_{irt}}{l_{irt}^{\alpha}} = w_{irt}, \tag{3.5}$$

$$l_{irt} = \left(\frac{\alpha A_{irt}}{w_{irt}}\right)^{1/\alpha}. \tag{3.6}$$

In term of growth rates, we can express the last equation as follows:

$$\log\left(\frac{l_{irt+1}}{l_{irt}}\right) = \frac{1}{\alpha}\log\left(\frac{A_{irt+1}}{A_{irt}}\right) - \frac{1}{\alpha}\log\left(\frac{w_{irt+1}}{w_{irt}}\right). \tag{3.7}$$

Following de Groot et al. (2009) and Glaeser et al. (1992), the growth of nationwide technology and local industrial structure—specialization, competition, and diversity—determine the growth rate of technology at the local level,

$$\log\left(\frac{A_{irt+1}}{A_{irt}}\right) = \log\left(\frac{A_{it+1,\text{national}}}{A_{it,\text{national}}}\right) + g(\text{specialization, competition, diversity, initial condition}). \tag{3.8}$$

Thus, subsequently, we can substitute Eq. (3.6) to obtain the growth rate of employment at the local level as follows:

$$\log\left(\frac{l_{irt+1}}{l_{irt}}\right) = \frac{1}{\alpha}\log\left(\frac{A_{it+1,\text{national}}}{A_{it,\text{national}}}\right) - \frac{1}{\alpha}\log\left(\frac{w_{irt+1}}{w_{irt}}\right)$$
$$+ g(\text{specialization, competition, diversity, initial condition}). \tag{3.9}$$

We specified the econometric model for testing the effects of dynamic agglomeration externalities on city growth into two specification models: the TFP growth model and the employment growth model. All specifications were estimated using OLS and IV estimations at the industry-city level and include industry dummies at the three-digit SIC level. We examined the estimations of local economic performance using TFP growth as a dependent variable compared to using employment growth. Detailed information on variable definitions and data sources is given in the Appendix (Table A.3.1).

Our TFP model extends the TFP growth regression formulated in Cingano and Shivardi (2004) by replacing initial city employment with employment market potential. We calculated TFP growth from 1990 to 2010 and set other variables to the conditions of the initial year, 1990. Furthermore, we ran OLS and then IV regressions to account for endogeneity stemming from the fact that market potential determines productivity growth, but the productivity growth might also determine market potential (via an influence on the location decision of firms and employees). We estimated the model using OLS and IV with a two-stage least-squares (TSLS) estimator and specified the TFP growth model as

$$\begin{aligned}\text{TFPgrowth}_{ir90-10} &= \alpha_0 + \beta_1 \text{lnTFP}_{ir90} + \beta_2 \text{lnMpemp}_{r90} + \beta_3 \text{lnArea}_{r90} \\ &\quad + \beta_4 \text{lnAge}_{ir90} + \beta_5 \text{Nonagriland}_{r90} + \beta_6 \text{lnSpe}_{ir90} + \beta_7 \text{lnComp}_{ir90} \\ &\quad + \beta_8 \text{lnDiv}_{ir90} + \gamma_i + e_{ir}, \qquad (3.10)\end{aligned}$$

where TFPgrowth is the TFP growth of industry *i* in region *r*, and TFP is the TFP level of industry *i* in region *r*. Mpemp is the variable for employment market potential, Area is the land area, Age is the average age of plants in industry *i* in region *r*, and Nonagriland is the share of non-agricultural land in region *r*. The main interest variables are the three types of dynamic externalities of industry *i* in region *r* noted as Spe, Comp, and Div for specialization, competition, and diversity, respectively. Finally, we added industry dummies γ_i for industry *i* to account for unobserved variables at the industry level, and *e* is the error component.

In the employment growth model, we used employment growth as a dependent variable. However, we substituted the initial TFP with the initial wage, and the model was formulated as follows:

$$\begin{aligned}\mathrm{Empgrowth}_{ir90-10} = \alpha_0 + \beta_1 \mathrm{lnWage}_{ir90} + \beta_2 \mathrm{lnMpemp}_{r90} \beta_3 \mathrm{lnArea}_{r90} \\ + \beta_5 \mathrm{Nonagriland}_{r90} + \beta_6 \mathrm{lnSpe}_{ir90} + \beta_7 \mathrm{lnComp}_{ir90} \\ + \beta_8 \mathrm{lnDiv}_{ir90} + \gamma_i + e_{ir}. \qquad (3.11)\end{aligned}$$

We measured dynamic externalities based on the employment number. The variable $\mathrm{emp}_{i,j,r}$ denotes the plant-level employment of plant *i* in industry *j* within region *r*. Variable $\mathrm{emp}_{j,r}$ represents the industry-level employment of industry *j* in region *r*, while $\mathrm{emp}_{j\prime,r}$ stands for the industry-level employment of industries other than industry *j* in region *r*. Furthermore, emp_r stands for the region-level employment of region *r*, while emp indicates the national total employment. These notations were applied to measure the specialization, competition, and diversity. To get a better identification between MAR externalities and Jacobs externalities, we calculated dynamic agglomeration externalities variables based on the three-digit industrial classification suggested in Beaudry and Schiffauerova (2009).

To choose variables representing agglomeration economies, we measured them using a relative measurement index, where the numbers were derived from comparisons among city-industry levels and national-industry levels. Following Combes (2000), scale (MAR) externalities using employment specialization (Spe) in industry *j* in region *r* at time *t* was calculated as the ratio of the employment share of industry *j* in region *r* to the employment share of industry *j* in the national industry. That is, we specified specialization as follows:

$$\mathrm{Spe}_{j,r} = \frac{\mathrm{emp}_{j,r}/\mathrm{emp}_r}{\mathrm{emp}_j/\mathrm{emp}}. \tag{3.12}$$

A value greater than 1 indicates that the industry in a district is locally more specialized than elsewhere in Indonesia. We expect that industrial specialization will increase productivity growth because knowledge flows are more important within industries.

Furthermore, we derived a variable representing Porter externalities, also following Combes (2000), as the ratio of the inversion of the local Herfindahl index using plant-level data to the inversion of the national Herfindahl index using industry-city data. Thus, industry competition (Comp) faced by a plant that belongs to industry *j* in region *r* was measured as follows:

$$\mathrm{Comp}_{j,r} = \frac{1/\sum_{i\epsilon j,r}\left(\mathrm{emp}_{i,j,r}/\mathrm{emp}_{j,r}\right)^2}{1/\sum_{j}\left(\mathrm{emp}_{j,r}/\mathrm{emp}_{j}\right)^2}. \tag{3.13}$$

According to Porter (1990), local competition could pressure firms to create innovative products, adopt new technology, and increase productivity growth. A value greater than 1 is interpreted that industry *j* in region *r* that is locally more competitive than elsewhere in Indonesia.

Coinciding with the view of MAR externalities, local competition and knowledge spillover effects within an industry can maximize agglomeration externalities in cities with specialized and competitive industries. Therefore, from this perspective, low competition is better. However, from the perspective of Jacobs externalities, local competition will force firms to learn from other industries in the region and enlarge the market. Subsequently, high competition gives firms an incentive to increase innovation and ultimately supports productivity growth.

Finally, we measured diversity (Div) to represent the Jacob externalities, following Marrocu et al. (2013) who modified the diversity index computed by Combes (2000). This index is more focused on the employment level of the rest of the industry in a given region; it directly measures the diversity level faced by a plant in a specific industry so that it simultaneously captures industrial and regional dimensions. Having already calculated the values of the Herfindahl index based on the employment numbers from the rest of the economy in the given region, this index provides a better measurement of Jacob externalities. Moreover, the estimated coefficient has a straightforward interpretation, as suggested in Marrocu et al. (2013). The diversity of industry *j* in region *r* is calculated as follows:

$$\mathrm{Div}_{j,r} = \frac{1}{\sum_{\substack{j' \\ j \neq j'}} \left(\frac{\mathrm{emp}_{j',r}}{(\mathrm{emp}_r - \mathrm{emp}_j)} \right)} . \tag{3.14}$$

A high value of diversity means a region is more diversified; therefore, productivity growth will increase if cross-industrial knowledge flows are more important than the other externalities.

The novelty of this paper is the introduction of employment market potential as a proxy for local size to control the relationship between dynamic agglomeration externalities and productivity growth. We followed Holl (2012), measuring the employment market potential as the sum of the own regional employment and the regional employments of neighboring areas weighted by the inverse of the GIS distance within a threshold. This variable assumes that the firms' or workers' decisions include geographical advantages and spatial environment considerations to enhance firm productivity and maximize profits. The employment market potential is formulated as

$$\mathrm{Mpemp}_{rt} = \mathrm{emp}_{rt} + \sum_{s \in R284} \frac{\mathrm{emp}_{st}}{d_{rs}}, \tag{3.15}$$

where Mpemp_r is the employment market potential in region r, emp_r and emp_s are the regional employments in regions r and s, respectively, and d is the distance from the district capital r to the district capital s. The threshold distance of d is 25 km, and $R284$ is defined as the total number of districts or cities referring to year 1990.

3.5. Estimation Issues and Instrumental Variables

Since the employment market potential in our empirical model is considered an endogenous variable, it is assumed to be correlated with the error term in the OLS regression and potentially results in biased estimates. Therefore, we employ the IV technique to correct this potential bias, following Combes et al. (2010) and Holl (2012).

The biggest challenge in an IV analysis is finding a credible instrument. The two conditions of relevance and exogeneity must be satisfied to achieve unbiased estimates (Combes et al., 2010). Combes et al. (2010) and Holl (2012) demonstrated sets of valid instrumental variables to deal with endogeneity between market potential and productivity growth in the cases of France and Spain. Following them, we use long-lagged variables, such as the market potential of population in 1983, which were determined a long time ago and may relate to market potential but which no longer plausibly influence current productivity growth. Moreover, we use geographic characteristics that may be sources of various influences on market potential like ruggedness, types of rocks, and type of physiography. Ruggedness might not only determine population and employment growth in certain areas, but it might also affect firms' or peoples' decisions in that area in construction of buildings, roads, and other infrastructure. Likewise, the geology and physiography variables describe the presence of various characteristics of the soil that may affect settlement patterns and direct human activity in a particular area (Combes et al., 2010; Holl, 2012).

We calculate population in 1983 from the Village Potential Survey (PODES) of BPS. Following Combes et al. (2010), we measure ruggedness as the difference between the highest and the lowest altitude within a city; it is also constructed from PODES. Furthermore, we identify 12 types of rocks from the geological map of 2010 published by the Geology Agency of Indonesia's Ministry of Energy. We simplify the 12 types into four—sedimentary, volcanic, cretaceous sedimentary, and other—and each city is accorded the type that dominates its landscape. Similarly, from the Geology Agency, we also gather physiography details from a map that shows 12 earth morphology types that also can be aggregated into four types of physiography: low plain, low hills, high plain, and mountain areas.

We check the validity of our instruments by calculating the partial correlation between the log of the employment market potential and the instruments, as suggested in Holl (2012). We find strong correlations between instruments and market potential, presented in Table 3.1. There is a consistent result between partial correlation and OLS estimation in both significance level and sign. Specifically, we identify the positive effects of the long-lagged market potential of the population in 1983 and the physiography on the market potential employment. On the other hand, we find negative effects of ruggedness and geology on the employment market potential.

Table 3.1. Partial Correlation of Instruments and Employment Market Potential

	Partial correlation coefficient with Mppemp (Ln)	**OLS estimation dependent variable : Mppemp (Ln)**
Mppop83 (Ln)	0.6046***	1.4997***
Ruggedness (Ln)	-0.1588***	-0.1070***
Geology	-0.1753***	-0.0152
Physiography	0.1107*	0.05814***

Notes: OLS estimations include dummies of industry and use robust standard errors.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.6. Results and Discussion

We presented summary statistics of the variables used in our empirical model in Table 3.2. At a glance, we can see larger heterogeneity in employment growth compared to TFP growth. It also shows a higher variation of regional employment than market potential employment, indicating that it is more viable to use market employment to proxy local city size while considering large quantities of regional employment. The table also demonstrates that specialization and competition measurements are incredibly more dispersed than that of diversity.

Table 3.2. Descriptive Statistics of Variables.

Variable	Label	Mean	SD	CV
Annual Growth 1990-2010 (# of observations = 1,869)				
Productivity growth	TFPgrowth	0.054	0.077	1.43
Employment growth	Employgrowth	0.014	0.069	4.85
Industry Region Initial Level 1990 (# = 1,869)				
Initial TFP level	Initial TFP	817	2426	2.97
Initial Wage rate level	Avg. Wage	2.14	6.52	3.05
Regional industry average age	Avg. Plant age	12.67	9.67	0.76
Regional Characteristics in 1990 (# = 232)				
Regional employment	Regemp	10964	24002	2.18
Market potential	Mpemp	22381	27914	1.25
Regional area	Area	5861	11508	4.69
Non-agriland	Nonagriland	0.39	0.22	0.56
Agglomeration Economies in 1990 (# = 1,869)				
Specialization	Spe	4.22	14.98	3.55
Industry competition	Comp	0.09	0.30	3.20
Industry diversity	Div	5.90	4.35	0.74

Note. SD = standard deviation. CV = coefficient of Variance

3.6.1. Analysis of the TFP Growth Models

Before we discuss the results from the estimation, we first scrutinize the validity of the instrumental variables to ensure the accuracy of our empirical approach. As we have several optional instruments (depicted in Tables 3.3 and 3.4), choosing the one with higher accuracy to instrument the market potential requires a large value of the first-stage F statistic and a high p value of the Hansen J test. The first-stage F statistic on the instruments is always significantly very large for our attempted instruments. According to Stock and Yogo’s (2005) critical values for weak instrument testing, our variables’ first-stage F statistics pass the test of weak instruments, giving us confidence that we have strong instruments. Likewise, the large p values of the Hansen J test (testing for overidentification of restrictions) confirm the first-stage F statistic, suggesting that we do not have weak instrument problems.

Table 3.3 indicates strong correlation between instruments and market potential. It also shows positive effects of long-lagged market potential of the population in 1983 and physiography on the market potential employment. On the other hand, we find the negative effects of ruggedness and geology on the employment market potential. This result is supported by statistical tests that indicate our instruments are valid for better estimation in the second-stage regression, as in Table 3.4.

Table 3.3. The First Stage Regression.

Dependent Variable	**Mpemp**			
Estimation Methods	**OLS**			
	(1)	**(2)**	**(3)**	**(4)**
Initial TFP	0.173***	0.172***	0.168***	0.174***
	[0.011]	[0.011]	[0.011]	[0.011]
Area	-0.086***	-0.064***	-0.082***	-0.083***
	[0.008]	[0.008]	[0.008]	[0.008]
Avg. plant age	-0.053***	-0.051***	-0.052***	-0.053***
	[0.013]	[0.013]	[0.013]	[0.013]
Non-agriland	0.218***	0.212***	0.224***	0.214***
	[0.047]	[0.047]	[0.046]	[0.047]
Spe	-0.162***	-0.163***	-0.161***	-0.161***
	[0.008]	[0.008]	[0.008]	[0.008]
Comp	0.248***	0.245***	0.243***	0.247***
	[0.014]	[0.014]	[0.014]	[0.014]
Div	0.104***	0.097***	0.078***	0.105***
	[0.019]	[0.018]	[0.019]	[0.019]
Mppop83(Ln)	1.037***	1.061***	1.065***	1.028***
	[0.032]	[0.032]	[0.032]	[0.032]
Ruggedness		-0.000***		
		[0.000]		
Physiography			0.047***	
			[0.008]	
Geology				-0.036***
				[0.011]
N	1869	1869	1869	1869
R^2	0.730	0.737	0.735	0.732
F-stage	611.7	561.0	559.3	534.5
Partial R^2	0.365	0.381	0.377	0.369

Notes: Estimations include dummies of industry.
Instrumented variable: market potential of employment (Mpemp).
White standard errors are reported in brackets.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] Estimated using STATA commands ivreg2; see Baum et al. (2007).

Table 3.4 shows that the estimated coefficients on the instrumental variables in columns (4)–(7) are smaller than OLS estimates in column (3). Additionally, we test for the endogeneity of the regressors using the Durbin-Wu-Hausman test. Rejecting the null hypothesis, we find statistical evidence of endogeneity in the TFP growth regression, and, therefore, the IV and OLS estimates are significantly different. Thus, we focus the discussion on the IV results, although we also report the OLS results (particularly for the analysis by period and industry). Ultimately, we prefer Mppop83 and ruggedness as the instrumental variables, with magnitudes presented in column (5) of Table 3.4.

After using the IV estimation approach to address the possible interactions between higher productivity growth and greater employment potential of a market, we find that market potential has a strong positive impact on productivity, supporting the result of Combes et al. (2010) and Holl (2012). The result indicates that employment market potential has strong effects on city size and, subsequently, affects the source type and magnitude of dynamic agglomeration externalities on productivity growth. The approach corrects the overestimation of the regional employment's influence on local size. We observe that instrumenting for market employment always results in a lower estimation of the corresponding point estimates. This indicates that OLS estimates are biased upwards due to simultaneity problems. For further analysis, we take up the estimates of column (5) as our benchmark estimates based on their results in the first-stage *F* test and Hansen *J* test. We use this benchmark to investigate the robustness of our results further, to analyze different periods of growth, and to examine the impact across industry groups.

Table 3.4 shows the positive effects of specialization and diversity on city-industry TFP growth, supporting the MAR and Jacob externalities. In this respect, the result seems to be consistent with the result in Henderson et al. (1995), finding evidence of MAR externalities in the traditional industries and of both Jacobs and MAR externalities in the new high-technology industries in the United States. Furthermore, our findings also parallel the work of De Lucio et al. (2002), which finds significant effects of specialization and diversity on TFP growth in the case of Spain.

Table 3.4. City-Industry Productivity Growth: TFP Growth Model

Dependent Variable	**TFP Growth**						
Estimation Methods	**OLS**			**IV**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Initial TFP	-0.041***	-0.041***	-0.041***	-0.039***	-0.039***	-0.039***	-0.039***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Regemp	0.012***	0.010***					
	[0.001]	[0.002]					
WRegemp		0.010***					
		[0.003]					
Mpemp			0.020***	0.011***	0.011***	0.012***	0.011***
			[0.002]	[0.004]	[0.004]	[0.004]	[0.004]
Area	0.005***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Avg. plant age	-0.005***	-0.005***	-0.004***	-0.005***	-0.005***	-0.005***	-0.005***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Non-agriland	0.017***	0.018***	0.017***	0.018***	0.018***	0.018***	0.018***
	[0.006]	[0.006]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]
Spe	0.006***	0.006***	0.005***	0.003**	0.003**	0.003**	0.003**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Comp	-0.001	-0.002	-0.001	0.003	0.002	0.002	0.002
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Div	0.006***	0.006***	0.006***	0.009***	0.009***	0.009***	0.009***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
_cons	0.158***	0.071**	0.051*				
	[0.019]	[0.031]	[0.027]				
Instruments							
Mppop83 (Ln)				Y	Y	Y	Y
Ruggedness				N	Y	N	N
Geology				N	N	Y	N
Physiography				N	N	N	Y
Weak IV test first stage F) [a]				1040.095	561.028	542.882	526.875
Wu-Hausman test (*p* value)				0.0011	0.0008	0.0026	0.0013
Over identification (J test)				0.000	0.049	1.734	0.379
(*p* value)					0.824	0.188	0.538
N	1869	1869	1869	1869	1869	1869	1869
R^2	0.418	0.422	0.421	0.362	0.362	0.363	0.362

Notes: Estimations include dummies of industry. Instrumented variable : employment market potential (Mpemp)
White standard errors are reported in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] Estimated using STATA commands ivreg2,see Baum et al., 2007).

