EMPLOYMENT GROWTH AND SPATIAL CONCENTRATION IN INDONESIA

Albert J. Sumell

Department of Economics, Youngstown State University, Youngstown, Ohio 44555, United States.

Francisco Javier Arze del Granado

International Monetary Fund, 700 19th Street, N.W., Washington D.C. 20431, United States.

ABSTRACT: This article examines the dynamics of employment concentration in Indonesia over the period 1994 to 2004. Using a spatial lag model, we analyze the relationship between districts' employment growth rates and their spatial characteristics, which includes natural geographic isolation, distance to urban centers and population of surrounding districts. The empirical models are estimated for the entire economy and nine employment sectors. The results suggest distance to larger population centers negatively affects growth. Employment became more evenly dispersed in Indonesian districts during the sample period, but this dispersion was primarily driven by the outward expansion of larger urban districts. It was also found that districts with higher levels of sectoral specialization (lower employment diversity) experienced lower growth rates.

1. INTRODUCTION

The spatial distribution of economic activity is altered over time by a very diverse array of factors. The level of technological development, sectoral composition, transport infrastructure, factor mobility, government policies, as well as more general socio-economic and cultural conditions all impact economic development and employment across space. Despite the fact that all of these characteristics are country specific, the majority of empirical research in this area has analyzed data from the U.S., either at the metropolitan area level (e.g. Henderson *et al*. 1995, Glaeser 1998, Carlino and Chatterjee 2002, Hansen 2004, Ioannides and Overman 2004, and Lee 2007) or county level (e.g. Beeson and DeJong 2002, Desmet and Fafchamps 2005, Partridge *et al*. 2008, 2009). Although the literature arrives at somewhat disparate conclusions, recent works have found that employment in U.S. large metropolitan areas has experienced de-concentration, while employment across U.S. counties has experienced concentration.

Given the heterogeneous nature of an economy's spatial distribution, other nations have inevitably experienced dissimilar dynamics in the geographical concentration of employment. For instance, differences in labour mobility, urban blight, transport infrastructure and pricing, and land use policies have altered the effects of agglomeration forces in the U.S. compared to other nations, which has resulted in a relatively greater level of suburbanization and lower employment density in U.S. cities compared to other nations (Mieszkowski and

Mills 1993, Cairncross 1997).

The primary objective of this paper is to examine the factors that influence the spatial evolution of employment in Indonesia for the years 1994 and 2004. In particular, this paper seeks to understand the effect of regional employment characteristics, natural surroundings, distance to urban centers, population of neighboring areas, and sectoral specialization on aggregate and sector-specific employment growth rates. The contributions of this article are based on both the methodology employed and the geographical idiosyncrasies of Indonesia. For one, Indonesia is located in one of the most volatile areas on earth (the so-called "ring-of-fire"), with many areas prone to earthquakes, tsunamis, volcanic eruptions, droughts, and/or flooding. As a result, migration flow may be more heavily influenced by natural immunity to these hazards and public infrastructure compared to other nations. The fact that Indonesia is an archipelago will also influence employment growth dynamics compared to geographically contiguous nations. For example, a locality surrounded by water could face suppressed growth due to its natural isolation from surrounding economic activity and higher transport costs. By controlling for districts' spatial dependence with surrounding areas, island location, and its accessibility to other districts in terms of land and water surroundings, the results provide insight into the impact of continguous geographical distance compared to natural isolation on employment growth.

Furthermore, the empirical models measure how distance to urban areas of different sizes impacts employment growth in districts. The majority of previous works that measure the effects of proximity to urban areas do so without considering the geographic size or population levels of the areas.[1] The dynamics of employment growth in any area will depend on not just whether it is near or neighboring a city, but both the relative size and employment density of that city. For instance, Carlino and Chatterjee (2002) suggest that regional employment patterns are driven by how aggregate employment changes affect agglomeration and congestion costs in cities. The ability of a city to accommodate a larger population will depend on its own population characteristics and those of neighboring areas. This is especially true in Indonesia, or any country with a highly fragmented infrastructure. Accordingly, we examine the role of the relative population of neighboring districts, as well as distance to higher tier population centers on employment growth.

The results suggest that proximity to more populous urban areas was positively related to employment growth, and that the impact was larger in magnitude the closer a district was to higher tier population centers. We find the population of the nearest urban district positively influenced employment growth independent of distance, suggesting that positive spatial externalities existed. These externalities were strongest for rural areas and small cities. In addition, the results indicate that isolation from urban districts negatively impacted

[1] Two important exceptions come from Partridge *et al*. (2008, 2009), which examined how distance from successively larger urban tiers influence employment growth in non-metropolitan areas in the U.S.

employment growth, but that the distance to employment centers was more important than whether the district was geographically contiguous to employment centers.

We also find evidence that localization economies, measured by the level of sectoral specialization, were not significant or had a negative association with growth. The effects of urbanization economies were not as clear. If measured by total initial employment level (as in Desmet and Fafchamps 2005), the results suggest a negative or insignificant urbanization effect, whereas if measured by employment diversity (as in Combes 2000), the results suggest a positive relationship for most sectors. Considering that initial employment likely has a stronger connection to congestion than employment diversity, these results are not conflicting.

The remainder of this paper is organized as follows. The next section presents the data and the empirical model, explaining how distance, urban hierarchy classification, localization and urbanization economies are measured and their potential impact to growth rates. The empirical results and interpretations follow in the third section. The final section concludes with a summary of major findings and implications as well as potential avenues for future research.

2. DATA AND ESTIMATION METHODOLOGY

The analysis includes 1994 and 2004 employment data from 280 districts[2] which cover the entire land area of Indonesia, thereby reducing the selection bias associated with only including large urban areas. The data come from Indonesian Central Bureau of Statistics, Badan Pusat Statistik (BPS), National Population Survey, Intercensal Surveys (*Supas*). Indonesian districts are similar in terms of designation to U.S. counties or French employment areas, but are substantially larger in terms of both size and population. On average, Indonesian districts had approximately 281,000 workers and were 3,960 square kilometers in 1994, which is almost 60% larger and three times as populous as the average U.S. county in 1994.

