ABSTRACT

A Test of Agglomeration Using Wage Behavior

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The neoclassical economic model of wage behavior over time and place predicts that firms spread out and wages converge, given assumptions such as no transactions costs, homogenous products, and same access to resources and technology. However, there are rents called agglomeration economies that can be extracted in certain occupations and occupational groups simply by being located near other similar firms. In this case, the firms agglomerate and wages diverge. We use data from the Bureau of Labor Statistics to test if agglomeration is happening in certain occupational groups based on whether wages are converging or diverging over the short term. Although agglomeration happens more often in the higher-ordered occupational groups, overall, the evidence is mixed concerning the presence of agglomeration economies.

A Test of Agglomeration Using Wage Behavior

by

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CHAPTER ONE

Introduction

The neoclassical economic model describes how firm location decisions and labor location decisions can affect the wage rate differential across locations. It argues that firms in the same occupational group locate away from other similar firms in order to reduce competition for customers and available factor market products, including labor. At the same time, workers also make choices about where to work and tend to relocate to take advantage of any wage differentials. This geographical relocation happens until wages converge in an occupation.

Interestingly, some firms choose to locate near other firms of a similar nature even though the result often is that they must pay higher wages due to a tighter labor market. These location decisions have been attributed to "agglomeration economies," which arise when the benefits of location clustering dominate the higher costs of labor. Agglomeration often occurs when there is uncertainty in the quality and quantity of the labor market. The result to wages, then, is divergence over time and place.

This paper uses wage data for occupations across cities in the United States from 1999 to 2005 to examine the effect of "localization" economies, which is a type of agglomeration that occurs due to the close proximity of firms in the same occupational group. We test for the presence of agglomeration based on evidence of occupational wage convergence or divergence. The findings suggest that agglomeration is more likely to happen in occupational groups with a higher percentage of employees who have high educational attainment. Overall, the Legal occupational group shows wage divergence,

although as the percentage of those with college or more education increases, the wages begin to converge. The Computer and Office occupational groups exhibit interesting patterns, as well. As the national annual median earningse rate of the occupations in these groups increases, the variation in wages does not increase, unlike all other occupational groupings. It is possible that the occupations in the Computer and Office occupational groups have stickier wages than the occupations in the other occupational groups.

CHAPTER TWO

The Neoclassical Economic Model

The neoclassical model of geographic wage differentials predicts that, when wages in an occupation differ across regions, mobility of capital and/or labor will lead to wage convergence. The basic theory can be explained using the traditional model of supply and demand[1]. As shown in Figure One, suppose that there are two cities with one occupation. Market conditions in each city result in City 1 paying higher wages (W_H) than are paid in City 1 (W_L) for the same occupation. First, as shown by the shift in the supply curve from S to S_1 in the first panel of Figure One, workers will move from City 2 to City 1 in search of higher wages. This decreases the wages in the high wage area by increasing the available pool of labor. The second panel of Figure One shows how labor mobility also increases the wages in the low wage area as the labor supply decreases, as shown by the shift in the supply curve from S to S_1. Given that labor mobility happens over time and is not instantaneous, wage convergence also happens over time, with wages in both cities converging to W*.

Also, capital mobility can occur from the high wage area to the low wage area, increasing productivity in the low wage area and decreasing productivity in the high wage area. As shown in Figure Two, suppose that there are two cities—one with a higher wage (City 1) and one with a lower wage (City 2) for the same occupation. When firms

[1] Of course, neoclassical theory acknowledges that a variety of factors can preclude complete wage convergence across regions, such as proximity to other resources, transportation costs, moving costs, labor search costs, the disutility of moving, and similar transactions costs. While these factors place a limit on how much wages will converge across regions, they do not reverse the basic prediction of convergence.

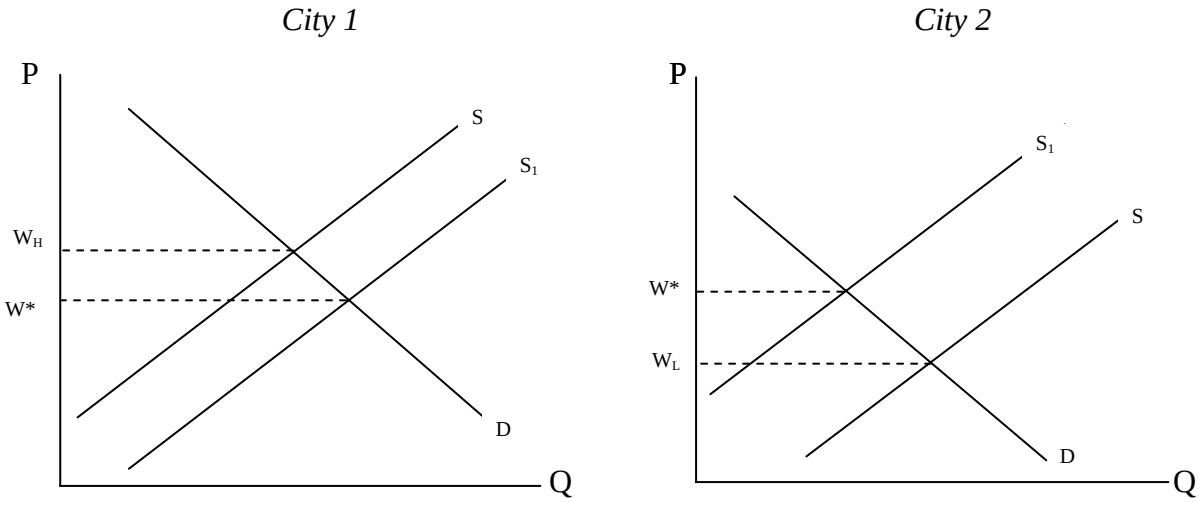


Fig. 1. Labor Mobility

relocate capital to City 2, demand for labor decreases in City 1 (moves from D to D_1 in the first panel), and demand for labor increases in City 2 (moves from D to D_1 in the second panel). Again, the wage differential vanishes over time as wages in both cities converge to W*. In fact, in a study of manufacturing plants, executives mentioned labor costs, proximity to markets, availability of skilled labor, industrial climate, the tax bill, and proximity to materials as the top six considerations in plant location decisions (Mueller and Morgan 1962, 207). Thus, in the neoclassical economic framework, labor mobility and capital mobility lead to convergence of wages within an occupation across regions.

In order for the neoclassical model to predict complete wage convergence, the conditions of the market must meet the following standard assumptions: perfect competition, one homogenous commodity, homogenous labor costs, zero transportation costs, regionally identical production functions, constant returns to scale, no technological differences or change, full employment equilibrium in the labor markets, and no transactions costs. However, in the short run the real world often does not follow

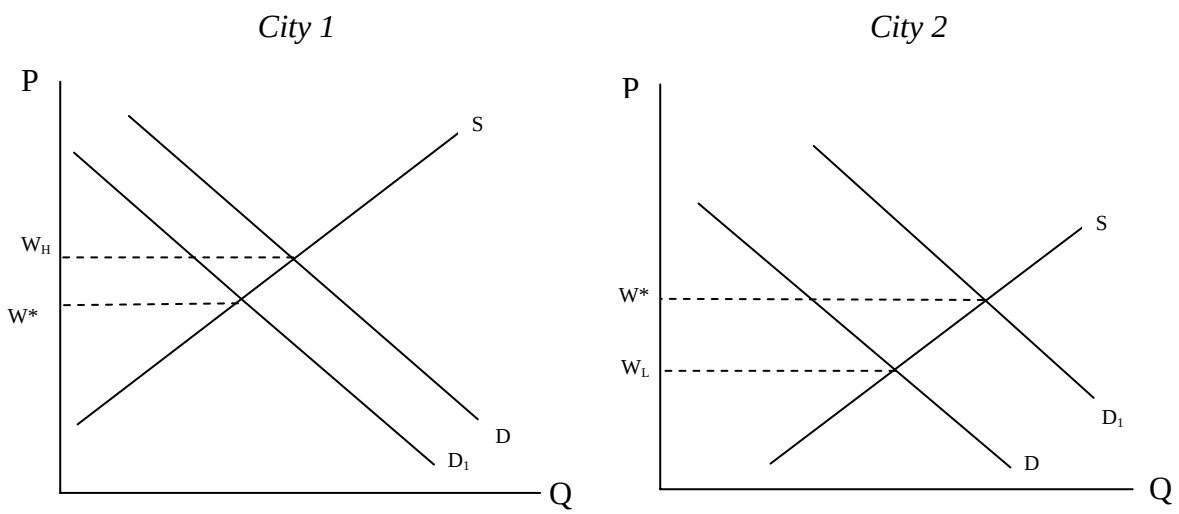


Fig. 2. Capital Mobility

all of the assumptions of these economic models. When examining wages in occupations within the United States, there is little evidence that convergence occurs except among segments of the population that historically experienced discrimination. Over time, women's wages and African Americans' wages have converged toward the general wage rate (Shapiro 1984, Fortin and Lemiuex 1998). The result of the assumption violations of the convergence model is the persistence of wage differentials (Scully 1969). These variations exist for reasons including the competitive structure of occupational groups (Wachter 1970) and general fluctuations due to the business cycle (Kydland and Prescott 1982).

Krueger and Summers (1988) found that wages were not converging over time and attribute the difference to efficiency wages, where some firms pay higher than normal wages in order to increase profits. Firms pay efficiency wages because they want to reduce turnover (Salop 1979, Stiglitz 1985), increase worker productivity (Calvo and Wellisz 1979) and provide incentives for younger workers (Lazear 1981), increase

loyalty (Akerlof 1982, also in context of other paradigms—Akerlof 1984) or attract a more highly qualified applicant pool (Malcomson 1981, Weiss 1980)[2].

However, wage differentials are not due to differences in unobserved variations in worker quality (Blackburn and Neumark 1992). In the short term, sticky wages and fluctuating demand causes wage dispersion and job market segmentation (Weitzman 1989). Borts (1960) found that migration from low wage to high wage areas alone does not produce wage convergence but that movement of capital was very important for wage changes over time. There is also evidence that wages do not converge due to immobility; for example, Venables (1995) found that if labor is not mobile, regional wage differentials and income inequalities will persist due to agglomeration economies.