In the case of Indonesia, the present paper partly supports the findings in Sjoholm (1999)—finding strong evidence of diversity on productivity growth—and the findings in Widodo et al. (2013)—identifying specialization as having positive effects on city growth and diversity having negative effects. However, our method is different from previous literature. We carefully applied methods ignored by previous authors to address input endogeneity of the firm production function and to set a strong approximation of local size to control local industrial structure. The control variables seem to have the expected signs. Larger land area and non-agricultural land leads to faster growth of a city industry, indicating comparative advantages of the city. Those factors can facilitate firms' accumulation of more resources in producing goods and finally supporting growth. However, we identify that as industry grows older, productivity growth decreases.

To confirm the robustness of our results, we performed robustness checks, reported in Table 3.5. The table presents the different specifications. The estimates from the benchmark model are presented in column (1) for comparison; excluding the high-technology industries and other manufacturing, the industries are presented in columns (2) and (3), respectively. Columns (4) and (5) provide results from alternative measures of productivity using different weights of TFP aggregation to calculate TFP growth and labor productivity growth. The initial related variable is also changed accordingly. Our results are consistent in both signs and significance levels, indicating that our empirical models are robust to a variety of specifications and alternative measures of productivity growth.

Table 3.5. City-Industry Productivity Growth: Robustness Test

Dependent Variable	TFP Growth				
	Full sample	**Excluding food & beverage sectors**	**Excluding resources-based sectors**	**TFP Growth (Weighted by employment)**	**Labor Productivity Growth**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Initial TFP	-0.039***	-0.039***	-0.039***		
	[0.002]	[0.002]	[0.002]		
Initial TFP (Emp weight)				-0.037***	
				[0.002]	
Initial-Labprod					-0.034***
					[0.001]
Mpemp	0.011***	0.011***	0.011***	0.006**	0.006**
	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]
Avg. plant age	-0.005***	-0.004**	-0.005***	-0.004***	-0.005***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Area	0.006***	0.006***	0.006***	0.005***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Non-agriland	0.018***	0.019***	0.016***	0.022***	0.020***
	[0.005]	[0.006]	[0.006]	[0.005]	[0.005]
Spe	0.003**	0.003**	0.003**	0.002*	0.002**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Comp	0.002	0.002	0.003	0.000	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Div	0.009***	0.009***	0.010***	0.009***	0.009***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Weak IV test (first stage F) [a]	561.028	541.116	532.002	560.105	570.026
Wu-Hausman test (*p* value)	0.001	0.001	0.001	0.000	0.000
Overidentification (J test)	0.049	0.059	0.007	0.000	0.532
(*p* value)	0.824	0.807	0.931	0.991	0.466
N	1869	1833	1809	1869	1869
R^2	0.362	0.361	0.37	0.353	0.343

Notes: Estimations include dummies of industry. Instrumented variable : employment market potential (Mpemp) Instrumental variables: mppop83 and ruggedness. White standard errors are reported in brackets.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] Estimated using STATA commands ivreg2,see Baum et al., 2007).

3.6.2. Productivity Growth by Period: Long Term and Medium Term

As was discussed in the Introduction, in order to avoid the effect of the 1997 Asian financial crisis and at the same time focus on the period after the decentralization policy in Indonesia, we provided an alternative, shorter, medium-term time-period analysis (2000–2010). Table 3.6 shows the OLS estimates in columns (1)–(4) and IV estimates in columns (5)–(8). The Wu-Hausman test for endogeneity in columns (5) and (6) indicates that the OLS and IV estimates of TFP growth regression are significantly different. However, this is not the case for the employment growth regression, in which the Wu-Hausman test in columns (7) and

(8) suggest that the results of both methods are relatively similar. It also should be noted that the effects of the employment market potential on TFP growth become insignificant when analyzed over a shorter period. We suspected that the growing number of larger cities within 2000–2010 might have reduced and eliminated the role of the employment market potential in controlling local size, though the employment market potential still influenced the coefficients of the agglomeration variables.

The table shows that specialization and diversity positively affect TFP growth in the long-term period 1990–2010 [column (5)]. However, a contrasting result was shown for employment growth, as we found that specialization had negative effects on employment growth, although diversity still had positive effects. The results generally confirm and incorporate the findings of both Glaeser et al. (1992) with employment growth and Cingano and Schivardi (2004) with TFP growth. More precisely, our results were consistent with the findings of Henderson et al. (1995) that specialization and diversity played important roles in employment growth, conditional on the industry type.

We obtained a different identification of larger effects of diversity with additional positive effects of competition instead of specialization in the medium-term period 2000–2010 [column (6)]. As far as the effect's magnitude is concerned, the role of externalities was stronger and broader on city growth, showing that the local industry may need to be adjusted accordingly. In that case, we need to take into account that the effects are obviously different between the long term and medium term. We believe that regional competition after the decentralization policy increased and enhanced local productivity growth.

Table 3.6. Long- and Medium-Term City-Industry Productivity and Employment Growth

Periods	OLS				IV			
Dependent Variable	TFP Growth		Emp Growth		TFP Growth		Emp Growth	
Periods	90-10	00-10	90-10	00-10	90-10	00-10	90-10	00-10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial TFP	-0.041***	-0.071***			-0.039***	-0.065***		
	[0.002]	[0.002]			[0.002]	[0.003]		
Initial Wage			-0.007***	-0.008***			-0.006**	-0.007*
			[0.002]	[0.002]			[0.003]	[0.004]
Mpemp	0.020***	0.033***	-0.001	0.005	0.011***	0.008	-0.003	0.001
	[0.002]	[0.003]	[0.004]	[0.005]	[0.004]	[0.006]	[0.007]	[0.010]
Area	0.006***	0.011***	0.006***	0.003**	0.006***	0.012***	0.006***	0.003**
	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.002]
Avg. plant age	-0.004***	-0.005*	-0.010***	-0.010***	-0.005***	-0.005	-0.010***	-0.010***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]
Non-agriland	0.017***	0.050***	-0.024***	-0.039***	0.018***	0.060***	-0.024***	-0.039***
	[0.006]	[0.011]	[0.007]	[0.010]	[0.005]	[0.011]	[0.007]	[0.010]
Spe	0.005***	0.010***	-0.009***	-0.010***	0.003**	0.003	-0.010***	-0.011**
	[0.001]	[0.002]	[0.002]	[0.003]	[0.001]	[0.002]	[0.003]	[0.005]
Comp	-0.001	0.001	-0.001	-0.003	0.002	0.009***	-0.001	-0.002
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]
Div	0.006***	0.005	0.010***	0.007**	0.009***	0.014***	0.010***	0.008**
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.004]	[0.002]	[0.003]
_cons	0.051*	0.061	0.114***	0.106**				
	[0.027]	[0.042]	[0.033]	[0.042]				
Weak IV test (first stage F) [a]					561.028	366.192	495.408	354.681
Wu-Hausman test (p value)					0.001	0.0000	0.680	0.7228
Overidentification (J test)					0.049	0.405	0.506	0.908
(*p* value)					0.824	0.524	0.477	0.341
N	1869	2513	1869	2513	1869	2513	1869	2513
R^2	0.421	0.389	0.283	0.168	0.362	0.33	0.188	0.102

Notes: Estimations include dummies of industry. Instrumented variable : employment market potential (Mpemp)
Instrumental variables: mppop83 and ruggedness. White standard errors are reported in brackets.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] Estimated using STATA commands ivreg2,see Baum et al., 2007).

Comparing the different growth measurements (see Table 3.6), we confirmed that the relationship between employment growth and productivity growth need not be positive, as noted by Combes et al. (2004) and Cingano and Schivardi (2004). Furthermore, we also found consistent negative effects of specialization on employment growth (consistent with the findings of Glaeser et al., 1992) in both terms, as is shown in columns (3), (4), (7), and (8). Duranton and Puga (2014) argued that price elasticity of demand is the main factor in determining the relationship between productivity and employment. They explained that for mature industries, which usually have inelastic demand, increased productivity growth was associated with lower employment growth. Therefore, using a TFP growth estimation does not necessary result in a positive effect of specialization on productivity growth if the manufacturing sectors are comprised of more small-sized firms or new-entry firms. Typically, these firms are more likely in favor of Jacob externalities due to their dependence on the external environment provided by diversity.

3.6.3. Productivity Growth by Industry

We classified the 23 industries of the two-digit SIC into six groups: (a) traditional, (b) heavy, (c) transportation equipment, (d) machinery and electronics, (e) high technology, and (f) other industries, following Henderson et al. (2001). We only reported the IV estimates by industry that showed large values from the first-stage *F* test and high *p* values of the Hansen *J* test. Thus, if those values were small due to a small number of observations, we did not include them in Tables 3.7 and 3.8. We, therefore, reported only the estimation results by industry for the traditional, heavy, and machinery and electronics industries.

The disaggregated analysis by industry is consistent with the aggregate analysis in attributing specialization and diversity as the major factors of city-industry growth. The impact of both externalities varies substantially across industries. We also observed that, between the long-term and medium-term analyses, the effect of specialization and diversity changed, seen in larger effects of diversity in the traditional industries and specialization in the heavy industries. Furthermore, we found that the productivity growth of the machinery and electronics industries strongly depended on diversity in the long-term analysis, but it then changed to depend on competition in the shorter analysis. The analysis by industry using employment growth shows that diversity has the strongest effects on the machinery and electronics in the long term. We also identified the positive effects of diversity in the traditional industries. Interestingly, we also observed positive effects of competition in the machinery and electronics industry in the medium term.

Table 3.7. Long-term City-Industry Productivity and Employment Growth by Industry

1990-2010	**IV**					
Industry Group	**Traditional**		**Heavy**		**Mach&Elect**	
Dependent Variable	**TFP**	**EMP**	**TFP**	**EMP**	**TFP**	**EMP**
	(1)	(2)	(3)	(4)	(5)	(6)
Initial TFP	-0.039***		-0.041***		-0.038***	
	[0.002]		[0.004]		[0.005]	
Initial Wage		-0.010***		-0.006		0.041**
		[0.003]		[0.004]		[0.017]
Mpemp	0.014***	0.007	0.009	0.006	-0.007	-0.134***
	[0.005]	[0.010]	[0.006]	[0.011]	[0.013]	[0.040]
Avg. plant age	0.005***	0.005***	0.007***	0.008***	0.010***	0.016***
	[0.001]	[0.001]	[0.002]	[0.002]	[0.004]	[0.005]
Area	-0.004*	-0.009***	-0.006	-0.011***	-0.007	-0.027***
	[0.002]	[0.003]	[0.003]	[0.004]	[0.006]	[0.008]
Non-agriland	0.007	-0.026**	0.039***	-0.019	0.026	0.007
	[0.008]	[0.010]	[0.010]	[0.012]	[0.018]	[0.023]
Spe	0.005***	-0.006	0.001	-0.007	-0.001	-0.073***
	[0.002]	[0.004]	[0.002]	[0.005]	[0.004]	[0.023]
Comp	0.000	-0.002	0.007	-0.006	0.009	0.031**
	[0.002]	[0.003]	[0.004]	[0.005]	[0.008]	[0.015]
Div	0.008**	0.006*	0.011***	0.016***	0.023**	0.019
	[0.003]	[0.003]	[0.004]	[0.004]	[0.009]	[0.014]
Weak IV test (first stage F) [a]	308.18	242.03	141.15	190.19	14.42	7.47
Wu-Hausman test (*p*-value)	0.0081	0.6308	0.0785	0.6109	0.918	0.0123
Overidentification (J-test)	0.527	4.635	0.120	2.566	0.217	0.695
(*p*-value)	0.468	0.031	0.729	0.109	0.641	0.405
N	1020	1020	542	542	114	114
R^2	0.368	0.186	0.387	0.228	0.468	0.153

Notes: Estimations include dummies of industry. Instrumented variable : employment market potential (Mpemp) Instrumental variables: mppop83 and ruggedness. White standard errors are reported in brackets.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] Estimated using STATA commands ivreg2,see Baum et al., 2007).

Considered as mature industries, traditional and heavy industries usually depend on specialization. However, our results showed that those industries were also affected by diversity. Looking at the data, about 55.83% of the traditional industries and 50.83% of the heavy industries are small firms (during 1990–2010). These statistics support the fact that mature industries also need diversified environments since the number of small firms is dominant. According to the theory of the "nursery city" by Duranton and Puga (2001), the authors argued that a diversified environment is suitable for new plants or small firms, whereas specialized cities are important for mature industries. Therefore, diversity is still important for productivity growth even in mature industries. Small firms usually depend on external environments to acquire knowledge and learn about innovation in large cities. These results are consistent with the product lifecycle theory provided by Duranton and Puga (2001). In this theory, diversity is more important for the firm in the initial development of a product in order to learn from a cross-industrial environment. Once the new product is established and the firm is ready to start mass production, the firm may relocate to specialized areas, benefiting from the surrounding mature industries.

Furthermore, the effect of competition on productivity growth is revealed in the medium term for the machinery and electronics industries. This finding supports the MAR externalities theory that suggests that firms in similar industries, or in a cluster, grow more rapidly due to their competition. However, at the same time, competition also validates the Jacobs externalities theory, since diversified environments create pressure for firms to innovate for survival. In general, our results partly fit the prediction of Duranton and Puga (2000) in that mature industries are more productive in specialized cities, while younger industries grow faster in diversified cities.

Table 3.8. Medium-term City-Industry Productivity and Employment Growth by Industry

2000-2010	IV					
Industry Group	**Traditional**		**Heavy**		**Mach&Elect**	
Dependent Variable	**TFP**	**EMP**	**TFP**	**EMP**	**TFP**	**EMP**
	(1)	(2)	(3)	(4)	(5)	(6)
Initial TFP	-0.064***		-0.073***		-0.070***	
	[0.003]		[0.005]		[0.008]	
Initial Wage		-0.012***		-0.010*		0.066**
		[0.004]		[0.006]		[0.031]
Mpemp	0.009	0.013	0.021*	0.025	-0.008	-0.208***
	[0.008]	[0.013]	[0.012]	[0.016]	[0.039]	[0.077]
Avg. plant age	0.009***	0.002	0.017***	0.005*	0.014	0.032***
	[0.002]	[0.002]	[0.003]	[0.003]	[0.012]	[0.011]
Area	0.000	-0.012***	-0.005	-0.013**	-0.024**	-0.003
	[0.004]	[0.004]	[0.007]	[0.007]	[0.010]	[0.014]
Non-agriland	0.041***	-0.063***	0.104***	-0.013	0.039	0.095
	[0.015]	[0.014]	[0.020]	[0.016]	[0.065]	[0.061]
Spe	0.005*	-0.005	0.009**	-0.004	0.001	-0.105***
	[0.003]	[0.006]	[0.004]	[0.007]	[0.008]	[0.039]
Comp	0.007	0.001	0.000	-0.017***	0.029*	0.024*
	[0.004]	[0.004]	[0.007]	[0.006]	[0.017]	[0.014]
Div	0.016***	0.003	0.011	0.012**	0.001	0.000
	[0.005]	[0.005]	[0.007]	[0.005]	[0.013]	[0.015]
Weak IV test (first stage F) [a]	225.70	197.49	96.87	93.06	5.92	13.72
Wu-Hausman test (*p*-value)	0.000	0.792	0.048	0.496	0.461	0.063
Overidentification (J-test)	1.357	0.812	2.248	11.54	0.961	0.269
(*p*-value)	0.244	0.367	0.134	0.001	0.327	0.604
N	1359	1359	718	718	157	157
R^2	0.322	0.106	0.386	0.133	0.475	-0.031

Notes: Estimations include dummies of industry. Instrumented variable : employment market potential (Mpemp) Instrumental variables: mppop83 and ruggedness. White standard errors are reported in brackets.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] Estimated using STATA commands ivreg2,see Baum et al., 2007).

3.7. Conclusions

This study was designed to determine the effects of dynamic agglomeration externalities on productivity growth in Indonesia. The result indicated that the employment market potential has strong effects on city size and subsequently affects the source type and the magnitude of dynamic agglomeration externalities on both productivity and employment growth. The overestimation of regional employment was corrected by controlling local size. The instrumental variables estimation further improved the estimation by solving the potential of reversed causality. The empirical evidence also showed that specialization and diversity positively impact TFP growth in long-term periods. It also showed that only diversity contributed to employment growth in the similar period. The results generally confirmed the importance of specialization and diversity for city-industry growth, as suggested by Duranton and Puga (2000) and empirically found by De Lucio et al. (2002) and Henderson et al. (1995).

The analysis of the medium-term period showed a different interpretation, indicating larger effects of diversity with an additional positive effect of competition on TFP growth. In general, the medium-term analysis indicated a more productive advantage of larger cities, since there was evidence of higher positive effects of diversity that did not similarly appear in the long-term analysis. Paralleling the major literature, we found a negative effect of specialization and positive effects of diversity on employment growth in the long-term analysis. Disaggregated by industry, the analysis indicated that small firms of mature industries (i.e., traditional and heavy industries) drove this local industrial structure.

CHAPTER 4. TRENDS AND DETERMINANTS OF THE GEOGRAPHIC DISTRIBUTION OF ECONOMIC ACTIVITIES: EVIDENCE FROM INDONESIAN MANUFACTURING

4.1. Introduction

As the world's biggest archipelago and the fourth most heavily populated country in the world, Indonesia—with a population exceeding 237 million across 33 provinces—has experienced a developmental divide due to inequality among its regions.[11] It is a fact that the population and economic activity there are concentrated in Java and its surrounding areas, even after establishing a decentralization policy. For instance, the manufacturing sector has traditionally been concentrated in West Indonesia, particularly in Java; as a result, manufacturing firms tend to be located in Java. As part of heightening democratization, a policy was introduced in 2001 that sought to boost the attractiveness of local government, build a new economic center, and invite new firms and new workers to agglomerate in those other regions.