The employment data is categorized into nine employment sectors. The numbers employed in each sector and changes during the sample period are shown in Table 1. Aggregate employment grew at an average rate of approximately 1.5% per year in Indonesia during the sample period. This modest growth masks what was a period of momentous economic and political turmoil in Indonesia, brought about by the Asian financial crisis in 1997. Within a year of its onset, the crisis caused a presidential resignation, 80% inflation, and most notably, a reduction in real income in excess of 13% (Levinsohn *et al*. 1999). Economic reform and stability gradually followed, and by 2004 real income had reached pre-crisis levels.

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[2] Due to changes in designation, there were a smaller number of employment districts in 1994 compared to 2004. For purposes of comparison, the analysis uses the 2004 designations for both years. Four districts were removed due to a lack of data.

Table 1. Indonesian employment 1994 - 2004

	Number Employed 94	Number Employed 04	Percentage Change 94-04
Total	75529968	83479246	10.5%
Agriculture	37020211	37391280	1.0%
Mining	816012	721785	-11.5%
Manufacturing	8031193	10338479	28.7%
Utilities	312658	183514	-41.3%
Construction	2972333	3754770	26.3%
Wholesale and retail trade	12181626	15498188	27.2%
Transportation	2645744	4710472	78.0%
Finance, insurance, and real estate (FIRE)	523765	1105847	111.1%
Public services	11026426	9774911	-11.4%

The financial crisis contributed to dramatic changes in the sectoral composition of employment. Although the Indonesian economy was still dominated by the agricultural sector in 2004, with more than half of all workers employed in agriculture, employment growth during the previous decade almost exclusively occurred in non-agricultural sectors. As shown in Table 1, employment in agriculture was virtually stagnant, having grown just 1%, while employment in all other sectors had grown nearly 20% over the sample period.[3] Wholesale and retail trade employment experienced the largest absolute employment growth and was responsible for 45% of all new jobs in the economy. The employment growth rate was largest in finance, insurance and real estate (FIRE), in which employment more than doubled over the sample period, followed by the transportation sector, which had grown at a rate of over 7% per year. Manufacturing and construction employment had also grown at a rate well above national average. On the contrary, mining, utilities, and public services employment contracted during the sample period. Contributing to the decline in utilities and mining employment was the substantial downturn in crude oil, condensate and natural gas production that Indonesia had experienced since 1995.[4]

Table 2 shows population and employment variable means of the main islands of Indonesia, and Figure 1 provides a visual context of their location and geographic size. The degree of economic disparity, which is of primary importance in determining the population distribution, is historically very large

[3] According to Duncan *et al*. (2002), agricultural employment expanded as much as 20% during the Asian financial crisis of 1997-1998, while employment in the industrial sectors saw a contraction of equal magnitude. Table 1 indicates that from 1998-2004 Indonesia experienced a reversal of this pattern.

[4] According to BPS Indonesia, crude oil, condensate, and natural gas production decreased 30%, 29%, and 32%, respectively from 1996-2003.

across regions in Indonesia (Deichmann *et al*. 2005). This disparity is at least partially driven by regions' non-contiguous nature, which leads to the agglomeration of economic activity in trade hubs and areas with easy access to markets, and the concentration of revenues from natural resource endowments such as those from petroleum production and/or soil fertility.[5]

Table 2. Variable means by island

	Sumatra	Jawa & Bali	Kalimantan	Sulawesi	NT&M	Papua
Total employment 94	15260542	46809173	4234038	4757951	3688298	779876
Total employment 04	16372009	51936552	4890999	5377836	3980977	920577
Employment growth	0.07	0.11	0.16	0.13	0.08	0.18
Area	4222	1223	10770	3419	4534	14567
Ethno. fraction (ELF)	0.54	0.23	0.62	0.44	0.48	0.85
Employment Shares 94						
Agriculture	0.535	0.404	0.542	0.584	0.693	0.663
Mining	0.017	0.008	0.024	0.009	0.006	0.015
Manufacturing	0.053	0.134	0.074	0.050	0.055	0.023
Utilities	0.005	0.005	0.004	0.003	0.003	0.004
Construction	0.033	0.045	0.033	0.025	0.019	0.028
Wholesale	0.155	0.190	0.131	0.122	0.079	0.073
Transportation	0.031	0.041	0.033	0.030	0.018	0.019
FIRE	0.005	0.009	0.004	0.003	0.002	0.005
Public Services	0.161	0.160	0.146	0.164	0.119	0.155

As shown in Table 2, the smallest island in terms of land area, Jawa and Bali, was the most populous and had the lowest proportion of the workforce employed in agriculture. The westernmost island of Sumatra was second largest in terms of population, and had a similar employment composition to the to the islands of Kalimantan and Sulawesi. On the other extreme of the urbanization scale are the easternmost islands of Nusa Tenggara and Maluku (NT&M) and Papua, which had approximately two-thirds of all workers employed in agriculture.

[5] Areas that are rich in natural endowments and are geographically secluded from the rest of the country may have stronger bargaining power over the distribution of royalties by the national government in order to minimize regional moves for independence. See Burgess and Venables (2004) and Venables (2005) for an examination of the role of initial natural endowment, or "first nature" geographies on agglomeration.