[2] See Yellen 1984 for a clear explanation of these four models. See also Thaler (1989) for a discussion about inter-industry wage differentials.

CHAPTER THREE

Agglomeration Economies

The tendency of firms in similar occupational groups and people in related occupations to cluster in certain geographic locations has been labeled "agglomeration." A vast literature has arisen to explain how agglomeration economies can lead to outcomes at variance with the prediction of neoclassical theory. The benefits of agglomeration are many. First, there are gains from reduced transportation costs if the company is located near the suppliers of inputs and also near the consumer (Krugman 1991). Black and Henderson (1999) found that capital-goods plants agglomerate in places with large amounts of manufacturing employment in order to save on transportation costs. However, the desire to reduce transportation costs is not the only reason why agglomeration occurs. In fact, as Glaeser (1998) remarked, "if cities' only advantage was eliminating transport costs for manufactured goods, then cities would indeed cease to exist." The companies that agglomerate thus must still overcome local competition in both labor and outputs.

The compensating differences hypothesis is that people who work in occupations with a higher chance of unemployment are paid higher wages to alleviate the risk of working in those occupations (Topel 1984, Li 1986). At the same time, there are cities which are considered "specialized" in that they have a high percentage of firms and workers from a particular occupation or occupational group. Thus, places with more specialization have higher unemployment due to labor immobility (Simon 1988).

So, higher wages in agglomerated occupations occur because there is a higher risk of unemployment in the city in which the agglomerated occupational group is located (Diamond and Simon 1990).

Although workers in agglomerated occupations may suffer from a higher risk of unemployment, another benefit of agglomeration is the sharing between firms of a common labor pool. This benefit is manifested in lower search costs for employees and employers. First, potential employees have access to job opportunities through indirect channels such as conversations with potential coworkers and employers, reducing their search costs. Also, workers face significantly reduced relocation costs because of the proximity to and availability of similar occupations.

Firms in agglomerated occupations have a trained pool of labor from which to hire, so they are better able to respond to variations in the market. Firms can easily hire and fire based on the whims of the market. Although they are constrained by paying higher wages to their workers in both good times and bad times, the gains to be made are greater in the good times than are the losses in the bad times.

Finally, workers' skills can be matched more adequately with various similar occupations in a location with agglomeration than if that worker was located in a more geographically isolated area. The better match between the worker and the job leads to higher worker productivity. In fact, McCall (1990) found that when one switches to another job but stays within the same occupation, a longer tenure for the worker at the previous job meant a lowered likelihood of separation from the current job. If a lowered likelihood of separation is a proxy for higher worker productivity, then it is beneficial to

switch jobs within an occupation and it is easier to find a job within the same occupation in the same town if agglomeration is occurring or has occurred.

There are also beneficial externalities because of agglomeration[1]. Papageorgiou and Smith (1983) argue that agglomeration could increase if the positive externalities of agglomeration continue to outweigh the external costs of congestion due to greater densities of populations and firms. Most of these externalities have been characterized as knowledge and technology spillovers from high tech or higher-education occupations (Jaffe 1989, Jaffe et al 1993). We especially see agglomeration happening within the high-tech sector in the United States (Black and Henderson 1999), especially in Silicon Valley and Austin, Texas. Those who are better qualified might want to live in areas that have amenities, such as access to natural resources (Roback 1982) and an abundance of other people who work in the same occupational group (Black and Henderson 1999).

Baldwin and Forslid (2000) use dynamic models to show the effects of agglomeration on growth. They note that rapid growth causes agglomeration due to technological and knowledge spillovers. However, they also argue that knowledge spillovers are a source of stability. Thus agglomeration spurred by knowledge spillovers is beneficial to overall economic growth.

[1] Black and Henderson (1999) found that occupational groups "with the greatest degree of scale externalities are the most agglomerated" (327).

CHAPTER FOUR

Wages

There are many different units of analysis for agglomeration studies. Many studies use the size of a city to predict general agglomeration activity (Black and Henderson 1999, Moomaw 1981, Segal 1976, Wheeler 2001), while others study a single sector such as manufacturing for evidence of agglomeration (Carlton 1983, Paul and Seigal 1999, Shaver and Flyer 2000). Segal (1976) finds that labor and capital are eight percent more productive in larger cities. Similarly, Ciccone and Hall (1996) use county-level data to show that an increase in employee density leads to an increase in employee productivity. This increase in productivity can lead to higher wages.

Due to gains from externalities (and as such, gains that often are not easily valued in monetary terms), certain occupational groups tend to agglomerate and make location decisions such that they are able to pay higher wages in a popular location. As compared to more rural areas, or areas which employ few of that type of worker, the wages are higher in the agglomerated areas. This leads to wage divergence over time and place. Beeson and Eberts (1989) argue that wage differentials between cities are a result of both productivity factors, which affect the demand for labor, and the amenities of the city, which affect labor supply.

Agglomeration of *people* in certain occupations occurs for many reasons, including city specialization and job availability. Again, given that job type and employer are a large part of wage variance (Groshen 1991), wage variance should be greater in agglomerated occupations. Angel and Mitchell (1991) found evidence of

interregional wage variance across cities in the United States in similar occupations, but did not test for convergence or divergence over time. Finally, higher-ordered occupations are more likely to be agglomerated (Baldwin and Forslid 2000, Wachter 1970) and agglomeration is indicated by higher wage variance (Diamond and Curtis 1990). Due to economic restructuring of the economy, we expect that wages are diverging across cities in the United States depending on the sector and nature of the job. We extend the work on wage variance and agglomeration by ascertaining if wages diverged or if the neoclassical convergence in wages happened within certain occupational groups across the cities in the United States for the six years ending in 2005.

CHAPTER FIVE

Data

The data is from the Occupational Employment Statistics (OES) from the Bureau of Labor Statistics. The OES is mailed to about 200,000 establishments every six months and asks questions concerning full and part time workers for non-farm establishments in order to construct wage and employment estimates for about 800 occupations. In 1999, the OES started using the Standard Occupational Classification System, so we used the years 1999 through the most current employment records for 2005. The occupations are based on the 6 digit occupational code, but the first two digits of each code represent an occupation group.

Each line in our dataset is the variance in earnings in an occupation in a year. In all, there are 822 different occupations in 22 occupational groups. The summary statistics are presented in Table 1.

Table 1. Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Variance	8279.323	5082.933	120.2938	56151.31
Log variance	8.8577	0.5895	4.7899	10.9358
Herfindahl	0.0706	0.1168	0.0081	0.9620
Median wage	38643.3	21291.82	12200	165585.90
Some college	26.6049	14.7903	0	71.7
College or more	33.5239	32.4424	0	99.4

Given that theory argues that agglomeration happens in occupational groups and occupations with higher education levels (Wachter 1970), we ordered the occupational groups by average educational level[1]. These results are presented in Table Two. Education, which includes post secondary education teachers such as college professors, secondary education teachers, preschool teachers, and librarians, has the highest average of those with a college degree or more by occupation at 84.37 percent. This result is not surprising because at least a Bachelor's degree is a requirement for the vast majority of those in the Education occupational group.

The Science occupational group includes those who work jobs such as microbiologists, physicists, chemists, economists, psychologists, historians, and various technicians, such as nuclear technicians and forest and conservation technicians. Like the education occupational group, most of these jobs also require at a minimum a Bachelor's degree, although many require much more. By occupation, the mean percentage of those with at least a Bachelor's degree is 77.29 percent. The technicians have markedly lower educational levels than those who are scientists, so the standard deviation in this occupational group is 22.91, which is the fourth highest.

The Community occupational group includes people who work as clergy, counselors, therapists, social workers and probation officers. Many of these jobs require special training and licenses. The mean percentage of those who have at least a college education level in this occupational group is 68.44 percent. However, the Community occupational group is interesting because although it has the third highest mean education level, it has the sixteenth highest standard deviation at 6.67. Thus, those who

[1] The mean "college or more" education level is just for the occupation codes in the industry and is not weighted by the actual number of workers in each occupation.

Table 2. Mean Percentage College or More Education Level by Occupational Group

Occupational Group	Observations	Mean Education	Standard Deviation
Education	379	84.37	15.27
Science	235	77.29	22.91
Community	92	68.44	6.67
Computer	98	66.96	12.69
Legal	57	66.19	31.45
Engineer	223	57.77	29.95
Healthcare	301	56.94	35.37
Management	206	55.43	20.68
Business	186	55.03	14.32
Entertainment	233	53.38	17.44
Sales	139	34.22	19.15
Protective	120	22.03	12.93
Service	216	19.33	12.39
Office	369	16.45	6.50
Health Support	100	14.84	7.69
Transportation	286	12.59	17.35
Food	106	8.52	4.62
Maintenance	57	7.34	4.90
Farming	80	8.66	7.71
Repair	330	6.94	4.67
Production	731	6.25	5.25
Construction	359	4.89	3.68

work in Community occupations are more similar in their educational attainment than 15 other occupational groups. This is possible given that this occupational group tends to be highly regulated.

The Legal occupational group includes lawyers, arbitrators, judges, paralegals, law clerks and court reporters. Although this occupational group has a high percentage average of those who have a college degree or more at 66.19 percent, this occupational group is also the second highest standard deviation with 31.45 percent. The Legal occupational group has a very spread-out distribution of education levels given that

lawyers, judges and arbitrators typically must have attended law school, while paralegals and court reporters tend to have lower levels of education.

The occupations in the Engineering occupational group include architects, surveyors, engineers of all types, drafters and technicians. The mean percentage of those in this occupational group who have college or more education level is 57.77 percent. At the same time, the standard deviation is very high at 29.95, implying that there is a wide range of education levels within this occupational group. Engineers, architects and surveyors have higher levels of education, while the drafters and technicians have much lower levels of education.

The Healthcare occupational group includes chiropractors, dentists, surgeons, doctors, specialists, physician assistants, nurses, therapists, veterinarians and laboratory technicians. This occupational group has a mean of 56.94 percent of workers who have at least a college degree. This occupational group has the highest standard deviation at 31.45. There is a vast difference in education levels between those with the most education, such as a doctor, and those with lower levels of education, such as a lab technician.