Since the mid 1960s, Indonesia has adopted an industrialization policy and positioned the manufacturing industry as being the most important sector for the Indonesian economy (Aswicahyono et al., 2010). However, the high concentration of manufacturing firms in Java characterized that province's economic dominance, and they remain a concern with regard to economic disparity. Accordingly, external shock that relates to economic distribution is decentralization policy, which seeks to foster regional competition and determine geographic concentration.

---

[11] These data are from 2010 and are taken from Indonesia's Central of Bureau Statistics http://webbeta.bps.go.id/tab_sub/view.php?kat=1&tabel=1&daftar=1&id_subyek=12&notab=1 (accessed July 3, 2014).

The decentralization policy is one way to promote long-term economic growth, based on the view that it leads to better resource allocation and a more productive and possibly smaller public sector (Oates, 1993). It is thought that an increase in transfers of economic activities from the Javanese center to other regions tends to increase the ability of those regions to improve the public goods provision locally, and this thinking affects firms' decisions on siting new facilities. Theoretically, fiscal decentralization as part of a decentralization policy can induce agglomeration economies both directly to lower tax competition as suggested by Tiebout (1956) and indirectly through public goods provision. Therefore, it is also important to examine the effect of a decentralization policy on the geographic concentration of economic activities.

To the best of our knowledge, research on regional specialization patterns and industrial concentration in the context of developing countries is scarce, except for that on China.[12] Studies on industrial concentrations in Indonesia tend to focus on concentration trends and fail to consider the locations of plants (e.g., Bird, 1999; Setiawan et al., 2012). Sjöberg and Sjöholm (2004) examined the spatial concentration of the manufacturing sector in Indonesia between 1986 and 1996, and they underlined its relationship to trade liberalization policy. However, that time has now long passed, and their findings may not reflect the current conditions: there have been marked changes since then, particularly after the 1997–98 economic crisis and the implementation of regional autonomy since 2001.

[12]See, for instance, Ge (2009), He et al. (2008), and Lu and Tao (2009).

The objectives of this study are to describe the distribution of economic activities by looking at the trends in regional specialization and geographic concentration, emphasizing how the economic crisis and decentralization policy changed the pattern and to examine determinant factors of the industry's spatial concentration. This study contributes to the literature by documenting the long-term regional specialization and concentration trends of the Indonesian manufacturing industry from 1990 to 2010. We also introduce the use of a spatially weighted EG proposed by Guimarães et al. (2011) in an empirical modeling of geographic concentration to account for neighboring agglomeration effects. In particular, we evaluate the changes that occurred in tandem with the external shocks of the 1997–98 Asian financial crisis and the implementation of decentralization policy.

This study determines the spatial distribution of the economic activities of the Indonesian manufacturing industry by measuring the regional specialization index (RSI), as originally proposed by Krugman (1991b), and the spatial Ellison-Glaeser index originally developed by Ellison and Glaeser (1997) and extended by Guimarães et al. (2011)—to account for neighboring effects. With spatial trends in hand, we then empirically investigate whether economies of scale, resources, international trade activities, and labor prices can explain the changes in geographical concentration.

This paper is organized as follows. This first section provides a brief overview of the importance and unique nature of this study. The second section surveys the related literature. In the third section, the empirical model used here is presented, including information on the data and variable construction. Analyses and the results thereof are presented in the fourth section. The final section provides concluding remarks.

4.2. Literature Review

The importance of geographic and locational characteristics as key determinants of production structure and trade is pinpointed by Fujita et al. (1999) and Krugman (1991a, 1991b). They attribute the spatial concentration of economic activity to natural advantages and spillover. Krugman (1991b) develops a model to explain how firms concentrate in a specific location.

To study the spatial distribution of economic activities, we start by distinguishing specialization from concentration. We define specialization in this research as the relative position of each city over the rest of the country. On the other hand, we define concentration as the distribution of a particular sector of the two-digit SICs across cities within the country. In a broader view, we see that agglomeration as the group of many industrial clusters or spatial concentration of many sectors in a particular city.[13] Understanding the distinction, these three definitions will help us look at how economic activities are spatially distributed. Brakman et al. (2009) illustrate and explain in detail the differences among concentration, specialization, and agglomeration. They suggest that concentration and agglomeration are similar and distinct from specialization. They argue that concentration and agglomeration are similar in that they both relate to how a specific economic activity takes place across locations. However, while agglomeration

[13]Brülhart (2001) speaks of specialization in terms of the distribution of a single country across several sectors and concentration in terms of the distribution of a single industry across several countries.

captures a broader set of aspects across industries within a sector, concentration tends to relate to a particular industry type. On the other hand, they assert that specialization focuses on how one can study countries or a regional economic structure by looking at a particular spatial unit across industries or sectors.

The first study to discuss long-term trends in regional specialization and the localization of economies within the context of manufacturing is by Kim (1995), for the case of the United States. He distinguishes between specialization and localization/concentration as follows: specialization is important when one looks at the development of the regional manufacturing structure across industries, while localization or concentration is important when one looks at the evolution of each industry across regions. Kim (1995) argues that regional specialization can bestow comparative advantages on a particular region. Furthermore, he notes that a higher level of regional specialization implies that the region has greater advantages in terms of economies of scale in production. He uses Krugman’s (1991a) RSI to compare relative regional specialization among nine census regions. He concludes that the degree of regional specialization among U.S. manufacturing industries increased until World War I, but then slightly declined thereafter, until the end of the study period.

Unlike Kim’s (1995) study—which makes use of Hoover’s localization index—the current study employs the geographic concentration index proposed by Ellison and Glaeser (1997; hereafter, EG index) and an extension of the spatially weighted EG index developed by Guimarães et al. (2011; hereafter, EGS index) to measure localization or concentration. The EG index first proposed the measurement of the geographic concentration of economic activity; it distinguishes between two agglomerative forces—namely, natural advantage and spillover—while controlling for industrial location. By providing empirical evidence that differentiates pure geographic forces and economic determinants, Ellison and Glaeser argue that geographic concentration stems not only from industrial concentration, but also from natural advantages inherent to area characteristics (e.g., natural resources and closeness to market) and locational spillover (e.g., input sharing, labor pooling, and knowledge sharing). They also assert that the index can control for the effects of internal economies of scale or large plant size. They demonstrate evidence of the industrial localization of U.S. manufacturing industries at the four-digit SIC level and also demonstrate that in industries with strong upstream-downstream linkages, localization stems from natural advantages and coagglomeration.

Since then, many empirical studies examined geographical concentration by using both the EG and MS indices. Rosenthal and Strange (2001) first used the EG index to empirically examine the microdeterminants of agglomeration using U.S. manufacturing employment data from 2000. They found a positive and statistically significant relationship between industrial agglomeration and those microdeterminants. Furthermore, Devereux et al. (2004) found geographic concentration mostly among low-tech industries in the United Kingdom, while Braunerhjelm and Borgman's (2004) study identified high geographic concentrations among Swedish industries, which they attribute to knowledge-intensive manufacturing industries and the intensive use of raw materials.

In the context of developing countries, a large body of research on geographic concentration relates in China (e.g., Ge, 2009; He et al., 2008; Lu & Tao, 2009). He et al. (2008) found that during 1980–2003, Chinese industries were geographically more heavily concentrated; this was particularly the case for the least-protected industries (e.g., rubber, chemical, education, and sporting goods). They also asserted that industries with stronger connections in foreign markets as part of the globalization process were more heavily concentrated, particularly in coastal regions. These findings agree with those of Ge (2009), who asserts that export-oriented and foreign-invested industries have a higher degree of agglomeration than others and tend to cluster in regions accessible to foreign markets (e.g., close to airports). Furthermore, local protections related to decentralization policy stymied geographic concentration or industrial specialization (He et al., 2008; Lu & Tao, 2009).

Despite being well known, the EG index has some drawbacks in terms of aligning with the criteria of localization measures as outlined by Combes and Overman (2004) and Duranton and Overman (2005). Guimarães et al. (2011) highlight crucial drawbacks of the EG index: it suffers from the modifiable areal unit problem (MAUP) and the checkerboard problem. They argue that the first issue relates to a possible aggregation bias within administrative boundaries or spatial units, while the second arises when we ignore neighboring effects and treat economic activity in adjacent spatial units in a manner similar to that of activity in the regional center. The EG index does not treat the geographic location of a plant as a particular point on a map, but rather as a simple aggregation of geographical areas, such as a city or province. Consequently, we treat plants similarly across regions and in neighboring regions and ignore any possible spatial dependence among plants along a border between regions. Marcon and Puech (2003) and Duranton and Overman (2005) each propose distance-based methods by which to measure geographic concentration. This approach is thought to be the best choice in examining the geographic location of plants, as it precludes the need for data that pertains to the specific location of a plant—data that are generally not available in most countries (including Indonesia). Therefore, to account for economic activity in neighboring regions, we adopt the spatially weighted EGS index. This index precludes MAUP and deals with economic clustering that occurs across borders (Guimarães et al., 2011).

4.3. Empirical Methods

4.3.1. Data and Measurement

This study analyzed data from the *Statistik Industri*, an unpublished electronic data set captured through an annual survey of large- and medium-sized firms conducted by Indonesia's Central Bureau of Statistics (BPS) between 1990 and 2010; the firms were classified in terms of two- or three-digit SIC codes. All values in this research were expressed in 2000 real values. We used the WPI published monthly in the BPS bulletin *Statistik Bulanan Indikator Ekonomi*. This study covered 66 industries at the three-digit SIC level and 23 sectors at the two-digit SIC level.

We defined the term "city" as the third administrative level of the Indonesian government, originally known as a district or municipality. Therefore, for the sake of simplicity, the term "city" in this study refers to a district or municipality. Since the number of cities in Indonesia changed over time, we referred to the 1990 configuration of 284 cities and 26 provinces (excluding Timor Leste) and considered any newly created districts as belonging to their original districts (cities).

To document regional specialization and concentration trends within the Indonesian manufacturing industry from 1990 to 2010, we first measured specialization as per Kim (1995) to examine the pattern of local economic structure, by calculating Krugman's RSI. Next, we measured geographic concentration—in line with the work of Ellison and Glaeser (1997) and Guimarães et al. (2011)—to calculate the EG index and EGS index, respectively. We followed Sjöberg and Sjöholm (2004) and measured those indices by using employment and value-added data. This approach was important, as it provided a better perspective in analyzing and comparing a variety of industries that might be influenced by input factors. Sjöberg and Sjöholm (2004) argued that employment data tend to bias toward labor-intensive industries, while value-added data tend to bias toward capital-intensive industries.

We measured the regional specialization index to compare each city's industrial structure with the rest of the country. From the Krugman Specialization Index we obtained the RSI for each city by calculating the share of industry *i* in that city's total employment or value added. We then calculated the same industry in other cities and took the difference between share of city *i* with other cities' share. After taking the absolute values of these differences, we summed over all industries to get the RSI for each city. The RSI is formulated as follows:

$$\mathrm{RSI}_{jk} = \sum_{i=1}^{n} \left| \frac{E_{ij}}{E_j} - \frac{E_{ik}}{E_k} \right|, \tag{4.1}$$

where E_{ij} is the level of employment in industry i = 1,….,N for region j, and E_j is the total industry employment in region j (and similarly for region k). If the index value equals 0, then the two regions j and k are completely despecialized. If the index value equals 2, the regions are completely specialized (Combes & Overman, 2004; Kim, 1995).

We used the EG index to measure geographic concentration, given its ability to separate the sources of industrial agglomeration from natural advantages and spillover. The EG index is a function of raw geographic concentration (*G*) and the Herfindahl Index (*H*) of industry, which are defined as follows:

$$G = \sum_{j=1}^{M}\left(s_j - x_j\right)^2, \tag{4.2}$$

$$H = \sum_{p=1}^{N} z_p^2 , \tag{4.3}$$

$$\mathrm{EG} = \gamma = \frac{\left[G - \left(1 - \sum_j x_j^2\right)H\right]}{\left[\left(1 - \sum_j x_j^2\right)(1 - H)\right]}, \tag{4.4}$$

where *N* is the number of plants and *M* is the number of regions. s_j stands for the share of an industry's total employment in region *j*, while x_j denotes the fraction of aggregate employment in region *j*. z_p refers to the share of plant *p* in industry employment. Ellison and Glaeser (1997) claimed that the use of the EG index can facilitate comparisons across industries, across countries, or over time. A positive or negative EG index value indicates the agglomeration or deagglomeration process, respectively. If industry *i* is concentrated in some region, the EG index will have a positive value. However, when industry *i* is not concentrated in some region (*j*) and is uniformly scattered following a random location process, the EG index takes the value of 0. To overcome the limitation of the EG index—as explained in the literature review above—we adopted the EGS index, which accounted for neighboring effects.

To capture regional externalities using a spatial-weights matrix, we followed Rodríguez-Pose et al. (2013) and defined the matrix of the neighboring spatial distance as follows:

$$D(\delta)\begin{cases} d^*_{jk}(\delta) = 0 \text{ if } j = k \\ d^*_{jk}(\delta) = d_{jk} \text{ if } d_{jk} \leq \delta \\ d^*_{jk}(\delta) = \sim \text{ if } d_{jk} > \delta, \end{cases} \tag{4.5}$$

where δ denotes a distance threshold between the capitals of neighboring districts in which we assume regional externalities still appear. If the Euclidean distance d_{jk} from capital district *j* to capital district *k* is smaller than δ, then the spatial distance $d^*_{jk}(\delta)$ is equal to d_{jk}. Now that we have a distance matrix, we can calculate W_{jk}, the weighted neighbor distance matrix for region *j* with respect to neighbor *k*:

$$W_{jk} = \frac{{}^{1}\!/_{d^*_{jk}(\delta)}}{\sum_k {}^{1}\!/_{d^*_{jk}(\delta)}}. \tag{4.6}$$

We set distance thresholds of 50 km between the capital cities, in line with Duranton and Overman (2005); we also set distance thresholds of 400 km between the capital provinces, in line with Rodríguez-Pose et al. (2013). Thus, we define EGS as follows:

$$\text{EGS} = \gamma_S = \frac{\left[G_S - \left(1 - \sum_j x_j W_{jk} x_k\right) H\right]}{\left[\left(1 - \sum_j x_j W x_j\right)(1 - H)\right]}, \tag{4.7}$$

where

$$G_s = G + \sum_{j=1}^{M}\left[\left(s_j - x_j\right) W_{jk} \left(s_k - x_k\right)\right]. \tag{4.8}$$

Here, G_s stands for spatially weighted *G*, and s_k stands for the industry's share of total employment in region *k*, while x_k denotes the fraction of aggregate employment in region *k*. W_{jk} is a weighted neighbor distance matrix for region *j* with respect to neighbor k . EGS stands for spatially weighted EG.

4.3.2. *Empirical Model for the Determinant of Geographic Concentration*

To understand the determinants of geographic concentration, we followed Kim (1995) to estimate the impact of industrial characteristics, particularly scale economies and resources, on geographic concentration in the following baseline equation:

$$\mathrm{LnEGS}_{it} = \beta_0 + \beta_1\mathrm{LnScale}_{it} + \beta_2\mathrm{Raw}_{it} + \beta_3\mathrm{Skill}_{it} + \beta_4\mathrm{Export}_{it} + \beta_5\mathrm{LnAge}_{it} + \beta_6\mathrm{LnWage}_{it} + \beta_7\mathrm{DResource} + \beta_8\mathrm{DLabor} + \beta_9\mathrm{DCrisis} + \beta_{10}\mathrm{DAutonomy} + \alpha_i + \varepsilon_{it}, \tag{4.9}$$

where the *i* subscripts (=1,2…,66) indicate 66 industries in the three-digit SIC and *t* (=1990–2010) indicates the period of study.

LnEGS stands for the log spatially weighted Ellison-Glaeser index, while Scale refers to the average plant size in each industry and Raw denotes the raw material intensity (cost of raw materials divided by the value added) as suggested by Kim (1995). In addition to the initial variable from Kim (1995), we included other industrial characteristics; we defined Skill as the fraction of the total wage of a non-production worker in industry and Export as the percentage of exports in total output. Especially for the variable of Export, careful attention should be taken concerning the potential reversed causality between localization and export activities. Rodríguez-Pose et al. (2013) found that localization externalities contributed to export intensity in Indonesia and this implies the possible endogeneity between concentration and export activities. Furthermore, Age and Wage stand for the log of the average firm age and wage rate of production workers in each industry.

Regarding the particular interest in how the 1997 economic crisis and decentralization policy are associated with geographic concentration, we tested the dummies, DCrisis and DAutonomy that referred to our years of interest. We also looked at specific categories of resource-based and labor-intensive industries using the dummies, DResource and DLabor as per the OECD (1987) classification. Finally, α_i stands for industry characteristics i, and ε_{it} denotes idiosyncratic errors.

We estimated the model using the OLS, random-effects (RE), fixed-effects (FE), and Hausman-Taylor models (HT). The Hausman test and Sargan-Hansen test are applied to test the equality of the coefficient estimates from RE to those from FE, or from HT to those from FE. Sargan-Hansen has an advantage in its ability to incorporate robust cluster standard errors. Moreover, the Wald test is conducted to test heteroscedasticity.

4.4. Results and Discussions

4.4.1. The Trend of Regional Specialization in Manufacturing

To evaluate the development of regional manufacturing structures, we begin by briefly summarizing the evidence pertaining to regionalization trends (Figure 4.1). The general trend is that the RSI increased during the economic crisis and following the initiation of regional autonomy, although it tended to decline after 2006. From Figure 4.1, we see that regional specialization among industries at the three-digit SIC level was higher than that among industries at the two-digit SIC level; this implies that externalities may exist in narrower industries—like those with four- or five-digit SIC codes, as suggested by Kim (1995). The recent decline in regional specialization in Indonesian manufacturing employment was likely due to increases in oil prices and an increase in the minimum wage. These two factors potentially push firms to diversify their product offerings.