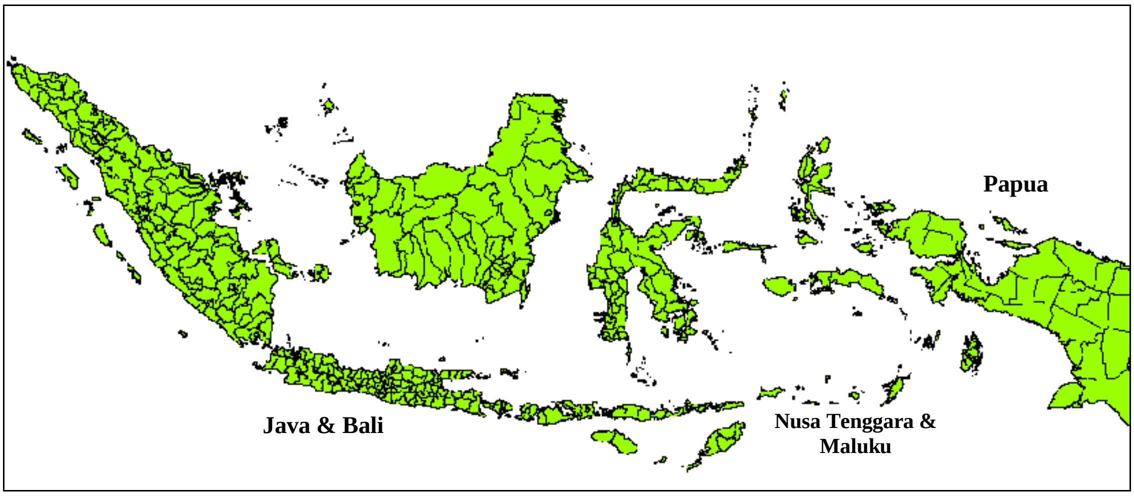

Figure 1. Map of Indonesia

2.1 Empirical estimation

The basic objective of the empirical model is to identify the determinants of employment growth and concentration across districts in Indonesia. A well known problem with employment changes in geographical units is the potential correlation among observations. This may be driven by shared factors that exhibit spatial dependence, ranging from geographic conditions to access to specific infrastructure facilities, and/or externalities. These factors are typically difficult to measure. When this form of spatial dependence is not controlled for in the specification, the random sampling hypothesis is violated and standard OLS estimates are inefficient and inconsistent (Cliff and Ord 1981, Lesage and Pace 2009). [6]

To account for this spatial dependence, a spatially-lagged dependent variable is included as a regressor and the spatial dependence takes the general form of the following spatial regression model:

$$Y = \rho WY + X\beta + \mu \tag{1}$$

where ρ denotes the autoregressive parameter, W is a weight matrix, X is a *(k x 1)* vector of explanatory variables, β is a *(k x 1)* vector of regressive parameters, and μ is a spatial white noise field such that $u \approx N(0;\sigma^2 I_n)$.

A parametric representation of the covariance structure of W is defined following assumptions made on the spatial auto-correlation of the observations.

[6] We test for the presence and significance of the spatial interaction in our data using the Moran I and spatial Lagrange Multiplier tests as explained in Arbia (2006). The null hypothesis of no spatial correlation in the residuals is rejected for both tests, indicating that spatial dependence between observations exists.

Since economic growth in one jurisdiction may spill over into neighboring jurisdictions, we theorize that district's *i*'s employment growth rate $y_{i,t}$ depends on its own characteristics – a (*k* x *1)* vector of explanatory variables, and also on employment growth in neighboring districts $y_{j,t}$ (with $j \neq i$). The nature of this interaction is examined by introducing a spatial lag operator, which is essentially a weighted average of the dependent variable of neighboring districts. The reaction function for employment growth rate in sector s = 1, ..., *S* of district *i* is written as follows:

$$y_{s,d} = \rho \sum_{j \neq d} w_{d,j} y_{s,j} + \alpha x_d + u_{s,d} \tag{2}$$

where ρ and α are parameters to be estimated, $w_{d,j}$ are weights defined according to the pre-defined criterion of neighborliness, x_d is a vector of regressors, and $u_{s,d}$ is a random error. For each row *d* in the weight matrix (a district) columns $j \neq d$ with non-zero values denote neighboring districts as specified by distance of neighboring districts, and $w_{d,j}$ is set to zero by convention.[7] In this model, the weight matrix elements take value 1 if districts are within a distance of 5 digitizing units from each other.[8] Different approaches have been followed in the literature, including the inverse distance (Anselin 1988), income and ethnic composition (Case *et al*. 1993), the structure of a social network (Doreian 1980), or a fixed amount of nearest neighbors (Pinkse and Slade 1998), among others. The vector of regressors includes initial total employment or district classification (explained further below)[9], employment density, employment diversity and specialization, an index of ethno-lingistic fractionalization, neighboring districts' population and distance variables, district's area and other geographic characteristics (dummies for landlocked districts, island-districts, and for each one of the "main six" islands). Appendix 1 presents the definitions, means, and standard deviations for all variables included in the empirical models. Further description of certain variables follows.

District classification: Each district is categorized either as primarily urban or rural and then into sub-tiers based on both the number of employed and the employment density in 1994.[10] There are five categories in total, two rural and

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[7] See Arbia (2006) for a full derivation of the log-likelihood function for this model.

[8] We use the Stata application developed by Maurizio Pisati, described in Pisati (2001). The specific number of units used is the minimum required to ensure that each district has at least one neighboring district.

[9] Our classification of districts is based on employment characteristics at the initial year, hence this set of variables is highly correlated with initial total employment density. We estimate two specifications, one with each classification measure.

[10] The reason both employment and employment density are used to categorize districts is because several geographically large districts have a substantial but sparse total employment without a significant urban center. Several different categorizations were

three urban. Specifically, a district is categorized as rural if employment was less than 100,000, regardless of employment density; it is a category-one rural district if the employment density was less than 100 and category-two rural if the employment density was greater than 100. A district is classified as urban if it had employment greater than 100,000 and employment density greater than 100. If employment was between 100,000 - 400,000 with density above 100 or if employment was above 400,000 with density below 100 it is a category-one urban district; if the employment was between 400,000 - 700,000 with a density above 100 it is a category-two; and it is a category- three if the employment was above 700,000. All districts with employment above 500,000 have an employment density above 100. Out of the 280 districts included in the analysis, 128 qualify as urban: 73 in category one, 37 in category-two, and 18 in category-three; 152 qualify as rural: 55 in category-one and 97 in category-two.