Toward the bottom of Table One, we find those occupations with the lowest means of “college or more” education level and also the lowest standard deviations. For example, for those in Maintenance, such as pest control workers, tree trimmers, maids, and janitors, as well as the first line supervisors of such workers, by occupation, the mean percentage of those with at least a Bachelor’s degree is 7.34 percent and the standard deviation is 4.90 percent. Those with the highest education levels in the Maintenance occupational group are the supervisors. Finally, Construction has the lowest incidence of

those who have at least a Bachelor's degree at 4.89 percent and also the lowest standard deviation at 3.68. Those occupations within the Construction occupational group include paper hangers, derrick operators, roofers, electricians, framers, first line supervisors and helpers.

CHAPTER SIX

Measures of Interest

We estimate a series of Ordinary Least Squares (OLS) equations with robust standard errors to control for heteroskedasticity that examine the effect of the density of occupations across cities on the log of the variance of the wages in occupations grouped by occupational group codes and ordered by mean educational attainment in the group "college or more." We also look at the effect of the educational groupings "college or more" and "some college" on the log variance to determine the effect of education on the variation in wages. The theory predicts that agglomerated occupations and higher-ordered occupations should have more wage variation.

We utilize the variance of wages in Metropolitan Statistical Areas (MSAs) and occupations as defined by the Bureau of Labor Statistics (BLS). We took the median annual wage[1] for an occupation in each MSA and calculated the variance by year. The BLS does not report annual wages above $145,600 and hourly wages above $70.00 per hour, so we top-coded the annual wages for the highest paid occupations at $146,000 per year. In order to normalize the distribution, we use the log transformation of the calculated variance as our dependent variable.

The Herfindahl index is used to measure the concentration of workers in occupations across Metropolitan Statistical Areas (MSAs) in the United States in a given

[1] If the median annual wage rate was missing, we calculated it using the median hourly wage rate multiplied by 2080 hours.

year. The Herfindahl index is calculated by occupation as the sum of the squared share of people in a particular occupation across the MSAs:

$$H = \sum_{i=1}^{n} s_i^2 \ ,$$

where s_i is the number of people who work in MSA i in that particular occupation divided by the total number of people who work in that occupation across all MSAs, and n is the number of MSAs present in the United States. There is a Herfindahl calculated for every occupation in every year and ranges between zero and one. A Herfindahl index that equals one indicates that employees in that occupation are located in one geographical area, namely in one MSA.

We control for variations in education levels within occupations by including two variables—one is the percentage of people in that occupation who have a Bachelor's degree or more education and the other is the percentage of people whose maximum amount of education is some college. The excluded group is those whose maximum amount of education is high school or less. This data is from the Current Population Survey (CPS) and was collected by the BLS from 2000 through 2002. Because the education percentages were compiled by the BLS into one measure, it does not change over time.

Wages diverge sharply as the education level of workers increases (Cardoso 2000). Douty (1961) found that wage variation was highest in the clerical positions and lowest in the unskilled labor positions with skilled labor positions falling somewhere in between. There is the perception that the productivity of those with higher levels of education is more variable than those with lower levels of education, especially depending on the subject of the degree (Cardoso 2000).

Real national annual median earnings for the occupation is used as a control variable because it is possible that the variance in wages is greater for higher-paying occupations. Real national annual median earnings by occupation is a yearly variable from the BLS. Again, we top-coded the annual wages at $146,000 per year where the data was missing due to being greater than $145,600.

Year dummies are used as control variables. occupational groupings control for wage variation differences across occupational groups. Borts (1960) notes that wage differentials and the drivers thereof are different between occupational groups. Keane (1993) explains that the occupational group of the occupation has a small effect on wage differentials. All of the national occupational employment and wage data is found on the BLS website, www.BLS.gov.

CHAPTER SEVEN

Findings

For each of the 22 occupational groups, we estimate an OLS regression of the log wage variance on the Herfindahl of the occupation, the median wage, year dummies from year 2000 to 2005 with year 1999 as our excluded group, the percentage of people in the occupation with only some college education and the percentage of people in the occupation with college or more education, with the comparison group being those who have not gotten more than a high school education. The complete results are set forth in the Appendix. However, Table Three reports just the coefficient estimates, the standard errors, and the significance levels for the Herfindahl variable in all 22 regressions. These results are ordered from the highest to the lowest education level by the category of "college or more," which is the mean across the occupations of the percentage of workers who achieved that education category.

For the top eleven occupational groups as sorted by educational attainment in the "college or more" category, there are seven positive and significant results, meaning that variance in wages is higher in more concentrated occupations. Such as pattern is consistent with the existence of agglomeration in the occupational groups. These occupational groups are Community, Engineering, Healthcare, Management, Business, Entertainment, and Sales. All but Sales are significant at the 0.01 level, while Sales is significant at the 0.05 level. For the bottom eleven occupational groups, only 4 results

Table 3. Results for Herfindahl by Occupational Group

Occupational Group	Herfindahl	Standard Errors
Education	0.2505	0.177
Science	0.0010	0.184
Community	3.4687***	0.929
Computer	-0.2544	0.559
Legal	1.3864	1.132
Engineer	0.8328***	0.272
Healthcare	2.1705***	0.569
Management	1.6155***	0.423
Business	2.9545***	0.284
Entertainment	1.3718***	0.298
Sales	0.9927**	0.471
Protective	0.1438	0.469
Service	0.7453**	0.305
Office	0.4154	0.742
Health Support	3.4475**	1.644
Transportation	0.3403	0.256
Food	-8.0727	9.600
Maintenance	2.6712*	1.505
Farming	0.5652	0.448
Repair	0.4252**	0.201
Production	0.3136	0.314
Construction	-0.4433	0.330

***p < 0.01, **p<0.05, * p<0.10

are significant and they are all positive. Service, Health Support and Repair are significant at the 0.05 level while Maintenance is significant at the 0.1 level. Also, the average log variance for the first 11 occupational groups is 1.9152, while the average for the occupational groups in the lower half is 1.8223.

Thus, there is some evidence that educational attainment matters for agglomeration, as seven out of the eleven higher-ordered occupational groups (i.e., those having the most educated workforces) show signs of agglomeration economies, compared to only four of the eleven lower-ordered groups.

Overall, lower-ordered occupations, which we proxy by education level, have less wage variation than higher-skilled occupations. This result implies that these occupations are not agglomerated. Of the occupations where at least 70 percent of the workforce has a high school education or less, the mean wage variation is $6,657 with a standard deviation of $4,085.

Higher-skilled occupational groups, or occupational groups that rely on a trained labor force, consist of occupations which have higher percentage of college educated workers. These higher-skilled occupations also have higher variance in wages. Of the occupations where at least 70 percent of the workforce is at least college educated, the mean wage variance is $12,316 with a standard deviation of $5,948. Again, given the theory of agglomeration and wage variation, these occupational groups show agglomeration, which means that the location of this labor force is less reliable. The firms employing high-skilled workers do not necessarily have as much a location choice as those firms employing low-skilled workers. Instead of geographically differentiating, these firms choose to go to where the supply of labor will be. At the same time, workers will choose to relocate to areas where there is a supply of jobs in their chosen occupations. In this way, we see agglomeration of higher-skilled occupations. Because of the tighter supply of high-skilled workers, these firms pay a wage premium and thus there is higher variance in wages (Wachter 1970).

Table Four shows the coefficient estimates, standard errors and p-values for the “some college” and “college or more” variables for the regressions of the log variance of wages in the occupation on the education variables, of course controlling for the agglomeration of workers, the median wage and time. The following occupational

Table 4. Schooling Determinants of Variation of Wages

Occupational Group	Some College	Standard Error	College or More	Standard Error
Education	0.0227***	0.008	0.0173***	0.004
Science	0.0258***	0.006	0.0202***	0.004
Computer	-0.0311	0.024	-0.0109	0.020
Community	0.0134	0.013	0.0027	0.007
Legal	-0.0456***	0.010	-0.0229***	0.006
Engineer	-0.0074***	0.002	-0.0015	0.002
Healthcare	0.0087***	0.002	0.0119***	0.002
Management	0.0008	0.003	0.0057***	0.002
Business	-0.0191***	0.004	-0.0020	0.002
Entertainment	-0.0171***	0.004	-0.0111***	0.002
Sales	0.0332***	0.008	0.0020	0.004
Protective	0.0109***	0.002	0.0015	0.002
Service	0.0032	0.005	0.0018	0.003
Office	0.0133***	0.003	0.0182***	0.004
Health Support	-0.0054	0.003	0.0307***	0.005
Transportation	0.0023	0.003	0.0047**	0.002
Food	0.0191***	0.006	-0.0393***	0.009
Maintenance	0.0038	0.006	-0.0189*	0.011
Farming	-0.0572	0.039	0.0425	0.029
Repair	0.0030***	0.001	0.0146***	0.004
Production	0.0028*	0.002	0.0008	0.002
Construction	0.0016	0.002	-0.0230***	0.004

**p < 0.01, *p<0.05

groups have more wage variance the more the workers have of the education level “some college:” Education, Science, Healthcare, Sales, Protective, Office, Food, Repair and Production. Also, Education, Science, Healthcare, Management, Entertainment, Office, Health Support, Transportation, Food, Maintenance, Repair, and Construction all have wage variance the more percentage of workers have attained the “college or more” educational level. These two results fit with the idea that as education increases, so too does variance in wages. Cardoso (2000) determines that “there is significant variability across firms in the way they reward the attributes of their workers” including schooling (348).

However, the occupational groups of Legal, Engineering, Business and Entertainment have less wage variance the higher the percentage of workers have of the education level "some college." The Legal occupational group has less wage variance the higher that the percent of workers in an occupation have at the college or more educational level. Thus, the wage variation in the Legal occupational group is mostly due to the difference between the highly paid workers with advanced degrees and the law clerks and those who are more likely to only have a high school diploma. For the Engineering, Business and Entertainment occupational groups, the wage variance is highest for those occupations with lots of college graduates. Not surprisingly, in these occupations we also see agglomeration effects. Finally, all of the occupational groups show more variance in wages as the real national annual median earnings increase, except for Computers and Office. This may be because wages are stickier in those occupational groups.