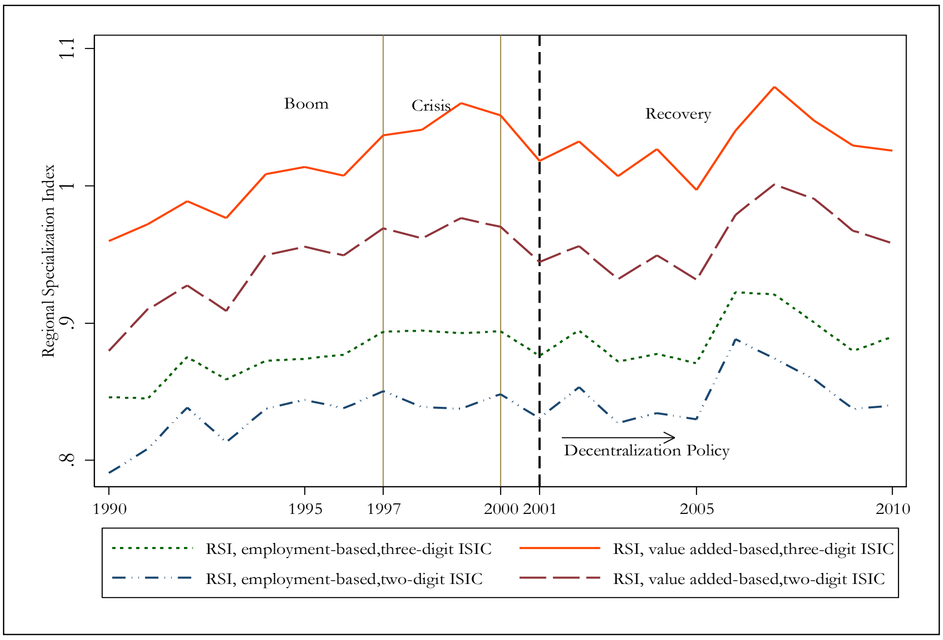


Figure 4.1. RSI patterns in Indonesia, 1990–2010

Table 4.1 reports the RSI values calculated for industries at the three-digit SIC level, in each province. We can compare the specialization patterns for each province in Indonesia by measuring in terms of employment [columns (1)–(5)] and value added [columns (6)–(10)]. In general, the RSI values calculated by using value-added data were higher than those garnered with employment-based data. Furthermore, Table 4.1 confirms the domination of regions in Java Island, which had index values exceeding 1—namely, DKI Jakarta, West Java, Central Java, and East Java. We can also identify from Table 4.1 an increasing trend toward higher specialization in Riau and East Kalimantan, which are known as the most affluent provinces in Indonesia, as they have an abundance of oil and mining resources.

Based on the value-added data, we found that the patterns of the various provinces did not run exactly parallel when we used employment data next to its larger index. The RSI values derived from value-added data were higher than those that were employment based, which indicated that capital-intensive industries contributed to regional specialization more so than labor-intensive ones. The use of value-added measurements also made it easier to identify those provinces with index values that exceeded 1—namely, North Sumatera, Riau, Jambi, Lampung, and East Kalimantan. Overall, regional specialization showed an increasing trend and was driven by provinces within Java and the most affluent provinces. We identified that North Sumatera, Jambi, and Lampung are provinces with an abundance of agricultural products from plantation and forestry.

Of the 26 provinces, 18 had a variety of positive RSI values between 1990 and 2010, as measured by using both employment and value added [columns (5) and (10), respectively]. This result implies that value added has a stronger identification with regional specialization than employment, as the value-added measurement is proportionately affected by capital intensity, which is characterized more by immobile production factors than by labor. Therefore, the picture we derived from looking at value-added measurements accurately reflected regional comparative advantages among regions—advantages that could lead to regional specialization.

Table 4.1 Specialization patterns in Indonesia, across provinces

Province	Employment-based ISIC 3					Value-added-based ISIC 3				
	Average				Change from 1990 to 2010	Average				Change from 1990 to 2010
	1990-96	**1997-00**	**2001-05**	**2006-10**		**1990-96**	**1997-00**	**2001-05**	**2006-10**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)=(4)-(1)**	**(6)**	**(7)**	**(8)**	**(9)**	**10=(9)-(6)**
NAD Aceh	0.645	0.662	**0.396**	0.652	0.007	0.744	0.834	**0.532**	0.906	0.162
North Sumatera	0.889	0.917	0.932	**0.823**	-0.066	**1.024**	1.081	1.092	1.039	0.015
West Sumatera	**0.549**	0.569	0.558	0.632	0.083	**0.686**	0.756	0.754	0.831	0.145
Riau	**0.939**	1.036	1.143	1.203	0.264	**1.081**	1.177	1.211	1.328	0.248
Jambi	0.981	0.865	0.975	**0.825**	-0.156	1.052	1.064	1.098	**1.050**	-0.003
South Sumatera	**0.741**	0.905	0.861	0.990	0.250	**0.880**	1.120	1.005	1.175	0.296
Bengkulu	**0.407**	0.544	0.474	0.840	0.433	0.559	0.875	**0.542**	0.768	0.209
Lampung	**0.927**	0.958	1.016	1.036	0.109	**1.160**	1.261	1.232	1.205	0.045
DKI Jakarta	**1.041**	1.086	1.108	1.110	0.069	**1.152**	1.266	1.210	1.253	0.101
West Java	**1.099**	1.119	1.122	1.106	0.007	**1.191**	1.201	1.205	1.206	0.015
Central Java	**1.096**	1.162	1.118	1.129	0.033	**1.199**	1.262	1.226	1.234	0.035
Di Yogyakarta	0.934	**0.881**	0.926	0.994	0.060	1.119	1.087	**1.022**	1.110	-0.009
East Java	**1.059**	1.091	1.091	1.148	0.089	**1.240**	1.275	1.264	1.286	0.046
Bali	0.906	0.875	**0.842**	0.876	-0.030	0.967	0.917	**0.869**	0.960	-0.007
West Nusa Tenggara	0.592	0.666	**0.586**	0.726	0.133	0.737	0.854	0.812	**0.674**	-0.063
East Nusa Tenggara	0.327	0.448	0.414	**0.319**	-0.008	0.586	0.551	0.552	**0.427**	-0.159
West Kalimantan	0.820	**0.680**	0.744	0.878	0.058	0.938	**0.810**	0.817	1.044	0.106
Central Kalimantan	0.463	0.472	**0.425**	0.757	0.294	**0.519**	0.576	0.585	0.873	0.354
South Kalimantan	**0.761**	0.776	0.818	0.839	0.078	**0.852**	0.866	0.942	0.980	0.129
East Kalimantan	**1.000**	1.094	1.011	1.092	0.092	1.104	1.257	**0.968**	1.129	0.026
North Sulawesi	0.763	0.722	0.746	**0.704**	-0.059	0.914	0.935	**0.868**	0.892	-0.022
Central Sulawesi	0.941	0.494	0.524	**0.402**	-0.540	1.018	**0.645**	0.798	0.731	-0.287
South Sulawesi	**0.584**	0.618	0.627	0.661	0.077	**0.669**	0.844	0.866	0.837	0.169
South East Sulawesi	**0.721**	1.035	1.007	0.891	0.170	**0.893**	1.269	1.179	0.997	0.104
Maluku	1.061	1.041	1.121	**0.594**	-0.467	1.147	1.104	1.150	**0.698**	-0.449
Papua	**0.626**	0.826	0.643	0.628	0.003	**0.723**	0.920	0.829	0.777	0.054
Indonesia	**0.803**	0.829	0.816	0.841	0.038	**0.929**	0.993	0.947	0.977	0.048

Notes: The RSI is calculated from the average of cities' RSI within province in the respective years. The underlined font indicates provinces that became more specialized, while the bold font indicates a minimum value for each province.

Despite the fact that the production structure might differ across provinces, we classified the provinces into five groups in terms of the island on which they were located. Figures 4.2 and 4.3 show the regionalization pattern of each province over the period of study, using employment and value-added data, respectively. We found a similar pattern between the two figures, although they did indicate different degrees of specialization. We also found that the Sumatera, Java, and Kalimantan Islands became more specialized, while Sulawesi and the other islands became more despecialized.

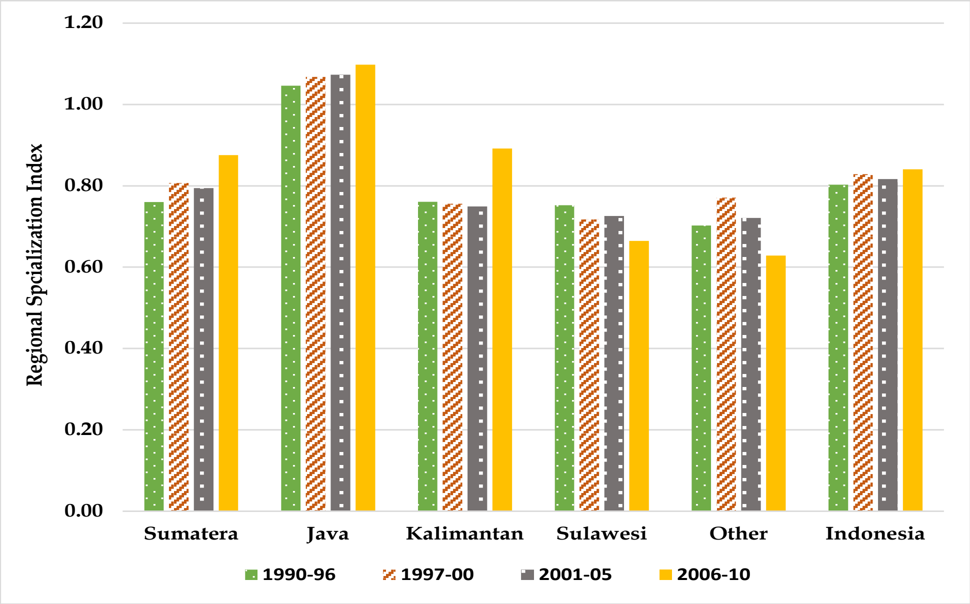


Figure 2. RSI Patterns in Indonesia, Using Employment

Notes: RSI is calculated based on the cities' RSI values in the year ranges shown, and among industries at the three-digit SIC level.

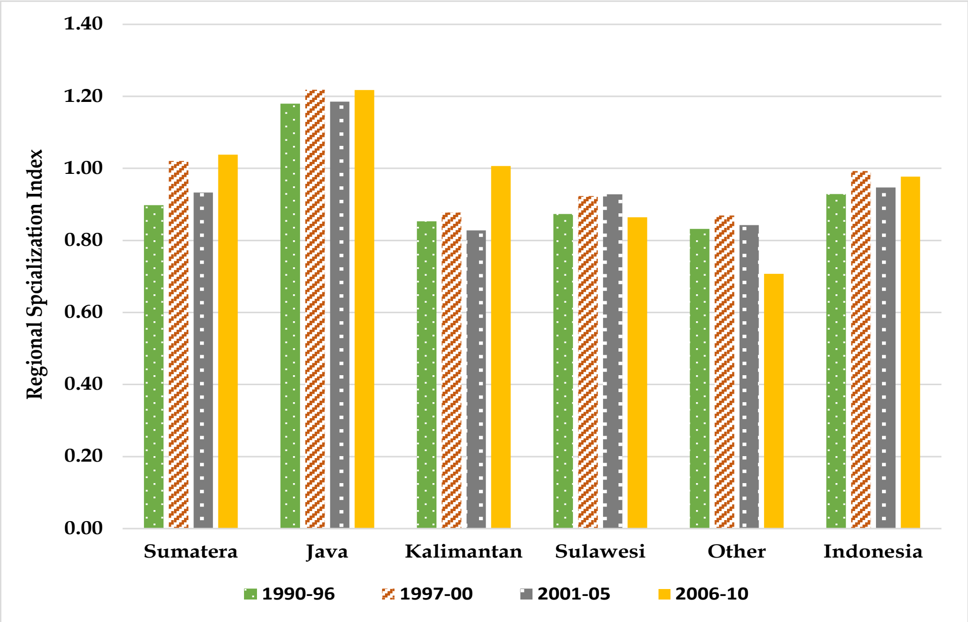


Figure 3. RSI Patterns in Indonesia, Using Value Added.

Notes: RSI is calculated based on the cities' RSI values in the year ranges shown, and among industries at the three-digit SIC level.

4.4.2. The Trend of Geographic Concentration in Manufacturing

Following Brülhart (2001), we classified the industries into five categories: resource-intensive, labor-intensive, scale-intensive, differentiated, and science-based industries (classification based on OECD, 1987). Appendix Table 4.1 lists the three-digit ISIC codes for each category; the classifications were based on the factors that influenced the competitive process. Abundant natural resources constitute a primary competitiveness factor for resource-based industries, while low labor costs constitute a comparative advantage for labor-intensive industries. For scale-based industries, having a competitive edge is a matter of production length, while among product-differentiated industries, being competitive means having the ability to satisfy market demand. Finally, science-based industries rely on the application of scientific knowledge.

Figures 4.4 and 4.5 show the geographic concentration trends for all manufacturing across cities and provinces, using the EG and EGS indices. At a glance, one can see that the geographic concentration slightly increased during the economic downturn and then became less concentrated following the implementation of decentralization policy. As a result, the general pattern over the period of study somewhat indicated a decline in geographic concentration. We also found the geographic concentration at the province level to be higher than that at the city level; this finding suggests that externalities may flow across cities within a province and result in a higher concentration at the province level and deconcentration at the city level. These findings agree with those of Kuncoro (2009), that deconcentration is driven by the relocation of firms to districts near major markets and international seaports (Deichmann et al., 2008). By following this strategy, firms continue to maintain the benefits that come with agglomeration due to minimizing transportation costs. Deichmann et al. (2005) also spoke to the difficulties that relatively unattractive regions face in attracting firms away from the leading regions, even when it improves its infrastructure.

By accounting for neighboring effects, we found that the EGS index is always greater than the EG index. Furthermore, the EGS index is more sensitive to capturing changes in the geographic concentration pattern, and this indicates that there is a strong connection among regions as externalities flow across cities and provinces. The deconcentration of economic activities seems to appear at around 2000 and become more spatially deconcentrated following the implementation of regional autonomy. The decline in concentration based on value-added data occurs at a brisker rate than that based on employment data; this implies that the movement of capital for production is more sensitive to external shocks than the shifting of employment. Another interpretation is that the concentration of the labor market within the manufacturing industry is more rigid, as the mature plants are already firmly established in the core regions.

Tables 4.2 and 4.3 indicate the geographic concentration trends of the average of the three-digit SIC level industries classified into 23 sectors over the 1990–2010 period. Of the 23 sectors, 12 experienced increases in agglomeration. This finding suggests a general trend of agglomeration among Indonesian manufacturing industries. Across geographies and various measurements, the five most agglomerated industries in the 1990–96 period in Indonesia were tobacco, textiles, publishing, printing and recording, other nonmetallic mineral, and chemicals and chemical products. However, the structure then changed, with the five most agglomerated industries in the 2006–2001 period becoming radio, TV and communication equipment, textiles, motor vehicles, trailers and semitrailers, tobacco, and recycling (see Table 4.4). This shift indicates that geographic concentration is now driven by industries with higher technological intensity—such as radio, TV and communication, and motor vehicles, trailers and semitrailers—besides traditional industries such as textiles and tobacco.

In the individual sectors, the general trend is that resource-based industries (e.g., food, tobacco, rubber, and wood) and labor-intensive industries (e.g., textiles, apparel, and tanning and leather) have become deconcentrated. On the other hand, differentiated goods (e.g., motor vehicles, radio, and TV) have become more concentrated. The pattern among individual sectors suggests that the effects of technology and intensity determine the relative strength of agglomeration and dispersion forces (Midelfart-Knarvik & Overman, 2002).

Figures 4.6 and 4.7 show that industrial concentration varies widely by industry group as per the OECD (1987) classification. In general, Figure 4.6 shows that the labor-intensive, differentiated goods and science-based industries are becoming more spatially concentrated. It is also clear that resource-based and scale-intensive industries have become more dispersed. However, at the province level, the geographic concentration of labor-intensive industries tends to be less concentrated (see Figure 4.7); this indicates that with regard to this industry group, in particular, the relocation of manufacturing appears within the province and is concentrated in certain cities.[14]

[14]A similar pattern is seen with this industry group when we use value-added data in the measurements.

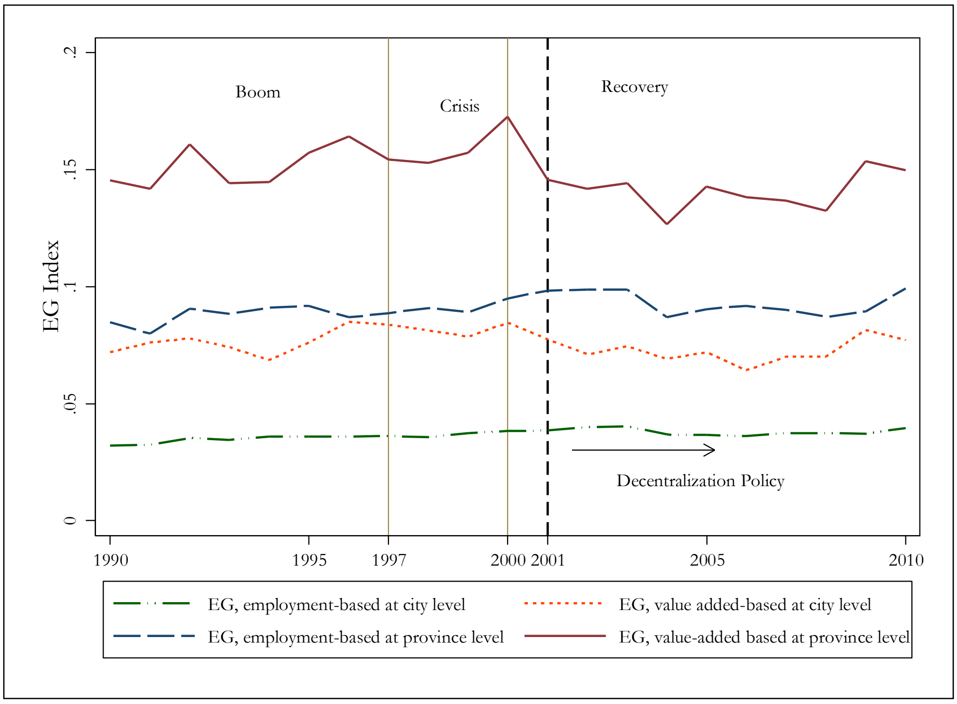


Figure 4.4. Geographic Concentration Pattern in Indonesia: EG Index, 1990–2010

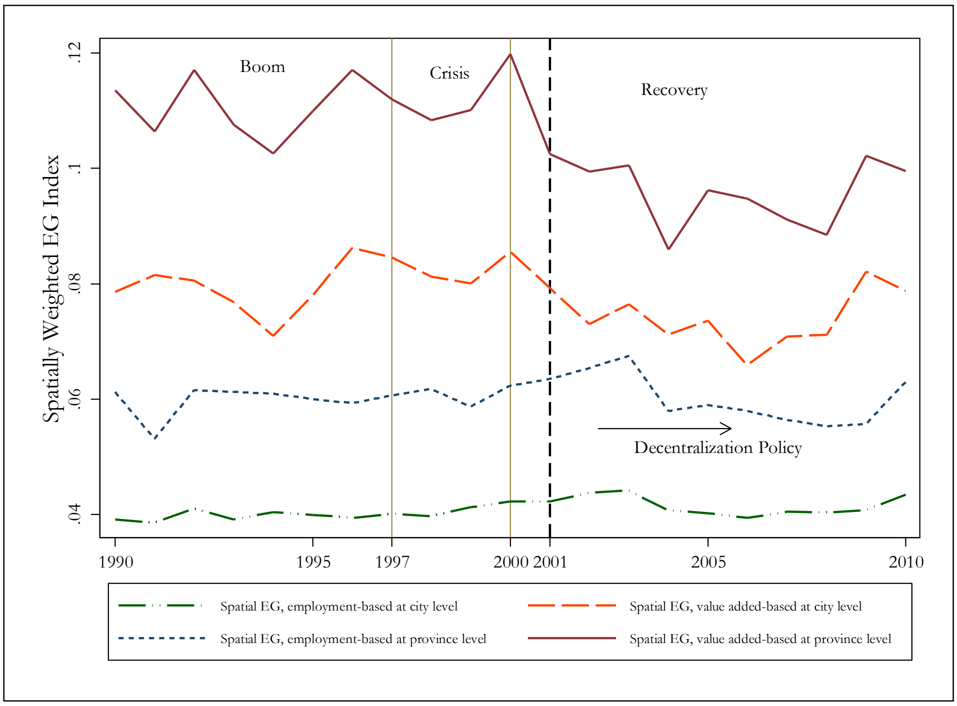


Figure 4.5. Geographic Concentration Pattern in Indonesia: EGS Index, 1990–2010

Table 4.2. Concentration (EGS) Pattern in Indonesia across Sectors, at the City Level.