Employment density: This is defined as $E = emp_{d,t_0} / a$, where employment in district *d* in time t_0, and a is district *d*'s area in square kilometers. This variable is aimed to proxy for the size of local markets which are quasi-proportional to the size of the local economy.

Specialization/Localization: This is defined as: $S = emp_{s,d} / emp_s$, where $emp_{s,d}$ is employment in sector s in district *d*, and emp_s is total national employment in sector *s*.

Diversity: This is defined as $D = 1/\sum_{\substack{s'=1 \\ s' \neq s}}^{S} (emp_{d,s'} / (emp_{d-} emp_{d,s}))^2$, which is the inverse of a Herfindahl index. This variable reaches a maximum when all sectors except the sector being measured have the same size in district *d* (as in Henderson et al. 1995 and Combes 2000).

Population and Distance Variables: The estimations include three variables measuring the impact of surrounding districts on employment growth. Two of them aim to capture population-size effects whereas the other explores the role of geographic distance. The variable *popnear_urb* equals the population of the nearest urban district, regardless of its classification or whether it is a higher- or lower-tier district. The impact of a district's population on a neighboring district's growth depends not only on the district's total population but also on the neighboring district's population size relative to its own population size. Therefore, the variable *incpop_urb* measures the relative disparity in population between each district and the nearest higher tiered urban district. For all rural districts, *incpop_urb* equals the difference between the nearest urban districts population and its own population; for category one or two urban districts, it equals the difference in population between the nearest category two or three urban district; and for category three urban districts it is assigned a value of zero. The variable *distnear_urb* measures distance in kilometers to the nearest higher tiered urban district.

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attempted using different benchmarks of employment and density, all of which had negligible effects to the results.

3. EMPIRICAL RESULTS

In order to investigate how specific factors affect employment growth within a district and test robustness of the results, the equations are estimated using two specifications. The first specification includes the districts' initial employment level, density, ethno-linguistic fraction, and geographical attributes. The second specification replaces initial employment level with the district's own classification in the urban hierarchy and includes distance to and population of surrounding urban districts. The equations are estimated for all districts and separately for urban and rural districts.

Table 3 presents the results. Each equation is estimated using the annual employment growth rate in all sectors as the dependent variable. A coefficient's sign indicates the variable's relationship with annual employment growth rate, e.g. a positive coefficient indicates an increase in the variable is associated with greater employment concentration, a negative coefficient suggests a growth penalty. The coefficient signs are highly consistent between the urban and rural district equations. However, the coefficients are generally larger in magnitude in rural districts, suggesting that employment changes were greater in rural districts.

3.1 Aggregate employment results

We begin with a discussion of the basic specification which does not include population or distance controls. The negative coefficients on both initial employment levels and employment density suggest that districts that were economically larger at the initial year grew at a slower rate than smaller ones, which is evidence of aggregate employment convergence at the district level. These results run contrary to Desmet and Fafchamps (2005, 2006), who found aggregate job concentration in U.S. counties between 1972 and 2000, but consistent with what Carlino and Chatterjee (2002) and Hansen (2004) document had happened in large U.S. cities and what Combes (2000) found in employment centers in France. The overall dispersion in employment does not reflect that employment has migrated from populous urban areas towards remote rural areas. The fact that the negative coefficient on employment is substantially larger in magnitude in the rural district equation suggests that rural districts had a larger growth penalty compared to urban districts, or that overall employment had migrated away from rural districts.

A possible explanation for these results is that national employment has migrated towards urban areas, but has become more dispersed within the urban areas and expanded outward towards rural districts. In other words, as urban populations increased during the sample period, congestion, pollution, and land rents had also increased in urban areas, which pushed employment spatially outward. Previous works and casual statistics support this explanation. For instance, according to the Indonesian Central Bureau of Statistics, Jakarta (Indonesia's capital and urban economic center) experienced a 30% increase in population from 1980 - 2000, while the area surrounding the periphery of Jakarta had more than tripled. In addition, Ford (1993) documented that since 1980, improved road networks and a growing middle class had led to the development

Table 3. Empirical results: Total employment: All, urban and rural districts

	ALL DISTRICTS		URBAN DISTRICTS		RURAL DISTRICTS	
Variable	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)
constant	0.2398 A (5.24)	0.1141 B (2.54)	0.1954 B (2.31)	0.1950 A (2.58)	0.2715 A (4.02)	0.0194 (0.29)
log employed	-0.0060 A (-4.68)	n/a	-0.0039 C (-1.76)	n/a	-0.0083 A (-3.91)	n/a
log empdens	-0.0015 C (-1.81)	-0.0017 C (-1.94)	-0.0010 (-0.75)	-0.0006 (-0.48)	-0.0030 B (-2.01)	-0.0031 B (-2.29)
landlocked	0.0017 (0.75)	0.0016 (0.73)	0.0017 (0.71)	0.0007 (0.28)	0.0030 (0.83)	0.0022 (0.65)
island district	0.0004 (0.11)	0.0025 (0.69)	-0.0002 (-0.03)	0.0012 (0.17)	-0.0018 (-0.38)	0.0010 (0.24)
log ELF	0.0029 A (3.62)	0.0031 A (3.63)	0.0017 B (2.15)	0.0022 A (2.57)	0.0055 A (2.94)	0.0040 B (2.27)
longitude	-0.0012 A (-3.24)	-0.0007 C (-1.86)	-0.0010 (-1.53)	-0.0015 B (-2.17)	-0.0012 B (-2.12)	0.0001 (0.23)
latitude	0.00001 (-0.01)	-0.00003 (-0.06)	0.0019 B (1.96)	0.0016 (1.60)	-0.0007 (-1.09)	-0.0008 (-1.43)
Sumatra	-0.0254 A (-4.44)	-0.0185 A (-3.24)	-0.0278 A (-3.84)	-0.0315 A (-4.31)	-0.0290 A (-2.93)	-0.0084 (-0.84)
Kalimantan	-0.0068 (-1.22)	-0.0005 (-0.10)	-0.0092 (-0.99)	-0.0034 (-0.36)	-0.0158 (-1.57)	-0.0058 (-0.59)
Sulawesi	0.0001 (0.01)	0.0015 (0.25)	-0.0017 (-0.12)	0.0078 (0.52)	-0.0062 (-0.59)	-0.0084 (-0.84)
NT & M	-0.0012 (-0.21)	0.0043 (0.71)	0.0049 (0.62)	0.0036 (0.46)	-0.0105 (-0.96)	-0.0069 (-0.68)
Papua	0.0154 (1.31)	0.0336 B (2.53)	n/a	n/a	0.0036 (0.20)	0.0168 (0.92)
RuralCat2	n/a	-0.0094 A (-3.51)	n/a	n/a	n/a	-0.0102 A (-3.47)
UrbanCat1	n/a	-0.0103 A (-2.87)	n/a	n/a	n/a	n/a
UrbanCat2	n/a	-0.0196 A (-4.61)	n/a	-0.0096 B (-2.35)	n/a	n/a
UrbanCat3	n/a	-0.0257 A (-3.91)	n/a	-0.0159 B (-2.14)	n/a	n/a
popnear_urb	n/a	0.000020 A (2.74)	n/a	0.000017 (1.47)	n/a	0.000017 (1.43)
incpop_urb	n/a	0.000017 A (2.83)	n/a	0.000014 (1.62)	n/a	0.000032 A (3.05)
distnear_urb	n/a	-0.0200 B (-2.26)	n/a	n/a	n/a	-0.0281 A (-2.68)
rho	-0.1944 (-1.05)	-0.3080 C (-1.67)	-0.6252 B (-2.33)	-0.6600 B (-2.55)	0.0680 (0.41)	-0.1581 (-0.93)