Unfortunately, there are some problems with our dataset. In order to address these problems, we estimated the regressions using fixed effects at the four digit occupational code level[1]. These results are presented in panel 1 of Table Five. The fixed effects estimator allows for control of unobserved heterogeneity across occupations within the occupational group but at a level closer to the actual occupation. The results using the fixed effect were very similar to the OLS results with a few exceptions. First, the Herfindahl for the Computer occupational group is negative and significant, while the result using OLS is negative and insignificant. This implies that within the Computer occupational group wages are actually converging. However, there are only two groups

[1] We cannot use the six digit occupational code for the fixed effects estimations because the educational levels do not vary over time.

Table 5. Results for Herfindahl by Occupational Group for Fixed Effects and Corrected Fixed Effects

	(1)		(2)	
Occupational Group	Herfindahl	Standard Errors	Herfindahl	Standard Errors
Education	0.0963	0.121	-0.0933	0.203
Science	0.0022	0.128	-0.1136	0.150
Community	2.2356**	0.989	5.6182***	1.876
Computer	-0.6217**	0.260	0.1670	0.271
Legal	1.3864	1.072	1.6561	1.510
Engineer	0.7308***	0.138	1.3318***	0.201
Healthcare	2.0311***	0.357	3.7911***	0.587
Management	1.3893***	0.390	3.4396***	0.785
Business	3.1767***	0.312	5.4712***	0.776
Entertainment	0.6357***	0.192	0.8708***	0.236
Sales	0.6550*	0.345	5.3032***	0.861
Protective	0.1291	0.294	0.1284	0.313
Service	0.7222***	0.258	0.8596**	0.359
Office	0.2297	0.553	1.6409**	0.730
Health Support	3.3542***	0.700	10.8677***	1.077
Transportation	0.3181	0.197	0.2912	0.200
Food	-7.7011	8.181	-7.7011	8.181
Maintenance	2.1039*	1.053	12.8449***	1.471
Farming	0.4935*	0.288	1.9009***	0.475
Repair	0.3190***	0.099	0.3819***	0.108
Production	0.4391***	0.109	0.6616***	0.138
Construction	-0.1870	0.137	-0.8598***	0.224

***p < 0.01, **p<0.05, * p<0.10

in the fixed effect model, so it is unclear if the results are statistically sound. Also, Farming and Production are significant at the ten percent level with a positive coefficient using fixed effects and they are positive and insignificant using OLS. These results are robust.

We also tried the fixed effects model excluding those observations that, due to missing data, seemed out of the ordinary. The results, presented in panel 2 of Table Five, were similar to the results from the OLS model. Given that the sign of the coefficient on

the Herfindahl variable is what is important, there is no indication that the data problems are driving the OLS results; however, there are some results of note[2].

Education and Science switch signs and show convergence, but the results still are not statistically significant. Computers switches signs and shows divergence, but again the result is not significant. All occupational groups that are positive and significant in the OLS model have positive, significant and larger effects in the fixed effects model except Entertainment and Repair which are positive, significant and smaller. Office is still positive but now significant, as is Farming and Production. This result implies that higher-ordered occupations do not matter when predicting wage divergence given that Office, Farming and Production are all lower-ordered occupations and they show signs of wage divergence. Finally, Construction is negative and significant as opposed to negative and insignificant in the OLS model.

[2] The BLS surveys establishments and asks for data on wages and employment. The BLS releases all wage data, but, in certain circumstances, not the data on number of employees in order to protect the privacy of establishments. Thus there is data missing on number of employees in certain occupations in various MSAs, especially in 1999. This leads to artificially high Herfindahl measures due to the missing data.

CHAPTER EIGHT

Conclusion

The neoclassical economic model predicts that wage convergence happens over time and place. Labor and capital mobility are important drivers of wage convergence as labor should flow from the lower wage area to the higher wage area, while capital should flow from the higher wage area to the lower wage area. Although true wage equilibrium may not happen for a variety of reasons, over time wages should show convergence. However, agglomeration economies allow firms to take advantage of certain externalities that exist in an area with a lot of workers of the same occupation and also many firms that hire those types of workers.

Agglomeration is beneficial due to decreases in transportation costs and knowledge and technological spillovers. Also, worker location theory predicts agglomeration in cities with higher amounts of amenities with higher wage variation. Finally, due to the existence of a compensating differential in occupations that have higher unemployment rates because they exist in more specialized or agglomerated cities, wage variation is higher in the agglomerated occupation.

We found that agglomeration is more likely to happen in higher order occupational groups and we hypothesized that it is due to decreased location choice for firms. There is also a significant difference between people in the Legal occupational group who work at lower-ordered jobs and those people who work at higher-ordered jobs with lower variance at the upper end of the spectrum. This may be because lawyers are not agglomerated and thus are appropriately geographically distributed such that it keeps

their wages less diverse. There may be some sticky wages in the Computer and Office occupational groups because variance does not increase in these occupational groups when the median wage increases. Finally, Engineering, Business and Entertainment occupational groups show higher agglomeration effects as well as higher wage variance for occupations with a high percentage of college graduates.

In conclusion, wage theory, especially agglomeration theory, matters because it helps to explain why wages have more variance. If a city is interested in attracting a certain type of occupation or occupational group that is of a higher order to the area, it should consider making agglomeration feasible. The higher order occupations agglomerate because they receive gains from doing so and the wages for those who work in the agglomerated occupational group will be higher than the median wage.

APPENDIX

Full Regressions by Occupational Group

Table A.1. Education

Variable	Coefficient	Robust Standard Error
Herfindahl	0.2505	0.144
Real national annual median (in 1000's)	0.0138***	0.000
Year 2000	0.2639***	0.0523
Year 2001	0.0504	0.0478
Year 2002	0.0161	0.049
Year 2003	0.0324	0.0560
Year 2004	0.0847*	0.0469
Year 2005	0.1378***	0.051
Some college percentage	0.0227***	0.008
College or more	0.0173***	0.004
Constant	6.6650***	0.426
Number of observations	376	
R-squared	0.5367	

***p<0.01, **p<0.05, *p<0.1

Fig. A.1. Regression of the Log Variance on the Herfindahl for the Education Industry

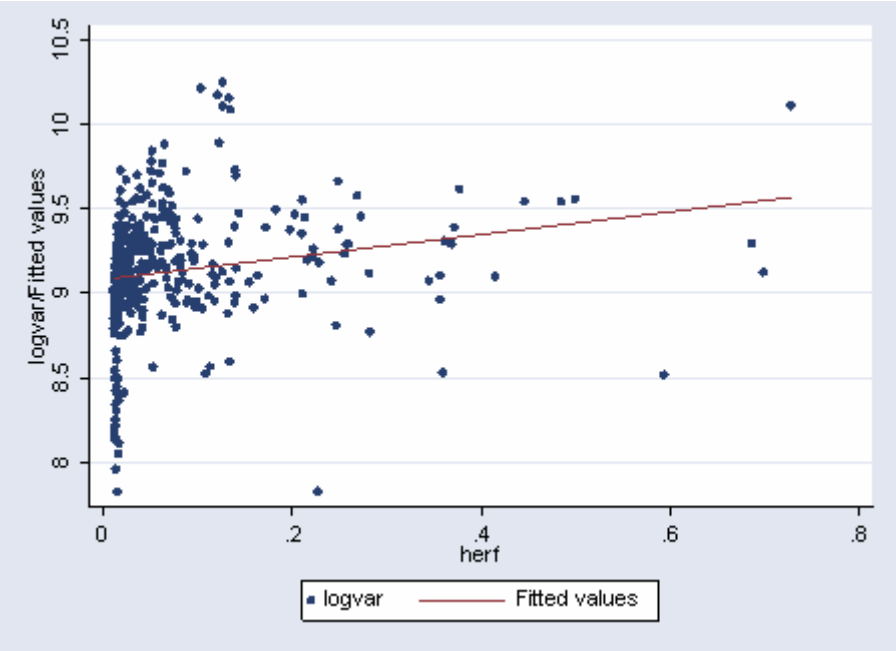


Table A.2. Science

Variable	Coefficient	Robust Standard Error
Herfindahl	0.0010	0.184
Real national annual median (in 1000's)	0.0437*	0.000
Year 2000	0.1776***	0.068
Year 2001	0.0704	0.082
Year 2002	0.0751	0.071
Year 2003	0.1830**	0.074
Year 2004	0.1789**	0.072
Year 2005	0.2550***	0.076
Some college percentage	0.026***	0.006
College or more	0.0202***	0.004
Constant	7.0122***	0.321
Number of observations	235	
R-squared	0.3665	

***p<0.01, **p<0.05, *p<0.1

Fig. A.2. Regression of the Log Variance on the Herfindahl for the Science Industry