3-Digit ISICs EGS by Sector	Employment-Based, City Level					Value Added-Based, City Level				
	Average				Change from 1990 to 2010	Average				Change from 1990 to 2010
	1990-96	1997-00	2001-05	2006-10		1990-96	1997-00	2001-05	2006-10	
	(1)	(2)	(3)	(4)	(5)=(4)-(1)	(6)	(7)	(8)	(9)	10=(9)-(6)
Food & beverage	0.031	0.031	0.029	**0.025**	-0.007	0.067	0.060	**0.056**	0.058	-0.010
Tobacco	0.060	0.058	**0.051**	0.064	0.004	0.247	0.230	0.178	**0.152**	-0.094
Textiles	**0.106**	0.125	0.142	0.180	0.073	**0.098**	0.107	0.140	0.242	0.145
Apparel	0.035	**0.029**	0.039	0.044	0.009	0.068	0.070	0.085	**0.034**	-0.035
Tanning & leather	0.043	**0.041**	0.053	0.057	0.014	0.066	0.071	0.084	**0.061**	-0.005
Wood & its products, except furniture	0.038	0.036	0.031	**0.025**	-0.013	0.052	0.046	**0.046**	0.054	0.002
Paper & paper products	0.009	0.001	**0.001**	0.002	-0.007	0.081	0.073	**0.040**	0.075	-0.006
Publishing, printing & recording	**0.051**	0.091	0.079	0.098	0.047	**0.125**	0.127	0.189	0.269	0.144
Coke, refined petroleum & fuel	**0.149**	0.325	0.281	0.241	0.092	**0.000**	0.298	0.181	0.229	0.229
Chemicals & chemical products	0.144	0.143	**0.099**	0.112	-0.031	0.166	0.230	**0.134**	0.240	0.074
Rubber & plastics	0.018	0.013	0.009	**0.009**	-0.009	0.035	0.038	0.022	**0.020**	-0.016
Other nonmetallic mineral	0.082	0.065	0.061	**0.058**	-0.024	0.169	0.167	0.127	**0.110**	-0.059
Basic metals	0.041	0.023	0.022	**0.022**	-0.019	0.107	**0.067**	0.073	0.094	-0.013
Fabricated metal, except machinery	0.027	**0.022**	0.031	0.025	-0.002	0.095	0.071	**0.042**	0.051	-0.044
Machinery & equipment n.e.c.	**0.023**	0.040	0.066	0.055	0.032	**0.055**	0.081	0.063	0.059	0.004
Office, accounting & computing machinery	0.052	**-0.027**	0.209	0.317	0.265	0.111	**0.092**	0.501	0.363	0.251
Electrical machinery & apparatus n.e.c.	0.112	0.017	0.027	**0.013**	-0.099	0.152	**0.018**	0.043	0.048	-0.104
Radio, TV & communication equipment	**0.044**	0.100	0.230	0.162	0.118	**0.062**	0.201	0.215	0.325	0.263
Medical, precision, optical, watches & clocks	0.122	0.223	0.131	**0.045**	-0.077	0.170	0.437	0.301	**0.069**	-0.101
Motor vehicles, trailers & semitrailers	0.141	0.170	**0.091**	0.157	0.016	**0.088**	0.172	0.103	0.233	0.144
Other transport equipment	0.056	0.070	0.133	**-0.064**	-0.120	0.065	0.209	0.160	**-0.102**	-0.168
Furniture; manufacturing n.e.c.	0.028	0.030	**0.026**	0.039	0.012	0.047	0.054	0.034	0.035	-0.013
Recycling	0.088	0.116	**0.047**	0.202	0.114	0.145	0.099	0.225	0.213	0.067
Indonesia	**0.071**	0.078	0.080	0.072	0.001	**0.106**	0.132	0.122	0.120	0.014

Notes: The spatially weighted EGS index is calculated based on the respective years of the three-digit ISICs EGS within sector.
The underlined font indicates the sectors that became more concentrated, while the bold font indicates a minimum value for each sector.

Table 4.3. Concentration (EGS) Pattern in Indonesia across Sectors, at Province Level.

3-Digit ISICs EGS by Sector	Employment-Based, Province Level					Value Added-Based, Province Level				
	Average				Change	Average				Change
	1990-96	1997-00	2001-05	2006-10	from 1990 to 2010	1990-96	1997-00	2001-05	2006-10	from 1990 to 2010
	(1)	(2)	(3)	(4)	(5)=(4)-(1)	(6)	(7)	(8)	(9)	10=(9)-(6)
Food & beverage	0.075	0.077	0.081	**0.060**	-0.015	0.099	**0.074**	0.076	0.092	-0.007
Tobacco	**0.308**	0.328	0.359	0.332	0.024	**0.422**	0.501	0.461	0.468	0.045
Textiles	0.141	0.154	**0.132**	0.152	0.011	0.186	0.197	**0.141**	0.212	0.026
Apparel	0.095	0.067	0.075	**-0.064**	-0.160	0.153	0.116	0.141	**0.008**	-0.146
Tanning & leather	0.061	**0.056**	0.070	0.078	0.017	0.080	**0.066**	0.104	0.095	0.015
Wood & its products,except furniture	0.150	0.150	0.131	**0.091**	-0.060	0.191	0.171	0.154	**0.150**	-0.041
Paper & paper products	0.018	**-0.001**	0.009	0.001	-0.017	0.070	0.033	0.010	**0.003**	-0.067
Publishing, printing & recording	0.099	0.059	**0.005**	0.060	-0.039	0.215	**0.104**	0.125	0.149	-0.066
Coke, refined petroleum & fuel	**-0.058**	0.019	-0.048	0.018	0.077	**-0.143**	0.059	-0.033	0.058	0.201
Chemicals & chemical products	0.045	**0.004**	0.039	0.047	0.002	0.095	**0.067**	0.085	0.069	-0.027
Rubber & plastics	0.032	0.017	0.014	**0.013**	-0.019	0.056	0.051	0.035	0.031	-0.025
Other nonmetallic mineral	0.042	0.042	0.038	**0.035**	-0.007	0.158	0.166	0.090	**0.084**	-0.074
Basic metals	-0.004	-0.004	**-0.013**	0.005	0.009	0.033	**0.018**	0.025	0.075	0.042
Fabricated metal,except machinery	0.015	**0.010**	0.019	0.027	0.012	0.098	**0.053**	0.056	0.064	-0.035
Machinery & equipment n.e.c.	**0.042**	0.068	0.071	0.074	0.033	0.095	**0.089**	0.101	0.111	0.016
Office, accounting & computing machinery	-0.009	-0.108	-0.330	**-0.504**	-0.496	0.141	0.062	-0.031	**-0.485**	-0.626
Electrical machinery & apparatus n.e.c.	0.014	-0.025	-0.013	**-0.042**	-0.056	0.098	0.001	0.013	**-0.038**	-0.136
Radio, TV & communication equipment	**-0.410**	0.037	0.186	0.145	0.554	**-0.395**	0.176	0.159	0.217	0.612
Medical, precision,optical,watches & clocks	0.046	0.242	0.126	**0.020**	-0.026	0.087	0.477	0.301	**0.024**	-0.064
Motor vehicles, trailers & semitrailers	0.080	0.154	0.259	0.287	0.207	**0.103**	0.182	0.290	0.273	0.169
Other transport equipment	-0.840	-0.808	-0.550	**-2.446**	-1.605	-0.898	-0.747	-0.599	**-2.469**	-1.571
Furniture; manufacturing n.e.c.	0.030	0.029	**0.027**	0.028	-0.002	0.063	0.067	0.043	**0.041**	-0.022
Recycling	-0.103	0.133	**-0.296**	0.069	0.172	-0.043	0.108	**-0.163**	0.114	0.157
Indonesia	-0.011	0.022	0.022	**-0.086**	-0.075	0.039	0.082	0.064	**-0.052**	-0.091

Notes: The spatially weighted EGS index is calculated based on the respective years of the three-digit ISICs EGS within sector.
The underlined font indicates the sectors that became more concentrated, while the bold font indicates a minimum value for each sector.

Table 4.4.Ranking of agglomerated industries.

3 Digit ISIC's EGS by Sector	**City Level**				**Province Level**				**Sum of Rank**	
	Employment Rank		**Value Added Rank**		**Employment Rank**		**Value Added Rank**			
	1990-96	**2006-10**	**1990-96**	**2006-10**	**1990-96**	**2006-10**	**1990-96**	**2006-10**	**1990-96**	**2006-10**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1+3+5+7)	(2+4+6+8)
The Five Most Agglomerated Sectors										
Radio, TV & communication equipment	13	**5**	18	**2**	22	4	22	3	75	14
Textiles	6	**4**	10	**4**	**3**	**3**	**4**	**4**	23	15
Motor vehicles, trailers & semitrailers	**3**	6	12	6	6	2	8	2	29	16
Tobacco	9	9	**1**	9	**1**	**1**	**1**	**1**	12	20
Recycling	7	**3**	6	8	21	8	20	7	54	26
Publishing, printing & recording	12	8	7	**3**	4	10	2	6	25	27
Chemicals & chemical products	**2**	7	**4**	**5**	10	11	12	13	28	36
Tanning & leather	14	11	16	14	8	6	15	9	53	40
Coke, refined petroleum & fuel	**1**	**2**	23	7	20	16	21	15	65	40
Machinery & equipment n.e.c.	21	12	19	15	12	7	13	8	65	42
Other nonmetallic mineral	8	10	3	10	11	12	5	11	27	43
Wood & its products, except furniture	16	16	20	17	**2**	**5**	3	5	41	43
Office, accounting & computing machinery	11	**1**	8	**1**	19	22	7	22	45	46
Food & beverages	18	17	15	16	7	9	9	10	49	52
Medical, precision, optical, watches & clocks	4	13	**2**	13	9	15	14	18	29	59
Basic metals	15	19	9	11	18	18	19	12	61	60
Fabricated metal, except machinery	20	18	11	18	16	14	11	14	58	64
Furniture; manufacturing n.e.c.	19	15	21	20	14	13	17	16	71	64
The Five Least Agglomerated Sectors										
Paper & paper products	23	22	13	12	15	19	16	20	67	73
Apparel	17	14	14	21	**5**	21	6	19	42	75
Rubber & plastics	22	21	22	22	13	17	18	17	75	77
Electrical machinery & apparatus n.e.c.	5	20	5	19	17	20	10	21	37	80
Other transport equipment	10	23	17	23	23	23	23	23	73	92

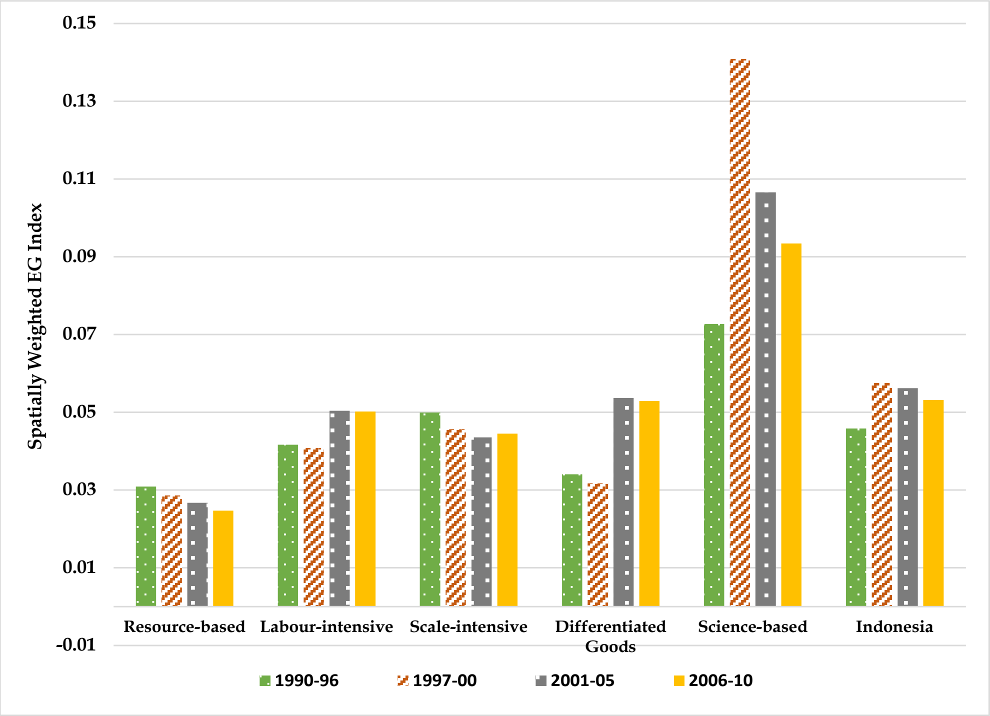


Figure 4.6. Geographic Concentration Pattern in Indonesia (Employment-Based), at City Level

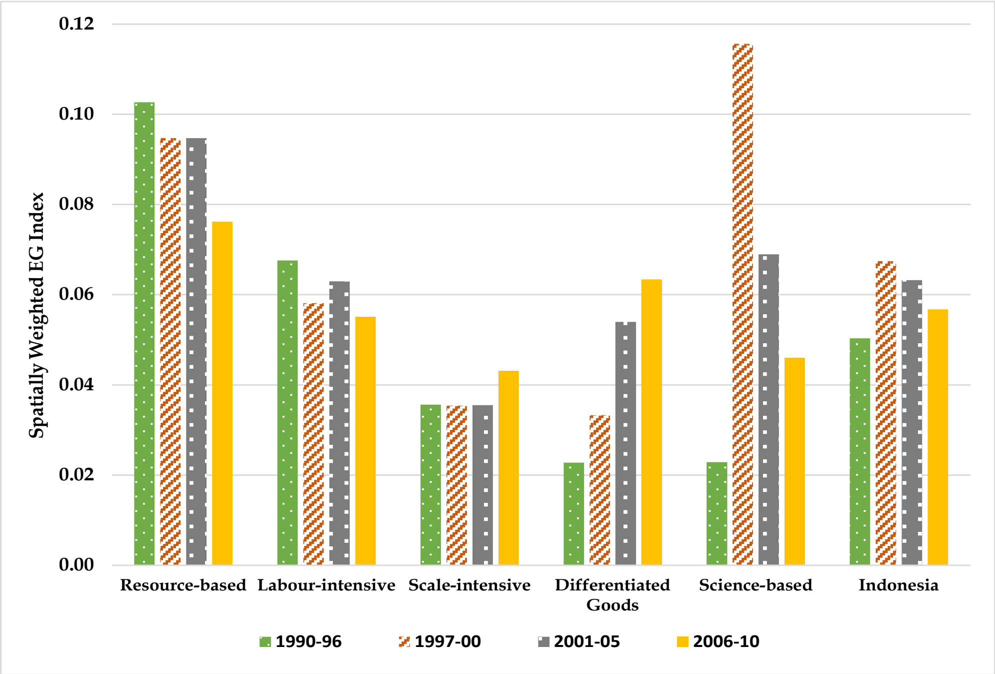


Figure 4.7. Geographic Concentration Pattern in Indonesia (Employment-Based), at Province Level

4.4.3. Determinant of Geographic Concentration

Before we discuss the determinant factor of geographic concentration, we first perform some tests to select the best model of our empirical modeling. We focus on the results of statistic test at city level as reported in Table 4.5.[15] The table indicates that the Hausman-Taylor estimation is the most efficient model. However, the Wald test of heteroscedasticity suggests applying robust standard errors. We will report the estimation results of both standard errors and robust standard errors.

Table 4.5. Testing for model selection.

Employment-Based at City Level

Methods	Aim	Statistic	Remarks
Chow-test	Pooled vs FE	F(63, 1263) = 25.88 F(18, 1263) = 1.04	Industry fixed effect No year fixed effect
Bruch-Pagan LM test	Pooled vs RE	chibar2(01) = 3173.59	RE is more efficient
Hausman-test Overid-test	RE vs FE	chi2(8) = 56.45 Sargan-Hansen statistic = 164.075	FE is more efficient
Hausman-test	HT vs FE	chi2(8) = 4.00	HT is more efficient
Wald test	To test heteroskedasticity	chi2(66) = 2.9e+05	Robust standard error is more appropriate

Value Added-Based at City Level

Methods	Aim	Statistic	Remarks
Chow-test	Pooled vs FE	F(63, 1263) = 20.53 F(18, 1263) = 1.37	Industry fixed effect No year fixed effect
Bruch-Pagan LM test	Pooled vs RE	chibar2(01) = 2326.68	RE is more efficient
Hausman-test Overid-test	RE vs FE	chi2(8) = 40.63 Sargan-Hansen statistic = 89.998	FE is more efficient
Hausman-test	HT vs FE	chi2(8) = 0.38	HT is more efficient
Wald test	To test heteroskedasticity	chi2 (66) = 80600.39	Robust standard error is more appropriate

Tables 4.6 and Table 4.7 report the regression results at the city level.[16] The results seem to be consistent with those found in the literature—namely, increasing returns to scale have positive effects at both the city and province levels. Nonetheless, the role of raw materials is found to be limited at the city level when we use the value-added

[15] We also perform similar tests at the province level and find relatively similar results.

[16] We focus on the city-level analysis since the empirical models at the city level are far better than those at the province level to determine factors of geographic concentration.

measurement. Kim (1995) found that production economies of scale supported localization in U.S. manufacturing, while He et al. (2008) concluded that internal economies of scale contributed to geographical concentration. However, those variables become statistically insignificant when we impose robust standard errors. Meanwhile, a higher skill or knowledge intensity is associated with lower concentration, suggesting that firms with higher-skilled workers tend to be more dispersed.