Note: A (B) [C] Statistically significantly different from zero at the 1% (5%) [10%] level of significance.

of large suburban centers and industrial parks around the periphery of cities into previously rural or uninhabited areas.

Somewhat surprisingly, the coefficients on employment density are negative and significant in the rural districts equation, and insignificant in the urban districts equation, suggesting that greater employment density had a negative association with growth in smaller, rural districts, but not in urban districts. These results run counter to the expectation that more populous urban districts would have experienced a larger density penalty due to the associated congestion and crowding out effects. One possible explanation is that more densely inhabited areas in the hinterland had a relatively high concentration of mining employment – a sector which experienced considerable decline during the sample period. Alternatively, it is plausible that sparsely populated districts near large urban areas were in a stronger position to receive positive employment spillovers from their urban neighbors compared to their denser counterparts.

The natural periphery of a district, whether it's water (*island*) or land (*landlocked*), does not have a discernable impact on a district's growth rate in any of the models. The negligible and insignificant estimates on *island* possibly reflect that the negative impact of isolation from large consumer markets on the mainland was offset by the advantage of improved accessibility to shipping export networks. The degree of demographic diversity within a district, as measured by the ethno-linguistic fraction (*ELF*), had a positive and significant relationship with job growth. The positive impact of *ELF* perhaps relates to the economic stagnation in purely rural districts, given that these areas are generally more homogenous than urban areas with respect to population and employment opportunities.

The negative and significant coefficient on *longitude* suggests employment had generally moved West, or closer to continental Asia, other factors constant. The relative position North or South of the equator, however, does not have a consistent or statistically significant relationship with job growth. We also control for unobserved regional effects by including island dummies. The island of Sumatra, which is nearest to mainland Asia and borders Singapore, had relatively slow job growth.[11] Perhaps benefiting by its large endowment of natural resources or by its proximity to Northern Australia, Papua experienced higher job growth compared to other islands.

Specification 2 considers the effect of neighboring districts on employment growth and replaces initial employment level with population category designation. The coefficients on the population category designations show that not only was job growth inversely related with initial employment levels, but inversely related to the rank in the urban hierarchy. In other words, smallest tiered districts grew at the fastest rate, largest tiered districts grew at the slowest rate, and districts in between grew according to size. Though rural districts had grown at a faster overall rate than urban districts, this does not indicate that it is

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[11] Sumatra is the island most severely impacted by the tsunami at the end of 2004. However, the tsunami's complete impact to the employment distribution in Indonesia was not reflected in the data.

advantageous to be distant from urban centers. The negative and significant coefficient on *distnear_urb* suggest that isolation from larger population centers resulted in a growth penalty. This is consistent with what Patridge, et al. (2008, 2009) found for the U.S., and likely reflects that remote districts face higher transport costs and suffer from a lack of access to the economic activity or information present in larger population centers.[12]

The coefficient on *popnear_urb,* measuring the population of the nearest urban district, is positive and significant, suggesting that a district's employment situation benefits from being more proximate to large population centers. Additionally, positive and significant estimates on *incpop_urb* suggest that the greater the disparity between a district's employment and the employment of the nearest higher tier urban district, the greater the job growth rate. Taken together, these results suggest that not only had employment spilled over from large urban centers to smaller ones, but, akin to a waterfall, it spilled over with greater ferocity the higher the fall. The impact of incremental population is substantially larger and significant for rural districts than for urban districts, suggesting that lower population districts benefited most from being near higher tier population centers. This corroborates the proposition put forth earlier that employment in urban districts had been expanding outward into lower population districts.

3.2 Sector specific employment growth results

Table 4 presents the empirical results for nine employment sectors. For brevity, the analysis is restricted to specification two which includes urban classification, distance to the nearest urban district and relative population variables. The first notable results are on employment diversity, which takes on a positive coefficient in all nine sectors, and is significant in all but two sectors – agriculture and construction. The lack of significance in the construction sector likely relates to the fact that inputs are costly to transport and that new suburban developments were growing outward into districts that were relatively homogenous. The negligible and insignificant coefficient on diversity in agriculture is hardly unexpected. Agriculture in Indonesia, as in many developing countries, often takes place in remote, sometimes self-subsistent villages, where production techniques are ensconced by tradition and void of the positive externalities generated from the exchange of ideas between industries.