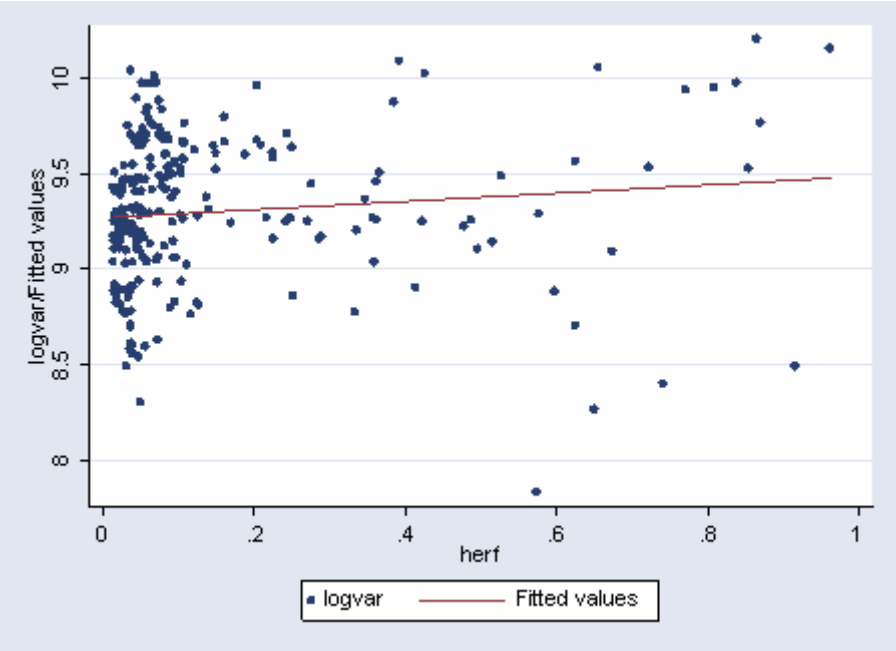


Table A.3. Community

Variable	Coefficient	Robust Standard Error
Herfindahl	3.4687***	0.929
Real national annual median (in 1000's)	0.0273***	0.000
Year 2000	0.3173***	0.079
Year 2001	0.0650	0.080
Year 2002	-0.0257	0.069
Year 2003	0.0293	0.076
Year 2004	0.0172	0.079
Year 2005	0.0834	0.085
Some college percentage	0.0133	0.013
College or more	0.0027	0.007
Constant	7.3461***	0.816
Number of observations	91	
R-squared	0.5589	

***p<0.01, **p<0.05, *p<0.1

Figure A.3. Regression of the Log Variance on the Herfindahl for the Community Industry

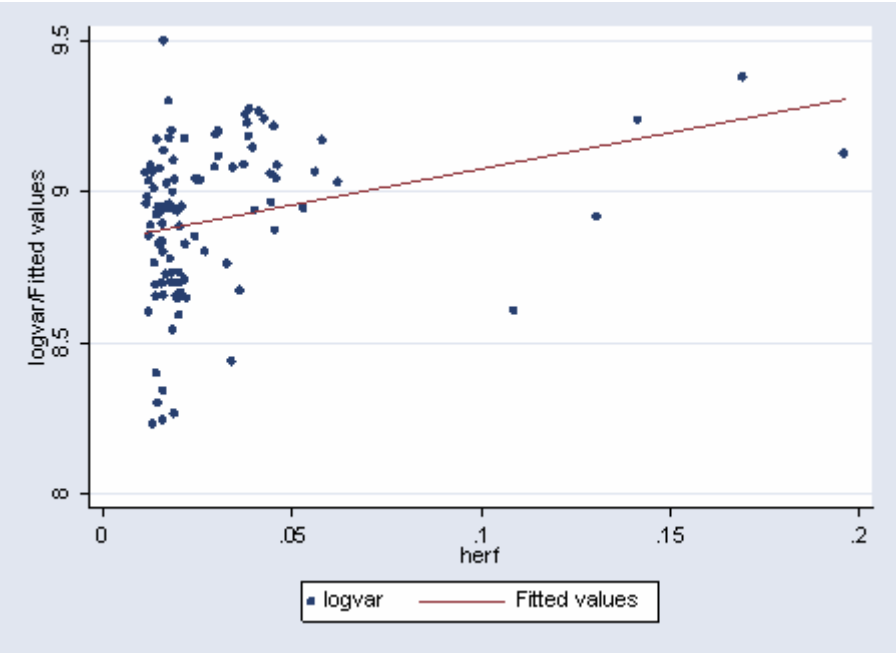


Table 4. Computers

Variable	Coefficient	Robust Standard Error
Herfindahl	-0.2544	0.559
Real national annual median (in 1000's)	0.0303	0.528
Year 2000	0.2003**	0.098
Year 2001	0.1826	0.122
Year 2002	-0.0082	0.122
Year 2003	0.1247	0.107
Year 2004	0.1511	0.113
Year 2005	0.3241**	0.131
Some college percentage	-0.0311	0.024
College or more	-0.0109	0.020
Constant		
Number of observations	98	
R-squared	0.3691	

***p<0.01, **p<0.05, *p<0.1

Figure A.4. Regression of the Log Variance on the Herfindahl for the Computers Industry

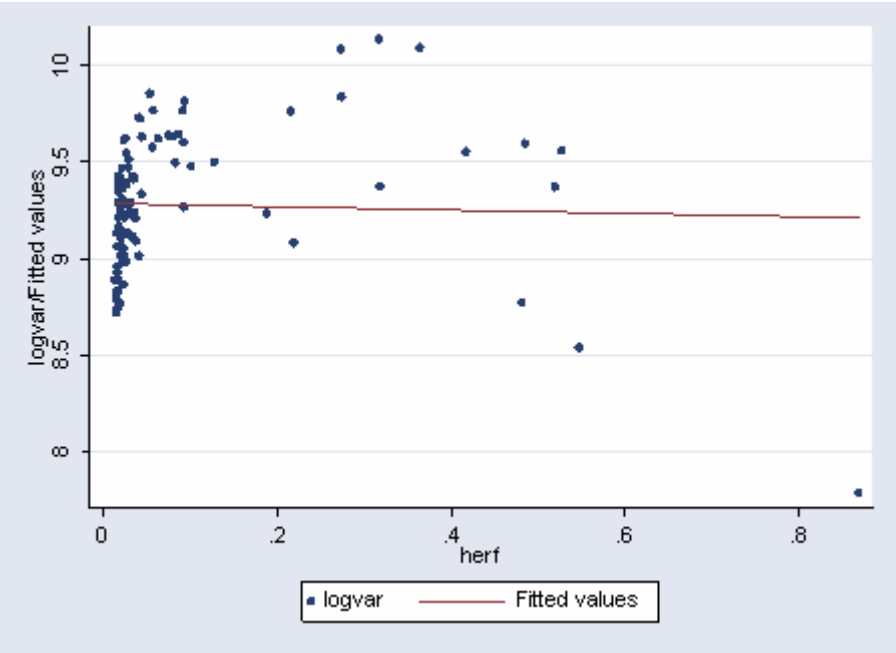


Table 5. Legal

Variable	Coefficient	Robust Standard Error
Herfindahl	1.3864	1.132
Real national annual median (in 1000's)	0.0128***	0.000
Year 2000	0.4700*	0.240
Year 2001	0.2816	0.201
Year 2002	0.2789	0.200
Year 2003	0.3118	0.204
Year 2004	0.2228	0.191
Year 2005	0.2636	0.188
Some college percentage	-0.0456***	0.010
College or more	-0.0229***	0.006
Constant	10.9773***	0.741
Number of observations	56	
R-squared	0.7929	

***p<0.01, **p<0.05, *p<0.1

Fig. A.5. Regression of the Log Variance on the Herfindahl for the Legal Industry

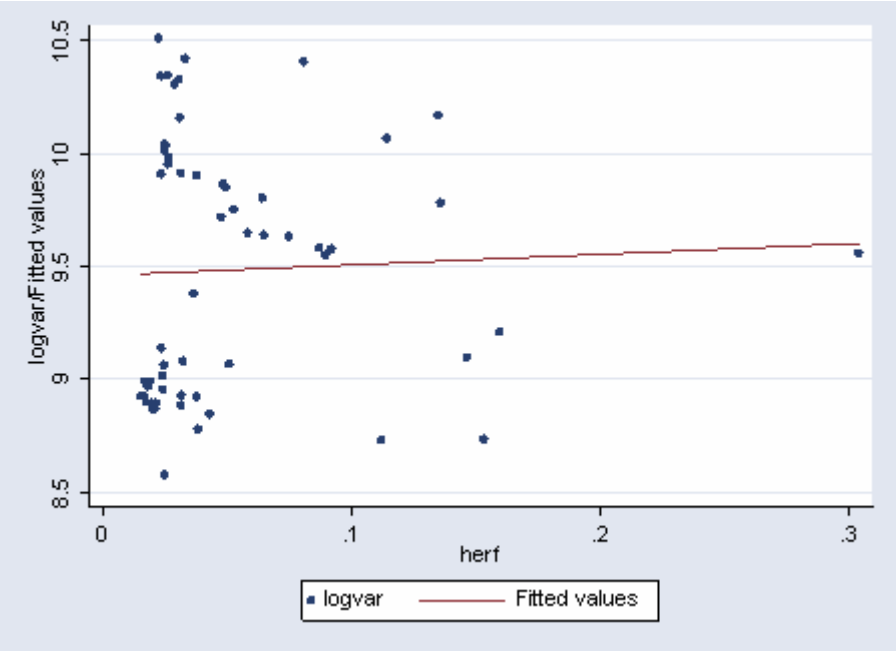


Table A.6. Engineering

Variable	Coefficient	Robust Standard Error
Herfindahl	0.8328***	0.272
Real national annual median (in 1000's)	0.0480***	0.000
Year 2000	0.1318**	0.051
Year 2001	0.0008	0.055
Year 2002	0.0143	0.051
Year 2003	0.0969*	0.052
Year 2004	0.1483**	0.057
Year 2005	0.2304***	0.056
Some college percentage	-0.0074***	0.002
College or more	-0.0015	0.002
Constant	9.0193***	0.132
Number of observations	223	
R-squared	0.6105	

***p<0.01, **p<0.05, *p<0.1

Fig. A.6. Regression of the Log Variance on the Herfindahl for the Engineering Industry