Furthermore, we found that interaction with the global economy encouraged firms to become more geographically concentrated; this finding is consistent with the results of Ge (2009) and He et al. (2008), both in the case of China. In the case of Indonesia, this result aligns with that of Henderson and Kuncoro (1996), who found there to be a stronger spatial concentration of private manufacturing firms in the large metropolitan areas of Java following the trade liberalization policies of 1983. By calculating a geographic concentration index, Sjöberg and Sjöholm (2004) also revealed that Indonesian manufacturing firms that participated in international trade were more spatially concentrated and that their spatial concentration grew more strongly than did that of nonparticipating firms over the 1980–1996 period. A higher geographic concentration of exporting firms is likely to be associated with the sharing of experience, knowledge, and infrastructure among firms (He et al., 2008). This result also supports the findings of Hill et al. (2008), who investigated regional development dynamics in Indonesia and found superior performance among the regions most connected to the global economy.

We found also that wage negatively affects concentration, which suggests that higher wage rates break down the concentration and push firms to attempt to relocate to other regions with lower wage rates. This finding is consistent with that of Henderson and Kuncoro (1996) and with the arguments of Deichmann et al. (2008) pertaining to the factor price of industrial location. In general, we identified that the effect of export activities on EGS is stronger in employment based and the effect of wage on EGS is larger in value-added based. It is suggesting the relative importance of input factors between labor and capital. Finally, there is evidence that geographic concentration stemmed from economic crisis and decentralization policy in the long term, suggesting that both external shocks changed the pattern of geographic concentration to one that is more spatially concentrated. We also found evidence that resource-based and labor-intensive industries experienced deagglomeration.

Table 4.6. Determinant Geographic Concentration, at City Level

Dependent Variables	**EGS, Employment-Based**					**EGS, Value Added-Based**				
	OLS1	**OLS2**	**RE**	**FE**	**HT**	**OLS1**	**OLS2**	**RE**	**FE**	**HT**
Scale (Ln)	0.125	0.113	0.190**	0.113	0.161*	0.128	0.085	0.143**	0.085	0.115
	[0.115]	[0.111]	[0.089]	[0.111]	[0.092]	[0.093]	[0.091]	[0.068]	[0.091]	[0.072]
Resouce (%)	0.012	0.019	0.022	0.019	0.021	0.047	0.065**	0.059**	0.065**	0.059**
	[0.037]	[0.036]	[0.036]	[0.036]	[0.036]	[0.030]	[0.029]	[0.029]	[0.029]	[0.029]
Skill (%)	-1.030***	-0.689***	-0.747***	-0.689***	-0.725***	-0.122	-0.187	-0.240	-0.187	-0.221
	[0.341]	[0.241]	[0.240]	[0.241]	[0.240]	[0.277]	[0.196]	[0.195]	[0.196]	[0.194]
Export (%)	0.006***	0.005***	0.004**	0.005***	0.005***	0.004***	0.004**	0.003*	0.004**	0.004**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Age (Ln)	0.092	0.116	0.027	0.116	0.039	0.004	0.049	-0.009	0.049	-0.001
	[0.129]	[0.121]	[0.118]	[0.121]	[0.118]	[0.105]	[0.098]	[0.095]	[0.098]	[0.095]
Wagerate (Ln)	-0.106	-0.130**	-0.129**	-0.130**	-0.127**	-0.121*	-0.161***	-0.162***	-0.161***	-0.162***
	[0.079]	[0.059]	[0.058]	[0.059]	[0.058]	[0.064]	[0.048]	[0.047]	[0.048]	[0.047]
Resource-based dummy	-0.813**	-0.826**	-1.225***		-1.247***	-1.347***	-1.273***	-0.965***		-0.986***
	[0.349]	[0.343]	[0.344]		[0.383]	[0.283]	[0.278]	[0.242]		[0.275]
Labour-intensive dummy	-0.978***	-0.994***	-0.454		-0.533	-1.413***	-1.344***	-0.404		-0.478*
	[0.332]	[0.326]	[0.359]		[0.401]	[0.269]	[0.265]	[0.253]		[0.288]
Crisis dummy	0.149	0.036	0.058	0.036	0.055	0.086	0.114*	0.128**	0.114*	0.127**
	[0.167]	[0.078]	[0.078]	[0.078]	[0.078]	[0.135]	[0.063]	[0.063]	[0.063]	[0.063]
Autonomy dummy	-0.219	0.146	0.176	0.146	0.171	-0.132	0.177*	0.197**	0.177*	0.198**
	[0.279]	[0.113]	[0.112]	[0.113]	[0.112]	[0.226]	[0.092]	[0.091]	[0.092]	[0.091]
Constant	-2.228***	-2.370***	-2.518***	-2.661***	-2.410***	-1.460**	-1.400***	-1.571***	-1.712***	-1.450***
	[0.716]	[0.625]	[0.658]	[0.736]	[0.677]	[0.580]	[0.507]	[0.513]	[0.597]	[0.533]
Industry dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time dummies	Y	N	N	N	N	Y	N	N	N	N
N	1355	1355	1355	1355	1355	1355	1355	1355	1355	1355
R^2	0.645	0.639		0.017		0.586	0.578		0.025	

Note: Standard errors are reported in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.7. Determinant Geographic Concentration, at City Level Using Robust SE

Dependent Variables	EGS, Employment-Based					EGS, Value Added-Based				
	OLS1	**OLS2**	**RE**	**FE**	**HT**	**OLS1**	**OLS2**	**RE**	**FE**	**HT**
Scale (Ln)	0.125	0.113	0.19	0.113	0.161	0.128	0.085	0.143	0.085	0.115
	[0.121]	[0.118]	[0.170]	[0.218]	[0.164]	[0.108]	[0.104]	[0.118]	[0.165]	[0.124]
Resouce (%)	0.012	0.019	0.022	0.019	0.021	0.047	0.065*	0.059	0.065*	0.059
	[0.053]	[0.054]	[0.062]	[0.063]	[0.059]	[0.034]	[0.034]	[0.036]	[0.036]	[0.043]
Skill (%)	-1.030**	-0.689***	-0.747***	-0.689***	-0.725***	-0.122	-0.187	-0.24	-0.187	-0.221
	[0.403]	[0.262]	[0.254]	[0.256]	[0.219]	[0.295]	[0.201]	[0.187]	[0.186]	[0.195]
Export (%)	0.006**	0.005**	0.004*	0.005**	0.005**	0.004***	0.004**	0.003	0.004*	0.004*
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]
Age (Ln)	0.092	0.116	0.027	0.116	0.039	0.004	0.049	-0.009	0.049	-0.001
	[0.161]	[0.153]	[0.136]	[0.149]	[0.160]	[0.129]	[0.127]	[0.135]	[0.140]	[0.135]
Wagerate (Ln)	-0.106	-0.130**	-0.129**	-0.130**	-0.127*	-0.121*	-0.161***	-0.162***	-0.161***	-0.162***
	[0.074]	[0.057]	[0.060]	[0.061]	[0.066]	[0.068]	[0.054]	[0.053]	[0.052]	[0.058]
Resource-based dummy	-0.813***	-0.826***	-1.225***		-1.247***	-1.347***	-1.273***	-0.965***		-0.986***
	[0.310]	[0.297]	[0.307]		[0.321]	[0.224]	[0.212]	[0.231]		[0.210]
Labour-intensive dummy	-0.978***	-0.994***	-0.454		-0.533	-1.413***	-1.344***	-0.404		-0.478
	[0.289]	[0.277]	[0.506]		[0.546]	[0.257]	[0.256]	[0.362]		[0.297]
Crisis dummy	0.149	0.036	0.058	0.036	0.055	0.086	0.114*	0.128**	0.114*	0.127**
	[0.133]	[0.076]	[0.087]	[0.085]	[0.085]	[0.133]	[0.065]	[0.060]	[0.058]	[0.053]
Autonomy dummy	-0.219	0.146	0.176*	0.146	0.171*	-0.132	0.177*	0.197**	0.177**	0.198**
	[0.278]	[0.113]	[0.098]	[0.095]	[0.102]	[0.231]	[0.092]	[0.085]	[0.080]	[0.078]
Constant	-2.228***	-2.370***	-2.518***	-2.661**	-2.410***	-1.460**	-1.400**	-1.571**	-1.712*	-1.450**
	[0.771]	[0.700]	[0.922]	[1.167]	[0.913]	[0.645]	[0.580]	[0.688]	[0.896]	[0.707]
Industry dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time dummies	Y	N	N	N	N	Y	N	N	N	N
N	1355	1355	1355	1355	1355	1355	1355	1355	1355	1355
R^2	0.645	0.639		0.017		0.586	0.578		0.025	

Note: Standard errors are reported in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5. Conclusions

This paper presented a general picture of the distribution of economic activities among manufacturing industries in Indonesia. We found that the provinces and cities became more specialized and experienced a greater degree of movement when they faced external shocks. The distribution of manufacturing activity overall slightly changed due to the 1997–98 economic crisis and the enactment of decentralization policy; evidence of this change was particularly compelling at the province and city levels, where firms were currently undergoing a “deconcentration” of sorts.

From the regional specialization data at the city level, we identified that spillover occurs among industries at the three-digit SIC level, rather than at the two-digit SIC level. Furthermore, we found evidence vis-à-vis industrial concentration and economic activity distribution that there are externalities across cities within provinces but not across the provinces themselves. This suggests that firms merely relocate their activities from core cities to periphery ones in the surrounding area so as to maintain benefit externalities, lower transportation costs, and retain market access to core regions. In the industry-group analysis, we found that resource-based industries had the highest level of geographic concentration but that it tended to decrease over time. Deconcentration is also experienced by scale-intensive industries, while differentiated goods and science-based industries became more dispersed. Especially among labor-intensive industries, there is more concentration at the city level but greater dispersal at the province level. These findings confirmed that agglomeration has shifted across cities within each province.

Our empirical results supported theory regarding economies of scale and resource endowment in determining agglomeration and concentration. Furthermore, a firm’s interaction with the global economy does influence the local pattern of that firm’s location; it also has a positive effect on geographic concentration. Meanwhile, the market factor of labor price pushed industries to relocate to areas with cheaper labor cost. Concerning external shocks, there was evidence that either the economic crisis or decentralization policy had a positive relationship with geographic concentration.

CHAPTER 5.

CONCLUSIONS AND POLICY IMPLICATIONS

5.1. Major Findings

This dissertation provided empirical analysis to enrich the study of agglomeration economies. The first paper presented new empirical evidence on the impact of agglomeration economies on plant-level productivity, while considering different economic situation. Aggregate estimates showed that the localization impact is stronger than urbanization. There is also a strong relationship between plant size and the type of agglomeration externalities, which provides clear-cut evidence of the nature of agglomeration economies. This research showed that agglomeration sources have changed with economic cycles. We found that small plants in traditional and heavy industries were relatively flexible in capturing the advantages of agglomeration economies in response to economic situations. These plants adjusted to the practice of having external benefits from urbanization during economic crisis and shifting to receive localization benefits in recovery periods. In other words, there was a change of the industrial structure in Indonesia after the economic crisis.

We also confirmed that the spatial environment of neighboring regions is important to support plant productivity. This conclusion holds, as we found strong evidence of the impact of neighboring agglomeration effects and identified the attenuation of agglomeration economies with greater distance. We identified the farthest agglomeration economies from neighboring regions, which appeared within a radial distance of 35 km. Geographic spillover achieved maximum impact in a shorter distance, between 5 and 20 km. In general, the productivity of plants is most influenced by localization economies of neighboring districts within 5 km, which is a shorter distance than the effect of neighboring urbanization economies (about 5–20 km). These findings likely explain that spatial environments indeed have an inherent tendency to expose regional-scale externalities on plant-level productivity.

The second paper pointed to a key finding that the employment market potential controlling local size has strong effects on determining the magnitudes of externalities and correcting overestimation for each city size classification. We found vigorous evidence of the positive impact of market potential on TFP growth in the long term but not on employment growth. We also provided strong evidence of the importance of specialization and diversity on city-industry growth and that, as suggested by Duranton and Puga (2000), specialized and diverse cities can coexist. It explains that MAR externalities and Jacobs externalities are important for Indonesian manufacturing growth, but the former appears stronger than the latter even though the latter captures a wider range of industries. Additionally, new evidence of Porter externalities appears in the machinery and electronics industries.

The evidence of changing local industrial structure identified in both long-term and medium-term analyses, toward stronger specialization, and new evidence of the role of competition in the medium-term were discovered. The positive effects of specialization on TFP growth and diversity on TFP growth is related to the industrial composition of the manufacturing sector in Indonesia. It suggests that as an industry becomes more mature, cities tend to become more specialized. Moreover, this evidence is supported by the fact that competition is important in stimulating innovation and increased productivity. However, because of the dominating small firms in traditional and heavy industries, the role of diversity is still important. This result supports the idea of the industry lifecycle theory by Duranton and Puga (2001).

Finally, the third paper identified an increasing trend in regional specialization and geographic concentration during the economic crisis, which became a decreasing trend at the onset of setting up a decentralization policy and then again pushed upward. On the other hand, we also identified a declining long-term trend in geographic concentration, albeit a very slow-moving one. We found that higher regional specialization on Java Island and on the most affluent provinces outside Java mark the economic center of the country. Moreover, resource-based and labor-intensive industries saw a declining trend in concentration over the period under study.

This paper provided empirical evidence that supports the assertion that there are relationships among economies of scale, resources, skill, wage rate, and the global economy and industrial location. Our estimations showed that the influence of economies of scale and resource intensity increases geographic concentration, but that of the latter is weaker. Our results also suggested a strong and positive relationship between export activities when there is a high concentration of firms. Furthermore, we found that a high skill rate and high wage rate among industries were associated with greater dispersal in the economic distribution of industries. Moreover, the empirical evidence confirmed that the crisis and decentralization policy influence the rise of geographical concentration.

5.2. Policy Implications

The study invites some policy implications. The first paper suggested the important role of small-sized plants, as we have seen their existence and contributions to Indonesian economy during the crisis period and afterwards. The government may provide financial aid for continuing small plants' productivity. Furthermore, the government should also promise a good investment climate for large plants to continue operating more productively. Finally, the central and local governments should together take into account the importance of agglomeration economies in designing its spatial industrial policy—for instance, in developing economic zones and building network infrastructure to facilitate spatial externalities across regions.

The second paper also suggested several policy actions to encourage productivity growth, including providing sufficient investment and infrastructure in both core and peripheral areas. For core regions, the investment will facilitate cross-fertilization of knowledge across industries benefiting from Jacob externalities especially for small firms. Meanwhile, an investment in periphery regions will also attract many firms to relocate their plants to these areas and form new cluster industries, which would benefit from MAR externalities.

Finally, the findings in third paper gave some policy implications. Policymakers would be well advised to harness an increase in regional specialization to improve economic distribution across the country. Furthermore, the governments of the periphery cities near the core cities should work as "buffer zones" and anticipate the relocation of firms. Finally, the strong connection between the global economy and geographic concentration points to the importance of having special economic zones that have good access to the international economy.

5.3. Limitations and Future Research

A limitation of this study was that we did not have precise coordinates for plants, so we counted the neighboring effects from aggregate levels of cities. Therefore, this study measured spatial agglomeration variables; i.e., neighboring localization, employment market potential, and spatially weighted Ellison-Glaeser index relied much on the spatial boundaries of the administrative units. We depended solely on the distance between cities instead of between plants. Unfortunately, the administrative boundary may not accurately reflect and capture the economic, social, historical, and political aspects of urban environments.

Therefore, further work needs to be done to define Indonesia's urban areas beyond the traditional administrative boundary. It should be based on certain criteria of workers' mobility between the core and periphery cities from commuting flows data. Therefore, future research should concentrate on the impact of agglomeration economies on plant-level productivity and local productivity growth based on that proposed urban areas definition.

APPENDIXES

Appendix to Chapter 2

Appendix 2.1 Data Management Process

The study employed the electronic and unpublished database of the annual survey of large and medium firms (*Statistik Industri*), which was conducted by Indonesia's Central Bureau of Statistics (BPS) for the period 1990–2010. The data covered all manufacturing industries, which allowed us to examine and enable the cross-industry and cross-region analysis. According to the BPS, the survey respondents were companies that employed 20 or more persons and also included new industrial companies that just started commercial production. The research referred to the individual observations, which could be either a firm or an establishments (or plant), as the information did not distinguish between a standalone establishment and a firm with many establishments. In the analysis, we referred to both the term "firm" and "establishment" interchangeably, but one should consider it as the latter concept primarily.

The BPS survey asks the firms and plants about several key variables of firm characteristics such as start of operations, number of employees, share of ownership distribution, wages, inputs, outputs, value added, and other variables. The respondents are all the manufacturing establishments employing at least 20 people. The observations of this survey have been identified based on a firm identifier, location and industrial classification, or the International Standard of Industrial Classifications (ISIC).

A. Data Codification

1) Bridging Firm Identifiers

While the manufacturing data sets are available from 1975 to 2010, we decided to skip the data before 1990 since the capital stock data, which is approximately by fixed investments, was available only from 1988. In order to ensure that the data we uses were reliable, a series data set was created by appending the plant observations based on individual establishment codes. Thereafter, a panel data set was constructed that spanned from 1990 to 2010.

In order to identify the firms during different periods of the survey, the BPS recorded two kinds of Indonesia firm identifiers, namely, plant identity codes (PSID) and *Nomor Kode Induk Perusahaan* (NKIP), which were used interchangeably. We were fortunate to have a data series that for some years contained both codes. It allowed us to develop a concordance firm's code between PSID and NKIP. From this table, we created a PSID for the remaining years when the PSID codes were not available or the code was suspiciously inconsistent, like in the 2001 survey.

2) Building Consistent Industrial Codes

The manufacturing data used the industrial codes that were published by BPS, namely, *Klasifikasi Lapangan Usaha Indonesia* (KLUI). The KLUI is the field of business classification that is based on the ISIC for all economic activities. Indeed, the KLUI has changed from its first development in 1968.

The span of this study was from 1990 to 2010 and included the three periods of ISIC from 1990 to 1997 where the data used were ISIC revision 2 (ISICrev2), while from 1998 to 2009, the data used were ISIC revision 3 (ISICrev3); however, since 2010, the office adopted UN standards to publish ISIC revision 4 (ISICrev4). Fortunately, we have a table of concordance of ISICrev2 and ISICrev3 codes and concordance of ISICrev3 and ISICrev4 codes that were provided by BPS. To obtain strongly consistent codes, we used both tables in the five-digit SIC industries to assign an industrial code for a complete time series by bridging the data from 1990 to 2010.[17]

3) Building Consistent Regional District Codes

In 1990, Indonesia consisted of 26 provinces and 284 districts after excluding East Timor. By 2010, the country had 33 provinces and 497 districts. As we concerned ourselves with the spatial aspect, we regrouped all newly created regions back into the original districts of 1990. This regrouping allowed us to have comparable regional characteristics across the entire period of this study.

B. Data Cleaning

Regarding data cleaning, there were primarily three main problems with the manufacturing data.