Of the positive and significant coefficients on diversity, financial services and utilities are the largest in magnitude. These results support previous works that non-traded goods benefit most from being proximate to diverse urban centers (as in Combes, 2000, Desmet and Fafchamps 2005; 2006, Partridge et al. 2008). Contrary to these works, however, we find that the positive impact of diversity also extended to the manufacturing sector in Indonesia. This perhaps reflects that manufacturing firms must locate in areas in which transport nodes and

[12] Patridge *et al*. (2008, 2009) show that distance to higher tier urban center was negatively associated with job growth in U.S. counties during the 1990s, and that there were positive spatial spillovers from metropolitan areas to surrounding areas for all but the highest tier metropolitan areas.

complementary service sectors (such as finance or insurance) are present, which would not be true in remote, homogeneous districts. In developed economies, however, transport nodes and complementary services would generally be available to firms regardless of the sectoral composition of the area.

In light of the reliably positive and significant coefficients on employment diversity, it may be surprising that the coefficient on employment density is not positive and significant in any sector. Though both employment density and diversity are connected to urbanization economies, Quigley (1998) has suggested that diversity plays a role in enhancing growth that is independent of city size. We propose that employment diversity is a stronger measure of the positive effects associated with clustering (such as more advanced infrastructure, knowledge spillovers, broader labor pool, and input-output linkages), while density is more closely tied to the costs of clustering (such as higher rents, greater competition, and congestion). To some extent this is supported by the fact that the density coefficient is negative and significant at the 10% level in agriculture and mining – both land intensive industries that are less likely to benefit from agglomeration economies. Furthermore, the positive (though not significant) estimates on density in all service oriented sectors likely captures economies that resulted from reduced transaction costs in more populous areas.

The coefficient on sector share is negative and significant in all sectors, suggesting a complete lack of localization economies throughout the economy during the sample period. Consistent with the findings on employment diversity, the coefficients on sector share are generally larger in magnitude in service sectors. One possible explanation for these coefficients is that the sector classifications are highly aggregated and the benefits of localization, such as sharing sector specific inputs or cost saving externalities, are more evident when measured at the firm level with finer classifications of sector (as in Graham 2009, Henderson 2003, or O'Donoghue 1999). However, the events following the Asian financial crisis in 1997 also likely played a role in these results. Works by Combes (1999; 2000) and Glaeser et al. (1992) have suggested that the effect of localization economies is inversely linked to the business cycle, decreasing growth during downturns which can outweigh their positive impact in expansionary periods. This may be what the negative coefficients on specialization reflect, given that the sample period was characterized by rapid decline until 1997 followed by steady growth through 2004. This idea is further supported by the fact that the negative coefficient on specialization is largest in financial services, which was most susceptible to the crisis, and smallest in agriculture, the sector most insulated from the impact of the crisis.

Regarding spatial variables, the population of the nearest urban district had a positive impact in eight of the nine sectors, and the coefficient is significant in agriculture and utilities, suggesting that these sectors gained from being near large consumer markets. In light of the positive coefficients on the population of the nearest urban centre, the negative coefficients on incremental population in mining and utility sectors are unexpected. These results imply that although these sectors benefited from being near a large consumer market, the gains were inversely related to the relative size of the market.

Table 4. Empirical results by sector: Coefficient, t-statistic in brackets

	Agriculture	Mining	Manufacturing	Utilities
constant	-0.0893 (-0.89)	-1.6105[A] (-2.91)	0.1260 (0.85)	-1.5875[B] (-2.29)
log diversity	0.0023 (0.14)	0.101[B] (2.41)	0.075[A] (5.31)	0.235[A] (4.28)
log sector share	-0.0147[A] (-4.20)	-0.0309[A] (-2.60)	-0.0349[A] (-7.18)	-0.0955[A] (-11.46)
log empdens	-0.0184[A] (-6.01)	-0.0529[A] (-4.09)	-0.0027 (-0.80)	0.0123 (0.78)
landlocked	0.0015 (0.33)	-0.0230 (-0.90)	0.0028 (0.39)	0.0249 (0.77)
island district	-0.0017 (-0.23)	-0.0340 (-0.80)	-0.0013 (-0.11)	0.0311 (0.58)
log ELF	-0.0056[A] (-2.85)	0.0110 (1.14)	0.0013 (0.49)	0.0544[A] (4.34)
longitude	0.0012 (1.35)	0.0150[A] (3.03)	-0.0021 (-1.60)	0.0056 (0.90)
latitude	-0.0014 (-1.43)	0.0003 (0.07)	-0.0011 (-0.73)	-0.0005 (-0.08)
Sumatra	0.0164 (1.32)	0.0117 (0.18)	-0.0515[A] (-2.75)	0.0497 (0.59)
Kalimantan	-0.0059 (-0.48)	-0.0596 (-0.90)	0.0024 (0.13)	-0.0098 (-0.11)
Sulawesi	-0.0102 (-0.78)	-0.3326[A] (-4.36)	0.0013 (0.06)	-0.1404 (-1.46)
NT & M	-0.0081 (-0.62)	-0.1478[A] (-2.03)	0.0220 (1.10)	-0.1397 (-1.48)
Papua	-0.0182 (-0.64)	-0.0718 (-0.46)	0.0641 (1.42)	-0.3260 (-1.60)
RuralCat2	-0.0027 (-0.46)	0.0297 (0.92)	-0.0149 (-1.60)	-0.0529 (-1.27)
UrbanCat1	-0.0013 (-0.16)	0.0233 (0.55)	-0.0038 (-0.31)	0.0192 (0.35)
UrbanCat2	-0.0234[B] (-2.51)	0.0489 (0.97)	0.0004 (0.03)	-0.0033 (-0.05)
UrbanCat3	-0.0234[A] (-1.66)	-0.0496 (-0.64)	0.0107 (0.49)	-0.2719[A] (-2.77)
popnear_urb	0.00043[A] (2.73)	0.00016 (0.19)	-0.00025 (-1.07)	0.0023[B] (2.17)
incpop_urb	0.00020 (1.60)	-0.0013[C] (-1.88)	0.00017 (0.86)	-0.0015[C] (-1.65)
distnear_urb	-0.0242 (-1.25)	-0.5250[A] (-4.78)	-0.0354 (-1.21)	0.0761 (0.59)
rho	0.1717 (0.89)	-0.4649[B] (-2.30)	-0.0836 (-0.41)	-0.3989[C] (-1.65)