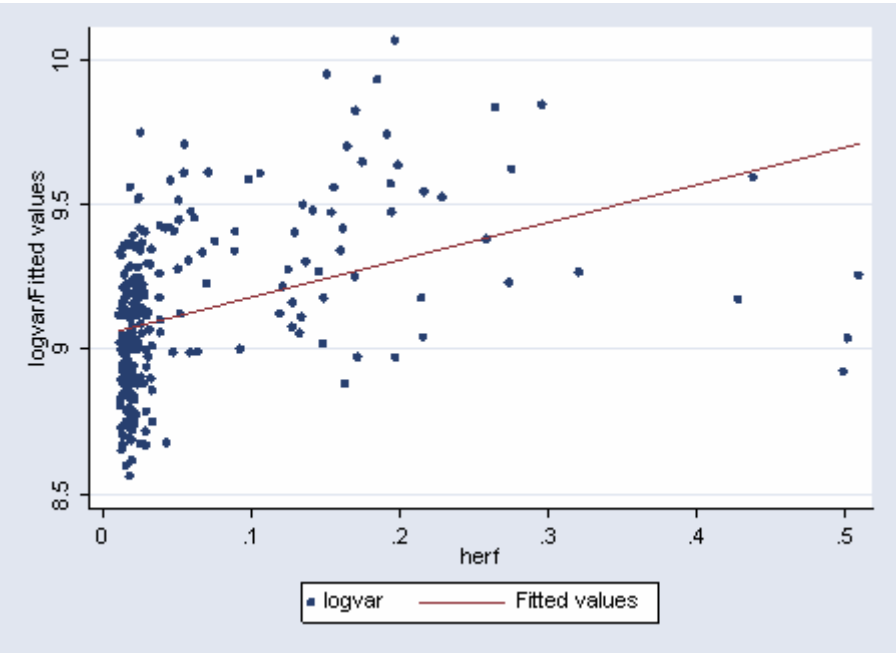


Table A.7. Healthcare

Variable	Coefficient	Robust Standard Error
Herfindahl	2.1705***	0.569
Real national annual median (in 1000's)	0.0591***	0.000
Year 2000	0.2122***	0.075
Year 2001	0.1440*	0.076
Year 2002	0.1307*	0.078
Year 2003	0.1734**	0.079
Year 2004	0.1615*	0.082
Year 2005	0.2285***	0.083
Some college percentage	0.0087***	0.002
College or more		
Constant		
Number of observations	299	
R-squared	0.6436	

***p<0.01, **p<0.05, *p<0.1

Fig. A.7. Regression of the Log Variance on the Herfindahl for the Healthcare Industry

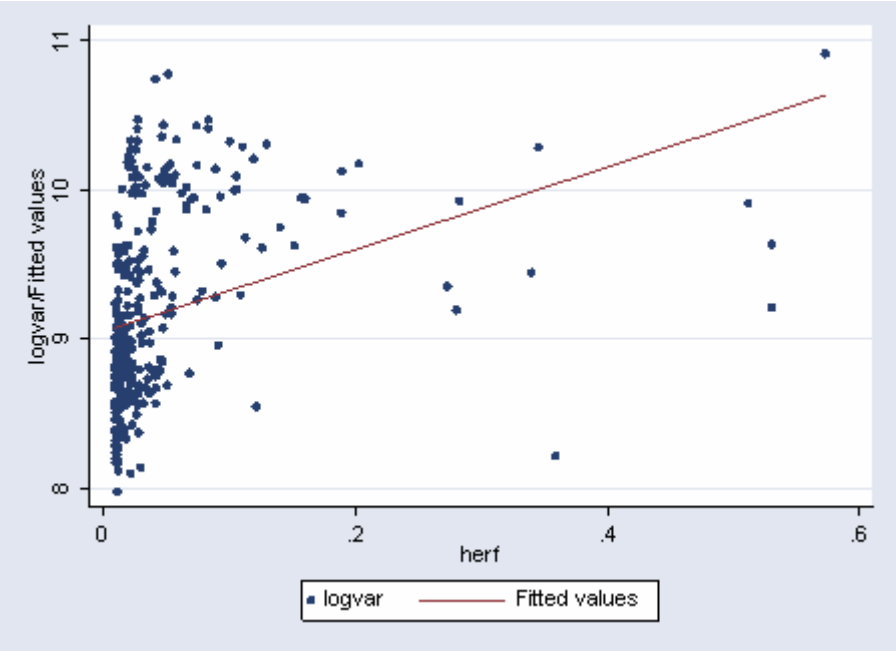


Table A.8. Management

Variable	Coefficient	Robust Standard Error
Herfindahl	1.6155***	0.423
Real national annual median (in 1000's)	0.0529***	0.000
Year 2000	0.1221	0.076
Year 2001	0.0296	0.074
Year 2002	0.0029	0.078
Year 2003	0.1023	0.083
Year 2004	0.1332*	0.079
Year 2005	0.2032**	0.081
Some college percentage	0.0008	0.003
College or more	0.0057***	0.002
Constant	8.6145****	0.165
Number of observations	205	
R-squared	0.3757	

***p<0.01, **p<0.05, *p<0.1

Fig. A.8. Regression of the Log Variance on the Herfindahl for the Mangement Industry

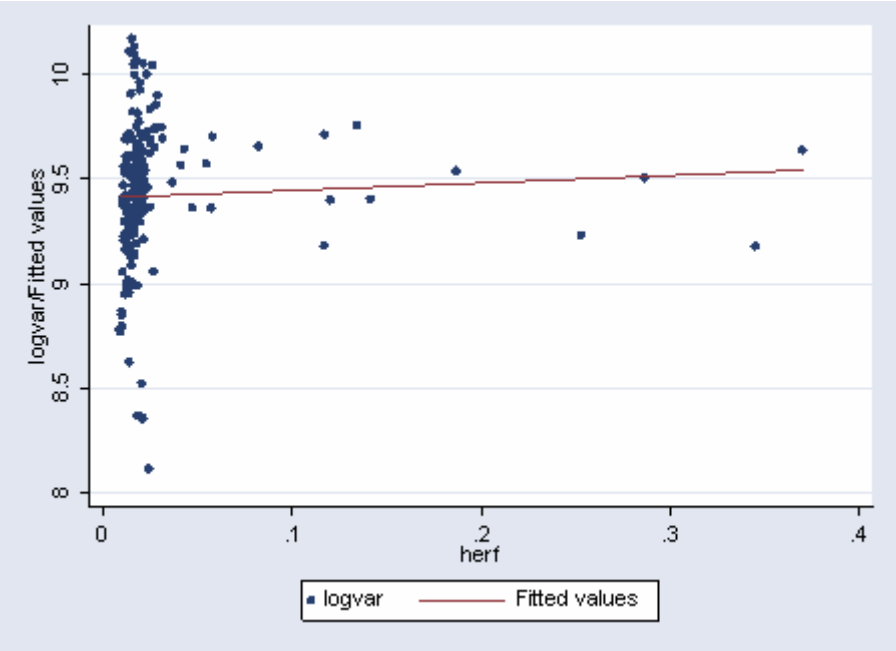


Table A.9. Business

Variable	Coefficient	Robust Standard Error
Herfindahl	2.9545***	0.284
Real national annual median (in 1000's)	0.0438*	0.000
Year 2000	0.1582**	0.071
Year 2001	0.1303*	0.068
Year 2002	0.0997	0.073
Year 2003	0.1816**	0.076
Year 2004	0.2080***	0.078
Year 2005	0.3071***	0.078
Some college percentage	-0.0191***	0.004
College or more	-0.0020	0.002
Constant	9.2909***	0.200
Number of observations	186	
R-squared	0.5466	

***p<0.01, **p<0.05, *p<0.1

Fig. A.9. Regression of the Log Variance on the Herfindahl for the Business Industry

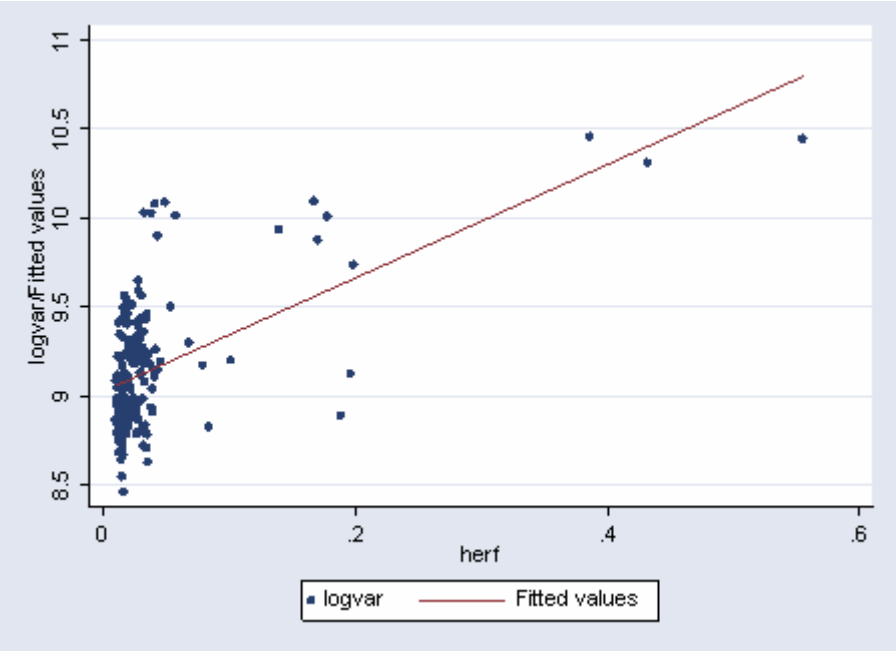


Table A.10. Entertainment

Variable	Coefficient	Robust Standard Error
Herfindahl	1.3718***	0.298
Real national annual median (in 1000's)	0.2190***	0.000
Year 2000	0.4064***	0.096
Year 2001	0.0937	0.086
Year 2002	0.0081	0.089
Year 2003	0.0350	0.087
Year 2004	0.0641	0.094
Year 2005	0.0694	0.102
Some college percentage	-0.0171***	0.004
College or more	-0.0111***	0.002
Constant	9.2669****	0.189
Number of observations	224	
R-squared	0.3411	

***p<0.01, **p<0.05, *p<0.1

Fig. A.10. Regression of the Log Variance on the Herfindahl for the Entertainment Industry