1. *Possible mistakes in data keypunching*: The constructed panel was adjusted for possible mistakes in data keypunching and inconsistencies in the input across firms or plants such as the starting year of operation, the different ISIC used, and the sum of the percentage of ownership. By spotting the firm identifier, we examined the consistencies of imputing the information of similar firms. If we found inaccurate

[17] The information is provided by BPS in Manual Manufacturing Survey (*Survei Industri Besar dan Sedang*) retrieved from http://sirusa.bps.go.id/index.php?r=sd/view&kd=2610&th=2012 accessed on June 1, 2013.

information, we made an adjustment to retain correct and consistent information. Furthermore, to generate variables such as output, value added, intermediate input, materials, and so on, we resorted to manual accounting to calculate those variables instead of using reported variables that may have contained mistakes due to typing errors.

2. *Missing observation and non-reporting items*: The data cleaning also addressed the problem of missing observations and non-reported items. These may be due to the fact that some firms opted out of the survey or they exited the market because they downsized to less than 20 employees, and the firm no longer met the definition of a medium or large manufacturer. To solve these problems, we estimated the cell value by conducting linear interpolation or an average of the value within a window of two consecutive years for certain variables. However, this approach does not apply for missing observations in the beginning or end period of series since we do not know whether firm still exists.

3. *Duplicate observations* were another problem that we saw, as was pointed by Jacob (2006). We found that a few observations had similar numbers for the main part of the variable set such as number of employees, output, value added, etc. We suspected confidently that these double observations were due to the plants that belonged to a similar firm. The manufacturing survey asked for plant-level information, so for a multiplant firm, the headquarters may have completed the questionnaire with the consolidated value of all the plants owned. Therefore, to account for this, we selected only one observation for these duplicate observations.

Finally, for generating a panel series with unique observations, we resorted to the following steps:

1. Exclude East Timor as part of Indonesia.
2. Remove the observations if it has zero values of a key variable such as input, output, value added, and labor.
3. Remove the observation with repeated values of the key variables or similar PSID.
4. Remove the outlier observations that have productivity values of the ratio between output to labor and value added to labor were below the lowest (1 percentile) and higher than the highest (99 percentile).
5. Remove the observation for which capital stock cannot be estimated.

C. Data Correction

The strategies to correct errors that were due to typographical errors and missing observations for some of the key variables are discussed below.

1. *Output, value added, and labor*: In general, we corrected these errors by using an "interpolation approach" within a consecutive window of two consecutive years in order to fill in the missing years. This was done especially for the labor variable, where if the missing number was in the beginning of an individual establishment series, we then replaced that empty value with a similar value of the following year.

2. *Location*: Because of the implementation of regional autonomy and fiscal decentralization, the number of districts almost doubled compared to 1990.

This, in turn, created some inconsistencies in the district codes across the years due to the change of regional codes. To ensure comparability from 1990 to 2010, we then revised the codes for the provinces and districts according to 1990's figures. We used the district level as a basis for our analysis.

3. *Industry classification:* To correct the missing observation of the ISIC, we assigned a median of ISIC number for the same establishment that we identified by PSID. Furthermore, we changed the ISICrev2 and ISICrev4 to ISICrev3 to make a comparison across the industries.

4. *Age*: The age of the firm was generated by calculating the period between the survey year and year of each establishment's inception. Unfortunately, there were some inconsistencies and varied years reported over time for some establishments. To solve this problem, we calculated the median of the starting years that were available for each establishment, and we replaced all values with the median value. However, in those cases where the median year was not available, we picked the earliest year reported among the starting years.

5. *Ownership:* We controlled the total percentage as 100%. We then cleaned the imputed percent value for the share of foreign, domestic, and government to remove false and omitted zeros from the keypunch error. We considered the share value of the preceding year and the closest following year to fill in these missing share values.

In the beginning of a panel series, we collected as many as 459,677 observations, but towards end of this step, we constructed an unbalanced panel of the cleaned observations with a sample of 442,157 unique observations. The unbalanced panel represents 96.19% of the reported observations. Table A.2.1 below shows the number of plant observations by size, economic cycles, and industry groups.

Table A.2.1. Plants' Observation by Size, Economic Cycles and Industry Groups.

		Plant Size			Economic Cycles			Industry Groups					
Year	**# Plants**	**Small**	**Medium**	**Large**	**Boom**	**Crisis**	**Recovery**	**Traditional**	**Heavy**	**Transport**	**Machinery & Electronics**	**High-Technology**	**Other Manufacturing**
1990	15,625	8,695	4,845	2,085	15,625	0	0	10,074	3,804	417	696	90	544
1991	15,983	8,459	5,084	2,440	15,983	0	0	10,208	3,945	430	765	104	531
1992	17,125	8,983	5,437	2,705	17,125	0	0	10,934	4,190	477	844	135	545
1993	17,638	8,902	5,836	2,900	17,638	0	0	11,197	4,342	510	899	140	550
1994	18,484	9,199	6,210	3,075	18,484	0	0	11,592	4,615	527	1,012	175	563
1995	20,929	11,139	6,595	3,195	20,929	0	0	12,974	5,355	562	1,215	200	623
1996	22,333	12,207	6,840	3,286	22,333	0	0	13,783	5,735	613	1,300	207	695
1997	21,753	11,656	6,835	3,262	0	21,753	0	13,415	5,609	583	1,250	217	679
1998	20,811	11,165	6,432	3,214	0	20,811	0	13,022	5,364	516	1,080	218	611
1999	21,448	11,405	6,694	3,349	0	21,448	0	13,523	5,494	538	1,034	232	627
2000	21,539	11,333	6,818	3,388	0	21,539	0	13,652	5,525	539	958	236	629
2001	20,767	10,741	6,646	3,380	0	0	20,767	13,463	5,193	552	730	228	601
2002	20,528	10,564	6,609	3,355	0	0	20,528	13,229	5,117	595	725	265	597
2003	19,758	10,020	6,437	3,301	0	0	19,758	12,668	4,969	579	688	268	586
2004	20,107	10,312	6,477	3,318	0	0	20,107	12,985	4,972	579	690	276	605
2005	20,093	10,376	6,490	3,227	0	0	20,093	13,089	4,910	563	665	257	609
2006	28,547	16,704	8,391	3,452	0	0	28,547	19,610	6,230	661	750	287	1,009
2007	27,224	15,844	7,964	3,416	0	0	27,224	18,588	6,000	651	730	283	972
2008	24,981	14,260	7,427	3,294	0	0	24,981	16,897	5,645	619	678	282	860
2009	23,804	13,349	7,189	3,266	0	0	23,804	15,985	5,492	606	656	269	796
2010	22,680	12,334	7,022	3,324	0	0	22,680	15,228	5,369	611	649	273	550
Total	442,157	237,647	138,278	66,232	128,117	85,551	228,489	286,116	107,875	11,728	18,014	4,642	13,782

Table A.2.2. Variable Definition and Data Source

Variable	Label	Definition	Source
Dependent Variable			
Total factor productivity	TFP	Total factor of productivity using the Letvin-Petrin control function approach	Estimated from SI 1990-2010, BPS
Plant Characteristics			
Age	Age	Age of plant as a difference between the year production started and year of survey	SI 1990-2010, BPS
Size	Size	Number of workers	SI 1990-2010, BPS
Foreign ownership	DFDI	=1 if foreign has at least 10% share of ownership	Constructed
Government ownership	DGov	=1 if central or local government has at least 50% share of ownership	Constructed
Exporter	DEexp	=1 if plant exports	Constructed
Regional Characteristics			
Coastal	Coastal	Percentage of villages located off shore in a district/city	PODES 1990-2011
Electricity	Electricity	Percentage of households who have access to electricity in a district/city	PODES 1990-2011
Road density	Roaddens	Length of road infrastructure per square kilometers in a province	BPS and Ministry of Home Affairs
Distance to intl. seaport	Distport	GIS distance from capital of district/city to capital of city where the closest international port is located	Constructed
Agglomeration Economies			
Localization (plants)	Locplant	Own industry plant in the district/city (plants)	Calculated from SI 1990-2010, BPS
Average industry-region employment	Avrindregemp	Average industry employment in the district/city minus own plant (person)	Calculated from SI 1990-2010, BPS
Urbanization	Urbanization	Employment density in the district/city	Calculated from SI 1990-2010, BPS
Neighbor Agglomeration Economies			
Localization (plants)	WLocplant-δ	Sum of weighted distance of Locplant from neighboring regions within threshold (δ)km distance	Constructed
Urbanization	WUrbanization-δ	Sum of weighted distance of urbanization from neighboring regions within threshold (δ)km distance	Constructed

Notes: BPS is the Indonesian Central Bureau of Statistics. SI is the Annual Survey of Large and Medium Firms. PODES is the Village Potential Survey.

Table A.2.3. Plant-Level Production Function Estimation

3 Digits-ISIC	Industry	OLS (Factor share)		Levin Petrin Production Function			
		α	β	α	β	α+β	Wald test
151	Meat, fish, fruit, vegetables, oils	0.296	0.704	0.086	0.666	0.752	44.3***
152	Dairy products	0.105	0.895	0.169	1.074	1.243	3.04*
153	Grain mill products, animal feeds	0.252	0.748	0.247	0.600	0.847	7.64***
154	Other foods	0.195	0.805	0.135	0.850	0.985	0.3
155	Beverages	0.154	0.846	0.213	0.876	1.089	2.1
160	Tobacco products	0.171	0.829	0.146	0.848	0.994	0.0
171	Spinning, weaving & textile finish	0.200	0.800	0.131	0.620	0.751	49.04***
172	Other textiles	0.166	0.834	0.250	0.747	0.997	0.0
173 & 174	Knitted, crocheted fab., articles, and Kapok	0.162	0.838	0.172	0.750	0.922	4.57**
181&182	Apparel and fur	0.145	0.855	0.188	0.783	0.970	1.7
191	Leather tanning and products	0.173	0.827	0.245	0.859	1.105	1.8
192	Footwear	0.076	0.924	0.021	0.876	0.897	2.4
201	Wood saw milling and planning	0.170	0.830	0.104	0.720	0.823	22.66***
202	Wood product	0.190	0.810	0.119	0.817	0.936	4.38**
210	Paper and products	0.177	0.823	0.224	0.836	1.060	1.3
221 & 222	Publishing and printing	0.087	0.913	0.151	0.800	0.951	2.0
223	Media recording reproduction	0.112	0.888	0.604	0.733	1.337	1.1
231 & 232	Coke oven and refined petroleum products	0.036	0.964	0.273	0.793	1.067	0.1
241	Basic chemicals	0.203	0.797	0.137	0.788	0.925	1.3
242	Industries other chemical products	0.230	0.770	0.170	0.672	0.843	15.66***
243	Manmade fibers	0.129	0.871	0.494	1.111	1.605	4.00**
251	Rubber products	0.251	0.749	0.191	0.573	0.764	32.99***
252	Plastic products	0.198	0.802	0.222	0.739	0.961	3.08*
261	Glass products	0.086	0.914	0.595	0.818	1.413	7.8***
262	Porcelain products	0.269	0.731	0.323	0.605	0.928	0.3
263	Clay products	0.162	0.838	0.278	0.774	1.051	0.2
264	Cement and lime products	0.193	0.807	0.261	0.838	1.100	1.8
265	Marble and granite product	0.167	0.833	0.246	0.817	1.063	0.8
266	Asbestos products	0.077	0.923	0.186	1.032	1.218	0.4
269	Other nonmetallic products	0.196	0.804	0.313	0.808	1.121	0.2
271	Basic iron and steel	0.167	0.833	0.011	0.835	0.845	0.8
272	Basic precious, nonferrous	0.311	0.689	0.039	0.479	0.519	4.81**
273	Iron and steel smelting product	0.248	0.752	0.264	0.525	0.789	1.5
281	Structural metal products	0.126	0.874	0.116	0.978	1.094	2.6
289	Other fabricated metal products	0.202	0.798	0.247	0.671	0.918	6.81***
291	General purpose machinery	0.139	0.861	0.235	0.845	1.080	1.3
292	Special purpose machinery	0.221	0.779	0.175	0.686	0.861	6.11**
293	Domestic appliances n.e.c.	0.027	0.973	0.044	0.798	0.842	1.8
311	Electrical motors, generators, etc.	0.194	0.806	0.333	0.741	1.075	0.2
312	Electrical distribution equipment	0.175	0.825	0.344	0.809	1.153	1.0
313	Insulated wire, cable	0.030	0.970	0.077	0.872	0.949	0.1
314	Batteries and cells	0.113	0.887	0.267	1.008	1.276	3.65*
315	Lamps and equipment	0.124	0.876	0.158	0.616	0.774	0.8
319	Other electrical equipment n.e.c.	0.039	0.961	0.508	0.715	1.224	0.3

Table A.2.3. Plant-Level Production Function Estimation (cont.)

3 Digits-ISIC	Industry	OLS (Factor share)		Levin Petrin Production Function			
		α	β	α	β	α+β	Wald test
300 & 321	Office, acc., computing machinery & electronic components	0.190	0.810	0.122	0.595	0.718	2.83*
322 & 323	TV and radio transmitters, and TV, radio, video equipment	0.083	0.917	0.060	0.809	0.869	1.0
331	Medical, measuring equipment	0.113	0.887	0.245	0.841	1.086	1.7
332& 333	Optical, photographic equipment, watches, and clocks	0.105	0.895	0.237	0.829	1.066	0.1
341	Motor vehicle assembly	0.035	0.965	0.935	0.600	1.535	0.2
342	Motor vehicle bodies	0.134	0.866	0.033	0.789	0.822	1.8
343	Motor vehicle components	0.214	0.786	0.291	0.740	1.030	0.0
351	Building and repairing ships and boats	0.225	0.775	0.213	0.854	1.067	1.3
352 & 353	Manufacture of railway and aircraft	0.540	0.460	0.826	0.673	1.498	0.3
359	Motorcycle, bicycle, other	0.126	0.874	0.200	0.797	0.997	0.0
361	Furniture	0.138	0.862	0.072	0.783	0.855	28.54***
369	Jewelry, sports goods, games	0.131	0.869	0.127	0.784	0.911	8.26***
371	Metal waste and scrap recycling	0.127	0.873	0.485	1.458	1.942	1.7
372	Non-metal waste and scrap recycling	0.080	0.920	0.326	0.808	1.134	0.4

Note. α is the capital coefficient and β is the labor coefficient. Wald test of constant returns to scale is a test where the sum of the coefficients equals 1. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix to Chapter 3

Table A.3.1.Variable Definitions and Data Sources.

Variable	Label	Definition	Source
TFP Growth	TFPgrowth	The Industry-Region of Total factor of productivity growth using Letvin Petrin control function approach	Estimated from SI 1990-2010, BPS
Employment Growth	Employgrowth	The Industry-Region of employment growth	Calculated from SI 1990-2010, BPS
Industry-Regional Characteristics			
Initial TFP	TFP	TFP level at the beginning year of growth estimation	Estimated from SI 1990-2010, BPS
Initial employment	Emp	Employment level at the beginning year of growth estimation	Calculated from SI 1990-2010, BPS
Initial wage rate level	Wage	Wage level at the beginning year of growth estimation	Calculated from SI 1990-2010, BPS
Regional industry average	Avg. Plant age	Age average of plant as a difference between year started production and year of survey in region	Calculated from SI 1990-2010, BPS
Regional Characteristics			
Regional employment	Regemp	Number of workers in region	Calculated from SI 1990-2010, BPS
Market Potential	Mpemp	Employment number in a district/city and respected its neighboring regions (Holl ,2014)	Calculated from SI 1990-2010, BPS
Land area	Area	Land area of region in square kilometers	Ministry of Home Affair
Non-agriland	Nonagriland	Share of non-agricultural land in a district/city	PODES 1990-2011
Agglomeration Economies			
Specialization	Spe	Ratio of the number of employments in the district/city-industry to the total number of employments in district/city, divided by the number of employments in the industry to the number of employment in the nation (Combes, 2000)	Calculated from SI 1990-2010, BPS
Competition	Comp	Index from inversion of district/city herfindahl index using plant's employment number(Combes, 2000)	Calculated from SI 1990-2010, BPS
Diversity	Diversity	Index from inversion of district/city herfindahl index using employment number from the rest of economy in respected region (Maroccu et al., 2012)	Calculated from SI 1990-2010, BPS

Note. BPS is the Indonesian Central Bureau of Statistics. SI is Annual Survey of Large and Medium Firm. PODES is Village Potential Survey.

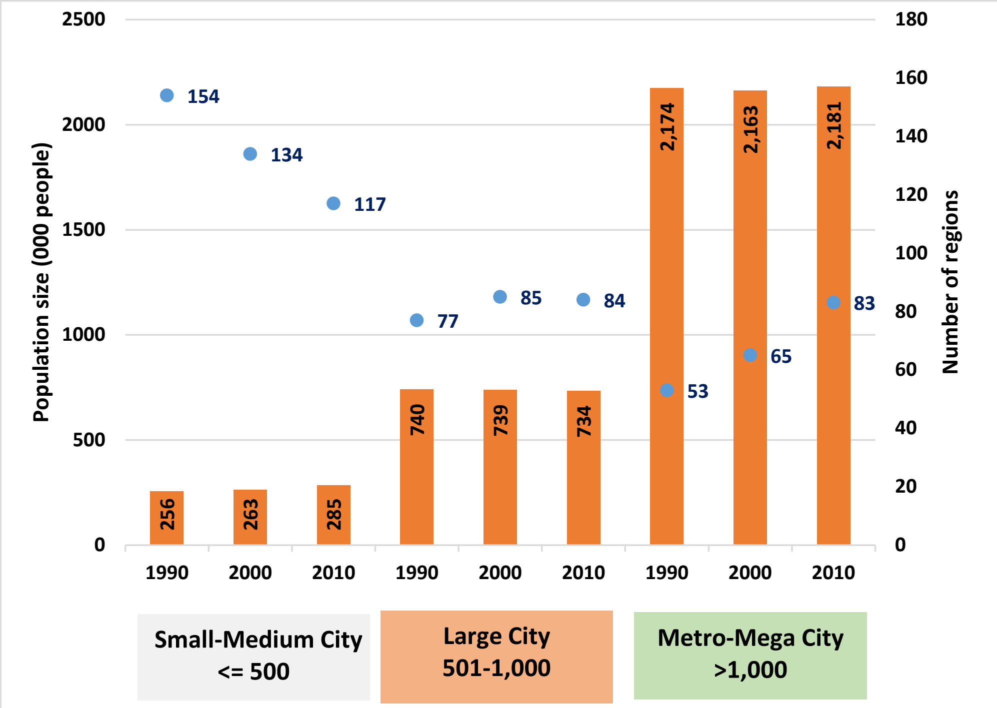


Figure A.3.1. Distribution of City Size.