Table 4 (Cont.). Empirical results by sector: Coefficient, t-statistic in brackets

	Construction	Retail	Transport	Financial Services	Public Services
constant	-0.1243 (-0.51)	0.2004 [B] (2.15)	0.0550 (0.45)	-0.4524 (-1.27)	-0.0482 (-0.57)
log diversity	0.028 (1.13)	0.041 [A] (4.34)	0.044 [A] (3.75)	0.224 [A] (7.57)	0.042 [A] (4.91)
log sector share	-0.0312 [A] (-3.19)	-0.0410 [A] (-7.22)	-0.0554 [A] (-10.84)	-0.0980 [A] (-24.97)	-0.0426 [A] (-7.64)
log empdens	-0.0031 (-0.55)	0.0016 (0.71)	-0.0014 (-0.51)	0.0020 (0.23)	0.0007 (0.33)
landlocked	-0.0106 (-0.90)	-0.0040 (-0.93)	-0.0119 [B] (-2.05)	0.0169 (0.98)	-0.0022 (-0.55)
island district	0.0044 (0.23)	-0.0027 (-0.37)	-0.0120 (-1.28)	-0.0388 (-1.37)	-0.0020 (-0.30)
log ELF	0.0047 (1.04)	0.0042 [B] (2.48)	0.0044 [B] (2.00)	0.0167 [B] (2.51)	0.0010 (0.62)
longitude	0.0006 (0.27)	-0.0023 [A] (-2.89)	-0.0018 [C] (-1.67)	-0.0007 (-0.21)	-0.0006 (-0.74)
latitude	0.0036 (1.38)	0.0001 (0.15)	0.0011 (0.87)	0.0085 (2.01)	0.0002 (0.26)
Sumatra	-0.0306 (-0.99)	-0.0356 [A] (-3.07)	-0.0160 (-1.07)	-0.0670 (-1.50)	-0.0095 (-0.91)
Kalimantan	0.0046 (0.15)	0.0086 (0.76)	0.0004 (0.03)	-0.0716 (-1.62)	-0.0114 (-1.10)
Sulawesi	-0.0194 (-0.59)	0.0135 (1.11)	0.0213 (1.33)	-0.0327 (-0.68)	-0.0114 (-0.99)
NT & M	-0.0275 (-0.83)	0.0086 (0.68)	0.0292 [C] (1.77)	0.0917 [C] (1.82)	0.0010 (0.08)
Papua	0.0397 (0.55)	0.0681 [B] (2.56)	0.1140 [A] (3.21)	0.0207 (0.20)	-0.0140 (-0.57)
RuralCat2	-0.0458 [A] (-3.06)	-0.0240 [A] (-4.28)	-0.0228 [A] (-3.12)	-0.0138 (-0.63)	-0.0205 [A] (-3.91)
UrbanCat1	-0.0153 (-0.77)	-0.0215 [A] (-2.90)	-0.0274 [A] (-2.82)	-0.0695 [B] (-2.39)	-0.0345 [A] (-4.96)
UrbanCat2	-0.0376 (-1.60)	-0.0298 [A] (-3.41)	-0.0321 [A] (-2.82)	-0.0588 [C] (-1.73)	-0.0451 [A] (-5.53)
UrbanCat3	-0.0631 [C] (-1.75)	-0.0424 [A] (-3.20)	-0.0372 [B] (-2.15)	0.0084 (0.16)	-0.0415 [A] (-3.39)
popnear_urb	0.00063 (1.60)	0.00015 (1.01)	0.00029 (1.54)	-0.00093 (-1.63)	0.00003 (0.20)
incpop_urb	0.00056 [C] (1.75)	0.00022 [C] (1.86)	0.00014 (0.90)	0.00088 [C] (1.87)	0.00034 [A] (3.05)
distnear_urb	-0.0832 [C] (-1.66)	-0.0617 [A] (-3.27)	-0.0312 (-1.31)	-0.1995 [A] (-2.64)	-0.0112 (-0.68)
rho	-0.0761 (-0.38)	-0.3474 [B] (-2.33)	0.0040 (0.03)	-0.3587 [B] (-2.19)	-0.4089 [B] (-2.08)

Notes to Table 4: A (B) [C] Statistically significantly different from zero at the 1% (5%) [10%] level of significance.

Amongst service sectors, there is evidence that proximity to an urban centre had the greatest positive impact in financial services and the retail sector. The estimates on *incpop_urb* are positive and significant in both of these sectors, suggesting that employment gains from proximity to cities were largest in lower tier districts near higher tier districts. This effect is also apparent in the construction and public service sectors. Distance to more populous urban districts had a negative impact in all sectors but utilities, and were largest in magnitude in the mining and financial services sector.

The final noteworthy result is the impact of districts' ethno-linguistic fraction. The models reveal a clear pattern - districts with greater demographic diversity experienced employment growth in all service sectors, while demographic diversity had a negative or negligible relationship with employment growth in non-service sectors.