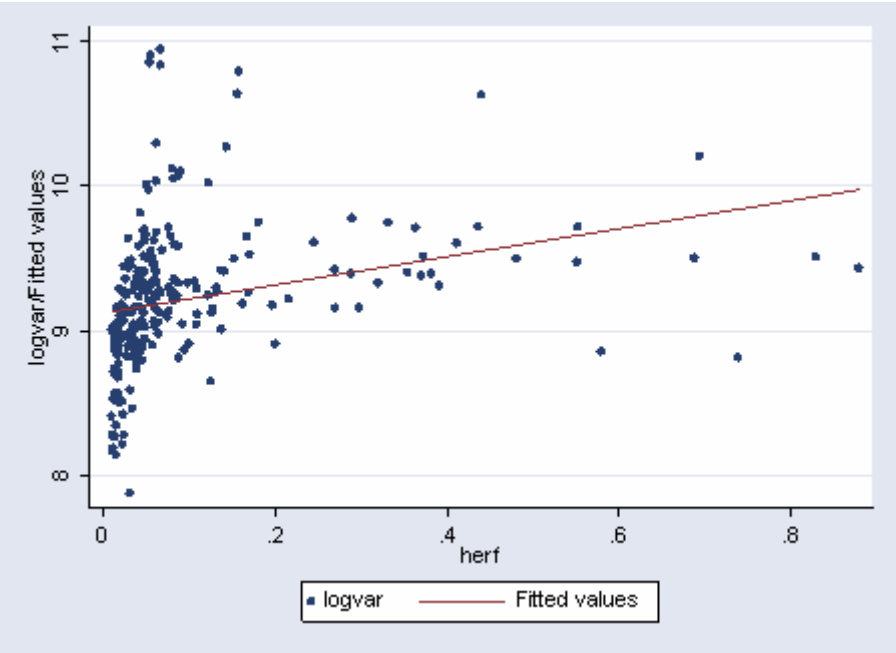


Table A.11. Sales

Variable	Coefficient	Robust Standard Error
Herfindahl	0.9927**	0.471
Real national annual median (in 1000's)	0.4270***	0.000
Year 2000	0.4674**	0.195
Year 2001	-0.0104	0.166
Year 2002	-0.0754	0.159
Year 2003	-0.0069	0.169
Year 2004	-0.1708	0.162
Year 2005	-0.1941	0.159
Some college percentage	0.0332***	0.008
College or more	0.0020	0.004
Constant	6.1857***	0.318
Number of observations	138	
R-squared	0.6544	

***p<0.01, **p<0.05, *p<0.1

Fig. A.11. Regression of the Log Variance on the Herfindahl for the Sales Industry

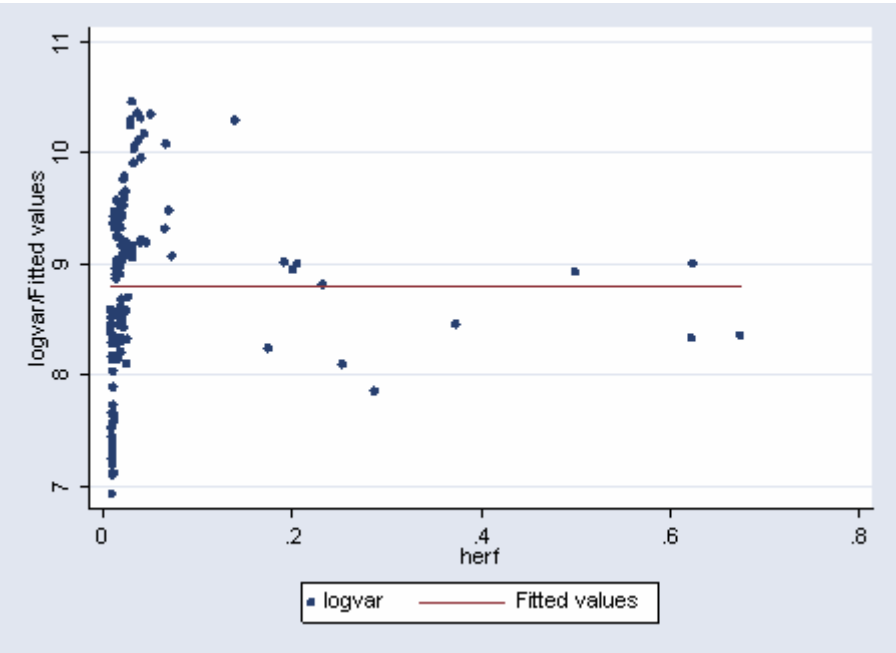


Table A.12. Protective

Variable	Coefficient	Robust Standard Error
Herfindahl	0.1438	0.469
Real national annual median (in 1000's)	0.2380***	0.000
Year 2000	0.1824*	0.107
Year 2001	0.0176	0.120
Year 2002	-0.2289	0.168
Year 2003	-0.1090	0.102
Year 2004	-0.0152	0.132
Year 2005	-0.2036*	0.114
Some college percentage	0.0109***	0.002
College or more	0.0015	0.002
Constant	7.6966***	0.146
Number of observations	118	
R-squared	0.5423	

***p<0.01, **p<0.05, *p<0.1

Fig. A.12. Regression of the Log Variance on the Herfindahl for the Protective Industry

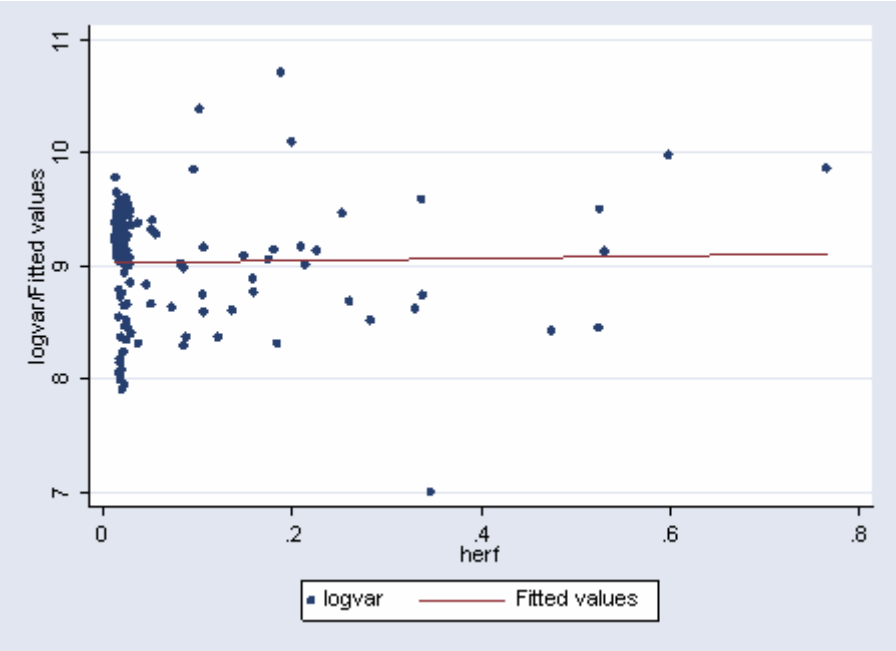


Table A.13. Service

Variable	Coefficient	Robust Standard Error
Herfindahl	0.7453**	0.305
Real national annual median (in 1000's)	0.5300***	0.000
Year 2000	0.4543***	0.135
Year 2001	0.0378	0.115
Year 2002	-0.0345	0.113
Year 2003	0.0120	0.115
Year 2004	-0.0188	0.120
Year 2005	0.0431	0.118
Some college percentage	0.0032	0.005
College or more	0.0018	0.003
Constant	6.9924***	0.239
Number of observations	215	
R-squared	0.5431	

***p<0.01, **p<0.05, *p<0.1

Fig. A.13. Regression of the Log Variance on the Herfindahl for the Service Industry

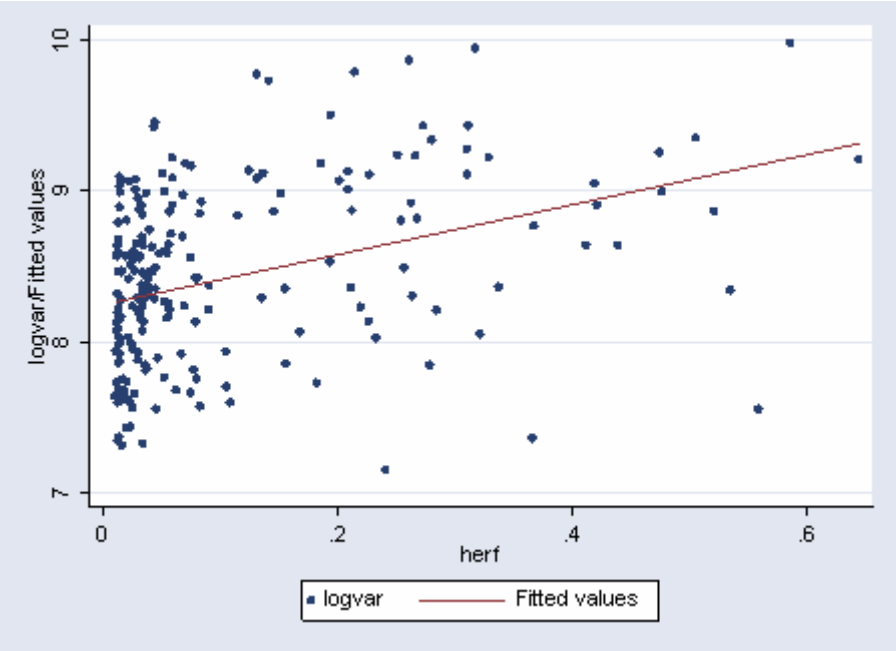


Table A.14. Office

Variable	Coefficient	Robust Standard Error
Herfindahl	0.4154	0.742
Real national annual median (in 1000's)	0.0583	0.000
Year 2000	0.1400	0.097
Year 2001	0.1917**	0.095
Year 2002	0.1540	0.099
Year 2003	0.2170**	0.104
Year 2004	0.3686***	0.110
Year 2005	0.4549***	0.122
Some college percentage	0.0133***	0.003
College or more	0.0182***	0.004
Constant	7.3200***	0.1519
Number of observations	366	
R-squared	0.1504	

***p<0.01, **p<0.05, *p<0.1

Fig. A.14. Regression of the Log Variance on the Herfindahl for the Office Industry