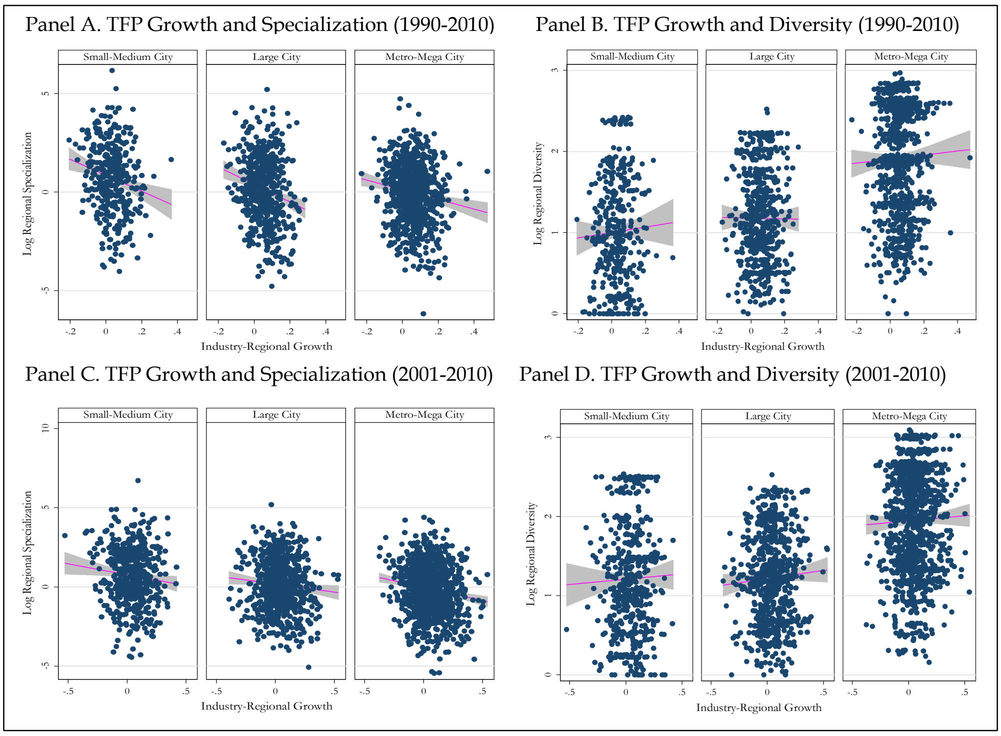


Figure A.3.2. The Relationship between TFP Growth and Agglomeration Externalities

Appendix to Chapter 4

Table A.4.1. List of Three-Digit ISIC Codes based on OECD (1987) Classification

SIC3	OECD Classification	SIC3	OECD Classification
	Resource-based industries		**Differentiated goods**
151	Meat, fish, fruit, vegetables, oils	291	General purpose machinery
152	Dairy products	292	Special purpose machinery
153	Grain mill products, animal feeds	293	Domestic appliances n.e.c.
154	Other foods	311	Electrical motors, generators, etc
155	Beverages	312	Electrical distribution equipment
160	Tobacco products	313	Insulated wire, cable
201	Wood saw milling and planning	314	Batteries and cells
202	Wood products	315	Lamps and equipment
210	Paper and products	319	Other electrical equipment n.e.c.
251	Rubber products	322	TV and radio transmitters
252	Plastic products	323	TV, radio, video equipment
		333	Watches, clocks
	Labor-intensive industries	341	TV color vehicle assembly
171	Spinning, weaving & textile finish	342	Motor vehicle bodies
172	Other textiles	343	Motor vehicle components
173	Knitted, crocheted fab., articles	351	Ship building, repair
174	Kapok	352	Railway equipment
181	Apparel	359	Motorcycle, bicycle, other
182	Fur articles		
191	Leather tanning and products		**Scale-intensive industries**
192	Footwear	221	Publishing
281	Structural metal products	222	Printing
289	Other fabricated metal products	223	Media recording reproduction
		231	Coke oven products
	Science-based industries	232	Refined petroleum products
242	Industries other chemical products	241	Basic chemicals
300	Office, accounting, computing machinery	243	Manmade fibers
321	Electronic components	261	Glass products
331	Medical, measuring equipment	262	Porcelain products
332	Optical, photographic equipment	263	Clay products
353	Aircraft, spacecraft	264	Cement and lime products
		265	Marble and granite product
		266	Asbestos products
		269	Other nonmetallic products
		271	Basic iron and steel
		272	Basic precious, nonferrous
		273	Iron and steel smelting product
		361	Furniture
		369	Jewelry, sports goods, games
		371	Metal waste and scrap recycling product
		372	Nonmetal waste and scrap recycling product

BIBLIOGRAPHY

Abdel-Rahman, H. M., & Anas, A. (2004). Theories of systems of cities. *Handbook of Regional and Urban Economics*, 4, 2293-2339.

Almeida, R. (2007). Local economic structure and growth. *Spatial Economic Analysis*, *2*(1), 65-90.

Almeida, R., & A.M. Fernandes. (2013). Explaining local manufacturing growth in Chile: the advantages of sectoral diversity. *Applied Economics*, *45*(16), 2201-2213.

Amiti, M., & Cameron, L. (2007). Economic geography and wages. *The Review of Economics and Statistics*, *89*(1), 15-29.

Arnold, J.M., & Javorcik, B. S. (2009). Gifted kids or pushy parents? Foreign direct investment and plant productivity in Indonesia. *Journal of International Economics*, *79*(1), 42-53.

Aswicahyono, H., Hill, H., & Narjoko, D. (2010). Industrialisation after a deep economic crisis: Indonesia. *Journal of Development Studies, 46*(6), 1084–1108.

Baum, C. F., Schaffer, M. E., & Stillman, S. (2007). Enhanced routines for instrumental variables/GMM estimation and testing. *Stata Journal, 7*(4), 465-506.

Beaudry, C., & Schiffauerova, A. (2009). Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Research Policy, 38*(2), 318-337.

Bird, K. (1999). Concentration in Indonesia Manufacturing, 1975–93. *Bulletin of Indonesian Economic Studies*, *35*(1), 43-73.

Blalock, G., & Gertler, P.J. (2008). Welfare gains from foreign direct investment through technology transfer to local suppliers. *Journal of International Economics*, *74*(2), 402-421.

Brakman, S., Garretsen, H., & Van Marrewijk, C. (2009). *The new introduction to geographical economics*. Cambridge: Cambridge University Press.

Braunerhjelm, P., & Borgman, B. (2004). Geographical concentration, entrepreneurship and regional growth: Evidence from regional data in Sweden, 1975-99. *Regional Studies, 38*(8), 929-947.

Brülhart, M. (2001). Evolving geographical concentration of European manufacturing industries. *Weltwirtschaftliches Archiv, 137*(2), 215-243.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business and Economic Statistics*, *29*(2), 238-249.

Cingano, F., & Schivardi, F. (2004). Identifying the sources of local productivity growth. *Journal of the European Economic Association*, *2*(4), 720-744.

Combes, P. P. (2000). Economic structure and local growth: France, 1984–1993. *Journal of Urban Economics*, *47,* 329-355.

Combes, P. P., & Overman, H. G. (2004). The spatial distribution of economic activities in the European Union. *Handbook of Regional and Urban Economics*, *4,* 2845-2909.

Combes, P. P., Magnac, T., & Robin, J. M. (2004). The dynamics of local employment in France. *Journal of Urban Economics*, *56*(2), 217-243.

Combes, P. P., Duranton, G., Gobillon, L., & Roux, S. (2010). Estimating agglomeration economies with history, geology, and worker effects. In Glaeser, E.L. (Ed), *Agglomeration Economics* (pp. 15-66). Chicago: University of Chicago Press.

Combes, P. P., Duranton, G., Gobillon, L., Puga, D., & Roux, S. (2012). The productivity advantages of large cities: Distinguishing agglomeration from firm selection. *Econometrica*, *80*(6), 2543-2594.

Day, J., & Ellis, P. (2013). Growth in Indonesia's manufacturing sectors: urban and localization contributions.*Regional Science Policy and Practice*, *5*, 343-368.

Deichmann, U., Kaiser, K., Lall, S. V., & Shalizi, Z. (2005). *Agglomeration, transport and regional development in Indonesia* (World Bank Policy Research Working Paper No. 3477). Washington, DC: World Bank.

Deichmann, U., Lall, S. V., Redding, S. J., & Venables, A. J. (2008). Industrial location in developing countries. *The World Bank Research Observer*, *23*(2), 219-246.

Devereux, M. P., Griffith, R., & Simpson, H. (2004). The geographic distribution of production activity in the UK. *Regional Science and Urban Economics*, *34*(5), 533-564.

De Groot, H. L., Poot, J., & Smit, M. J. (2009). Agglomeration externalities, innovation and regional growth: theoretical perspectives and meta-analysis. In Capello, R., & Nijkamp, P. (Eds.), *Handbook of regional growth and development theories* (pp. 256-281). Cheltenham, UK: Edwar Elgar.

De Lucio, J. J., Herce, J. A., & Goicolea, A. (2002). The effects of externalities on productivity growth in Spanish industry. *Regional Science and Urban Economics*, *32*(2), 241-258.

Dekle, R. (2002). Industrial concentration and regional growth: evidence from the prefectures. *Review of Economics and Statistics*, *84*(2), 310-315.

Duranton, G., & Overman, H. G. (2005). Testing for localization using micro-geographic data. *The Review of Economic Studies*, *72*(4), 1077-1106.

Duranton, G., & Puga, D. (2000). Diversity and specialisation in cities: why, where and when does it matter?. *Urban Studies*, *37*(3), 533-555.

Duranton, G., & Puga, D. (2001). Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review*, 1454-1477.

Duranton, G., & Puga, D.(2014). The Growth of cities. In Aghion, P., & Durlauf, S. *Handbook of economic growth* 2 (pp. 781-853). Oxford,UK: North Holland. http://dx.doi.org/10.1016/B978-0-444-53540-5.00005-7.

Ellison, G., & Glaeser, E. L. (1997). Geographic concentration in US manufacturing Industries: a dartboard approach. *Journal of Political Economy*, *105*(5), 889-927.

Fujita M., Krugman, P. & Venables, A. (1999). The Spatial Economy. Cities, Regions and International Trade. Cambridge: MIT Press

Ge, Y. (2009). Globalization and industry agglomeration in China. *World Development*, *37*(3), 550-559.

Gill, I. S., & Goh, C. C. (2010). Scale economies and cities. *The World Bank Research Observer*, *25*(2), 235-262.

Graham, D. J. (2009). Identifying urbanisation and localisation externalities in manufacturing and service industries. *Papers in Regional Science*, *88*(1), 63-84.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). *Growth in Cities. Journal of Political Economy*, *100*(6), 1126-52.

Glaeser, E.L. &Maré, D.C. (2001). Cities and Skills, *Journal of Labor Economics*, *19*(2), 316–342.

Glaeser, E. L., & Resseger, M. G. (2010). The complementarity between cities and skills. *Journal of Regional Science*, *50*(1), 221-244.

Guimarães, P., Figueiredo, O., & Woodward, D. (2011). Accounting for neighboring effects in measures of spatial concentration. *Journal of Regional Science*, *51*(4), 678-693.

Hanson, G.H. (2001). Scale economies and the geographic concentration of industry. *Journal of Economic Geography*, *1*(3), 255-276.

He, C., & Pan, F. (2010). Economic transition, dynamic externalities and city-industry growth in China. *Urban Studies*, *47*(1), 121-144.

He, C., Wei, Y. D., & Xie, X. (2008). Globalization, institutional change, and industrial location: Economic transition and industrial concentration in China. *Regional Studies*, *42*(7), 923-945.

Henderson, J. V. (1986). Efficiency of resource usage and city size. *Journal of Urban Economics*, *19*(1), 47-70.

Henderson, J.V. (2003). Marshall's scale economies. *Journal of Urban Economics*, *53*(1), 1-28.

Henderson, J.V., & Kuncoro, A. (1996). Industrial centralization in Indonesia. *The World Bank Economic Review*, *10*(3), 513-540.

Henderson, J.V., Lee, T., & Lee, Y. J. (2001). Scale externalities in Korea. *Journal of Urban Economics*, *49*(3), 479-504.

Henderson, J.V., Kuncoro, A., & Turner, M. (1995). Industrial development in cities. *Journal of Political Economy*, 1067-1090.

Hill, H., Resosudarmo, B. P., & Vidyattama, Y. (2008). Indonesia's changing economic geography. *Bulletin of Indonesian Economic Studies*, *44*(3), 407-435.

Holl, A. (2012). Market potential and firm-level productivity in Spain. *Journal of Economic Geography*, 12, 1191-1215.

Jacob, J. (2006). International Technology Spillovers and Manufacturing Performance in Indonesia, Ph.D. Dissertation at Technische Universities Eindhoven, the Netherlands.

Jacob, J., & Meister, C. (2005). Productivity gains, technology spillovers and trade: Indonesian manufacturing, 1980-96. *Bulletin of Indonesian Economic Studies, 41*(1), 37-56.

Kim, S. (1995). Expansion of markets and the geographic distribution of economic activities: the trends in US regional manufacturing structure, 1860-1987. *The Quarterly Journal of Economics*, 881-908.

Midelfart-Knarvik, K. H., & Overman, H. G. (2002). Delocation and European integration: is structural spending justified?. *Economic Policy*, *17*(35), 321-359.

Krugman, P. (1991a). Geography and trade, MIT Press, Cambridge, MA.

Krugman, P. (1991b). Increasing returns and economic geography. *Journal of Political Economy, 99*(3): 483:499.

Kuncoro, A. 2009. Spatial agglomeration, firm productivity and government policies in Indonesia: concentration and deconcentration in manufacturing sector, in: Yukon, H., and Bocchi, A.M. (Eds.), *Reshaping Economic Geography in East Asia*, a companion to the World Development Report 2009.

Lee, B. S., Jang, S., &Hong, S. H. (2010). Marshall’s scale economies and Jacobs’ externality in Korea: the role of age, size and the legal form of organization of establishments. *Urban Studies*, *47*(14), 3131-3156.

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, *70*(2), 317-341.

Lu, J., & Tao, Z. (2009). Trends and determinants of China's industrial agglomeration. *Journal of Urban Economics*, *65*(2), 167-180.

Marcon, E., & Puech, F. (2003). Evaluating the geographic concentration of industries using distance-based methods. *Journal of Economic Geography*, *3*, 409-428.

Maré, D. C., & Graham, D. J. (2013). Agglomeration elasticities and firm heterogeneity. *Journal of Urban Economics*, *75*, 44-56.

Marrocu, E., Paci, R., & Usai, S. (2013). Productivity growth in the Old and New Europe: the role of agglomeration externalities. *Journal of Regional Science*, *53*(3), 418-442.

Martin, P., Mayer, T., & Mayneris, F. (2011). Spatial concentration and plant-level productivity in France. *Journal of Urban Economics*, *69*(2), 182-195.

Melo, P. C., Graham, D. J., & Noland, R. B. (2009). A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics*, *39*(3), 332-342.

Moulton, B.R. (1990). An illustration of a pitfall in estimating the effects of aggregate variables on micro unit. *The Review of Economics and Statistics*, *72*(2), 334-338.

Narjoko, D., & Hill, H. (2007). Winners and losers during a deep economic crisis: Firm-level evidence from Indonesian manufacturing. *Asian Economic Journal*, *21*(4), 343-368.

Nichols, A., & Schaffer, M. E. (2007). Clustered standard errors in Stata. Paper presented at United Kingdom Stata Users' Group Meeting.

Oates, W. E. (1993). Fiscal decentralization and economic development. *National Tax Journal*, *46*(2), 237-243.

OECD (1987). Structural Adjustment and Economic Performance, OECD, Paris.

Petrin, A., Poi, B. P., & Levinsohn, J. (2004). Production function estimation in Stata using inputs to control for unobservables. *Stata Journal*, 4, 113-123.

Poczter, S., Gertler, P., & Rothenberg, A. D. (2014). Financial Crisis and Productivity Evolution: Evidence from Indonesia. *The World Economy*, *37*(5), 705-731.

Porter, Michael. 1990. The Competitive Advantage of Nations. London: MacMillan.

Rigby, D. L., & Essletzbichler, J. (2002). Agglomeration economies and productivity differences in US cities. *Journal of Economic Geography*, *2*(4), 407-432.

Rodríguez-Pose, A., Tselios, V., Winkler, D., & Farole, T. (2013). Geography and the determinants of firm exports in Indonesia. *World Development*, *44*, 225-240.

Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of Urban Economics*, *50*(2), 191-229.

Rosenthal, S.S., & Strange, W.C. (2003). Geography, industrial organization, and agglomeration. *Review of Economics and Statistics*, *85*, 377-393.

Rosenthal, S.S, & Strange, W.C. (2004). Evidence on the nature and sources of agglomeration economies, in: Henderson, J.V., and Thisse, J.F. (Eds.), *Handbook of Regional and Urban Economics*, vol. 4 (pp. 2119-2171). Amsterdam: Elsevier.

Setiawan, M., Emvalomatis, G., & Lansink, A. O. (2012). Industrial concentration and price-cost margin of the Indonesian food and beverages sector. *Applied Economics*, *44*(29), 3805-3814.

Sjöberg, Ö., & Sjöholm, F. (2004). Trade liberalization and the geography of production: agglomeration, concentration, and dispersal in Indonesia's manufacturing industry. *Economic Geography*, *80*(3), 287-310.

Sjöholm, F. (1999). Productivity growth in Indonesia: the role of regional characteristics and direct foreign investment. *Economic Development and Cultural Change*, *47*(3), 559-584.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In Andrews, D.W.K. & Stock, J.H. (Eds). *Identification and Inference in Econometric Models: Essays in Honor of Thomas J. Rothenberg*, (pp 80-190). New York: Cambridge University Press.

Tiebout ,C.M., (1956)., "A pure Theory of Local Expenditure," *Journal of Political Economy* 64, 416-424.

Timmer, M.P. (1999). Indonesia's ascent on technology ladder: capital stock and total productivity in Indonesia manufacturing, 1975-95. *Bulletin of Indonesia Economic Studies*, *35*(1), 75-97.

Van Beveren, I. (2012). Total factor productivity estimation: a practical review. *Journal of Economic Surveys*, *26*(1), 98-128.

Viladecans-Marsal, E. (2004). Agglomeration economies and industrial location: city level evidence. *Journal of Economic Geography*, *4*(5), 565-582.

Widodo, W., Salim, R., & Bloch, H. (2014). Agglomeration Economies and Productivity Growth in Manufacturing Industry: Empirical Evidence from Indonesia. *Economic Record*, *90*(s1), 41-58.

World Bank. (2012). Picking up the pace: reviving growth in Indonesia's manufacturing sector. Washington, DC: World Bank. http://documents.worldbank.org/curated/en/2012/09/16814551/picking-up-pace-reviving-growth-indonesias-manufacturing-sector.