4. CONCLUSION

This article has examined the determinants of changes in the spatial concentration of employment in Indonesia for the years 1994 and 2004. Indonesia is remarkably diverse and fragmented compared to most nations, both in terms of geography and population, which lends itself to a high level of spatial concentration of economic activity. The analyses suggest that overall, Indonesian employment became more evenly dispersed across districts during the sample period. Although this result is encouraging to policymakers wanting to see a more even distribution of wealth, the analysis does not suggest that growth has occurred in the isolated regions where policymakers generally concentrate their development efforts. In particular, low population districts neighboring large urban districts experienced the most rapid growth, suggesting that Indonesian cities were expanding spatially outward, whereas rural districts distant from larger urban centers experienced slower growth. We do not find a significant relationship between districts' natural surroundings (water or land) and its growth rate. Taken together, the results imply that policymakers' infrastructure projects should focus less on decreasing the impact of natural transport barriers and more on increasing the spatial dependence between large metropolitan areas and the hinterland.

Moreover, the coefficients on distance suggest that the degree of spatial inequality between secluded rural districts and populous urban districts, or those bordering urban districts, expanded. Studies of population migration have drawn similar conclusions regarding spatial inequality in other developing countries such as China (Fujita and Hu 2001) or India (Ravallion and Datt 2002, Lall and Taye 2004). Though we cannot measure the specific reason for this distance penalty, it is reasonable to surmise that remote regions lack the required infrastructure to exploit location specific advantages. Consequently, access to large markets and export networks are more important to potential employers than sector specific location advantages or input advantages such as low cost labor. This is supported by the reliably positive growth estimates on employment diversity, and negative or insignificant estimates on sector specialization.

The coefficients are qualitatively consistent with a number of studies on employment concentration from developed nations. We find that more populous urban areas experienced de-concentration, which is consistent with the results of Desmet and Fafchamps (2006) and Carlino and Chattergie (2002), and that districts neighboring populous cities experienced concentration, which is consistent with the findings of Partridge et al. (2008; 2009). Furthermore, the negative association between specialization and growth, and positive urbanization economies in service sectors are consistent with the growth dynamics documented by Combes (2000) for France, as well as what Desmet and Fafchamps (2005) found in the U.S.

To the extent that a district's isolation from potential markets, rather than just its distance, is the root determinant of a growth penalty, a measure of remote districts' accessibility, such as drive time to nearest higher tiered districts, would enhance our ability to estimate the benefits of potential policy scenarios such as infrastructure investment projects. Moreover, the broad sector categorization used in this analysis may have camouflaged the impact of agglomeration forces that could be exposed if analyzed at a finer level. Finally, the precise impact of the Asian financial crisis on employment growth – a topic that is currently relevant to the global economy – could be improved if the data could be stratified to estimate pre- and post-crisis changes.

APPENDIX

Table A1. Variable definitions and summary statistics

	Variable Definition	Mean	Std. dev.
Employment growth rates (94-04)			
Total Employment	Percentage change in total number of employed individuals from 1994 through 2004.	0.014	0.17
Agriculture	Percentage change in number of individuals employed in agriculture from 1994 through 2004.	-0.01	0.37
Mining	Percentage change in number of individuals employed in mining from 1994 through 2004.	-0.659	1.98
Manufacturing	Percentage change in number of individuals employed in manufacturing from 1994 through 2004.	-0.077	0.56
Utilities	Percentage change in number of individuals employed in utilities from 1994 through 2004.	-0.569	2.84
Construction	Percentage change in number of individuals employed in construction from 1994 through 2004.	0.008	0.87
Wholesale	Percentage change in number of individuals employed in wholesale from 1994 through 2004.	0.002	0.36
Transportation	Percentage change in number of individuals employed in transportation from 1994 through 2004.	0.156	0.56
FIRE	Percentage change in number of individuals employed in Finance, Insurance and Real Estate from 1994 through 2004.	0.717	2.43
Pub Services	Percentage change in number of individuals employed in Public Services individuals from 1994 through 2004.	0.022	0.33
Distance and Population Variables			
employed	The number of employed individuals in the district in 1994.	270975	230374
empden	The number of employed individuals in the district per square kilometer in 1994.	482.7	1077.6
ethno-linguistic fraction (ELF)	Measure of disparity of ethnicities in the district, where one is perfectly heterogeneous and zero is perfectly homogeneous.	0.416	0.34
longitude	The longitude coordinates of the center of the district.	111.81	8.85
latitude	The latitude coordinates of the center of the district.	-4.16	3.88
popnear_urb	The number of employed individuals in the nearest urban district in 1994.	362436	218110
distnear_urb	The distance in kilometers to the nearest higher tiered urban district.	136.1	281.9
incpop_urb	The difference between a districts employed population and the population in the nearest higher tiered urban district in 1994.	263727	192340
Dummy Variables			
landlocked	Zero-one dummy indicating whether district is completely surrounded by land.	0.382	0.49
island	Zero-one dummy indicating whether district is completely surrounded by water.	0.086	0.28
Sumatra	Zero-one dummy indicating whether district lies on major island of Sumatra.	0.250	0.43
Jawa & Bali	Zero-one dummy indicating whether district lies on major island of Jawa & Bali.	0.396	0.49

Kalimantan	Zero-one dummy indicating whether district lies on major island of Kalimantan.	0.104	0.31
Sulawesi	Zero-one dummy indicating whether district lies on major island of Sulawesi.	0.136	0.34
Nusa Tenggara & Malucu (NT&M)	Zero-one dummy indicating whether district lies on major island of Nusa Tenggara & Malucu.	0.082	0.28
Papua	Zero-one dummy indicating whether district lies on major island of Papua.	0.032	0.18
RuralCat1	Zero-one dummy indicating whether district population is below 100,000 with a density below 100/km.	0.196	0.40
RuralCat2	Zero-one dummy indicating whether district population is below 100,000 with a density above 100/km.	0.346	0.48
UrbanCat1	Zero-one dummy indicating whether district population is above 100,000 and below 400,000 with a density above 100/km or above 400,000 with a density below 100/km.	0.261	0.44
UrbanCat2	Zero-one dummy indicating whether district population is below 400,000 and above 700,000 with a density above 100/km.	0.132	0.34
UrbanCat3	Zero-one dummy indicating whether district population is above 700,000.	0.064	0.25
No. Obs.= 280			

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