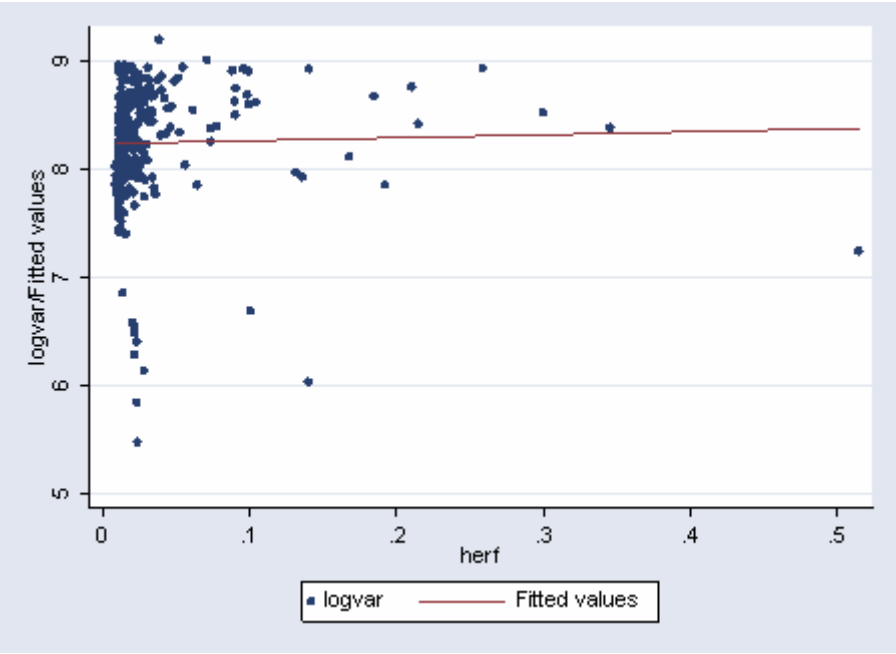


Table A.15. Health Support

Variable	Coefficient	Robust Standard Error
Herfindahl	3.4475**	1.644
Real national annual median (in 1000's)	0.2760***	0.000
Year 2000	0.2371**	0.101
Year 2001	0.0715	0.093
Year 2002	0.0366	0.089
Year 2003	0.0333	0.086
Year 2004	0.0808	0.084
Year 2005	0.0856	0.087
Some college percentage	-0.0054	0.003
College or more	0.0307***	0.005
Constant	7.3548***	0.141
Number of observations	100	
R-squared	0.6783	

***p<0.01, **p<0.05, *p<0.1

Fig. A.15. Regression of the Log Variance on the Herfindahl for the Health Support Industry

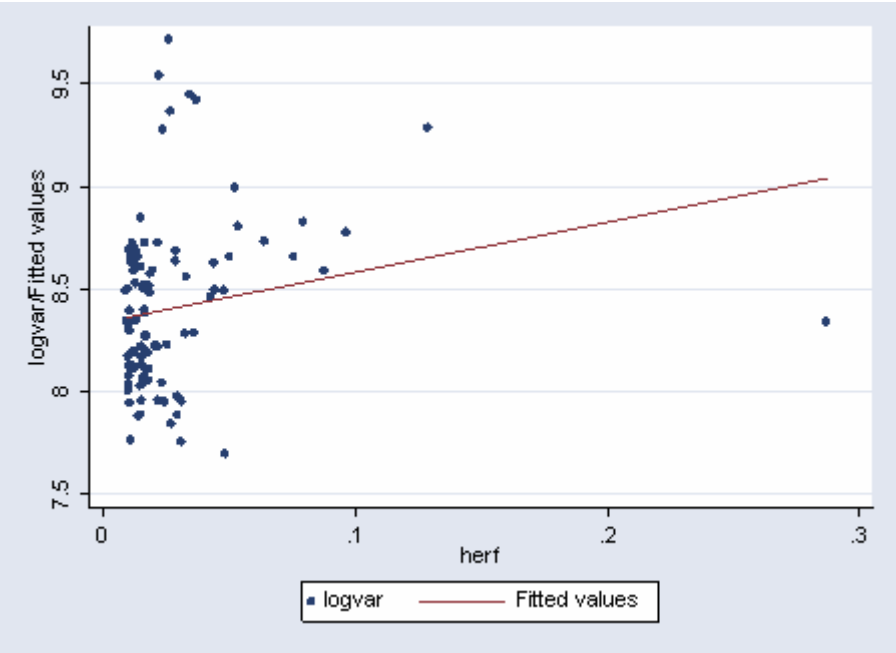


Table A.16. Transportation

Variable	Coefficient	Robust Standard Error
Herfindahl	0.3403	0.256
Real national annual median (in 1000's)	0.1840***	0.000
Year 2000	0.2587**	0.108
Year 2001	0.0706	0.106
Year 2002	-0.0412	0.117
Year 2003	-0.0304	0.111
Year 2004	0.0547	0.105
Year 2005	0.0740	0.096
Some college percentage	0.0023	0.003
College or more	0.0047**	0.002
Constant	7.9635***	0.120
Number of observations	100	
R-squared	0.6783	

***p<0.01, **p<0.05, *p<0.1

Fig. A.16. Regression of the Log Variance on the Herfindahl for the Transportation Industry

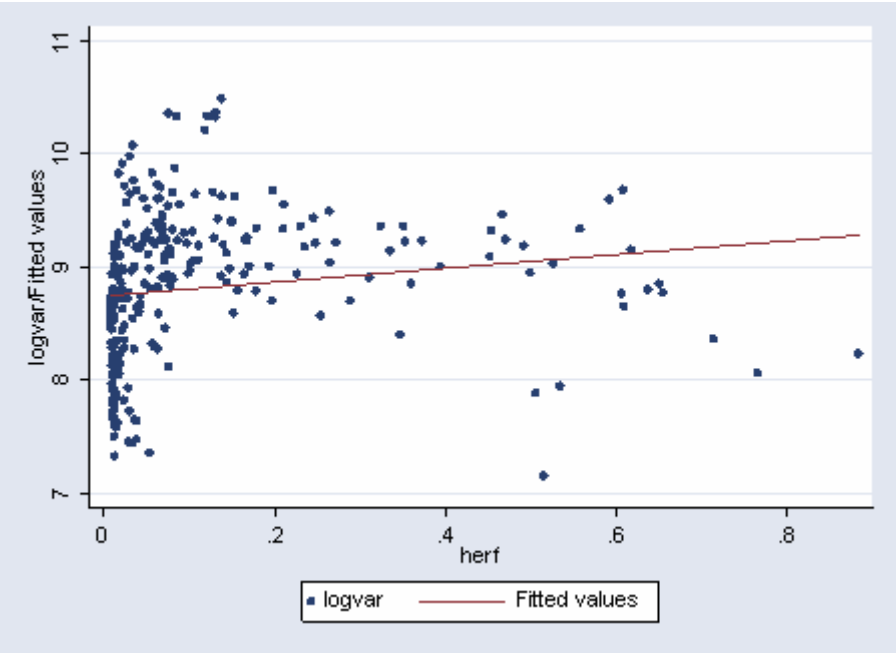


Table A.17. Food

Variable	Coefficient	Robust Standard Error
Herfindahl	-8.0727	9.600
Real national annual median (in 1000's)	1.055***	0.000
Year 2000	0.4553***	0.159
Year 2001	0.0963	0.142
Year 2002	-0.0330	0.144
Year 2003	-0.0132	0.141
Year 2004	-0.0129	0.142
Year 2005	-0.0607	0.147
Some college percentage	0.0191***	0.006
College or more	-0.0393***	0.009
Constant	5.7718***	0.286
Number of observations	105	
R-squared	0.7554	

***p<0.01, **p<0.05, *p<0.1

Fig. A.17. Regression of the Log Variance on the Herfindahl for the Food Industry

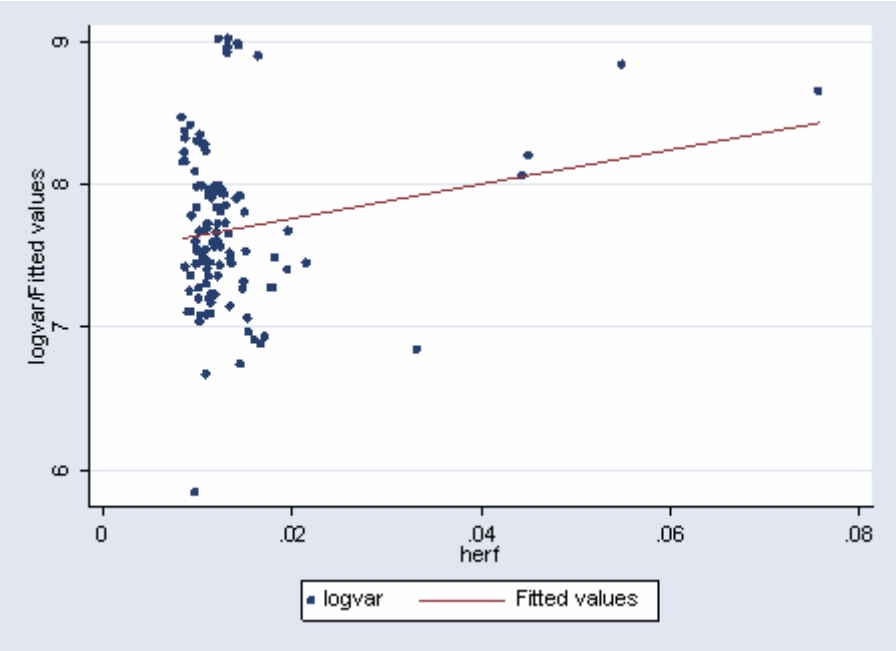


Table A.18. Maintenance

Variable	Coefficient	Robust Standard Error
Herfindahl	2.6712*	1.505
Real national annual median (in 1000's)	0.7570***	0.011
Year 2000	0.5882***	0.158
Year 2001	0.1430	0.130
Year 2002	0.0071	0.123
Year 2003	-0.0172	0.127
Year 2004	-0.0549	0.143
Year 2005	-0.1005	0.155
Some college percentage	0.0038	0.006
College or more	-0.0189*	0.011
Constant	6.4054***	0.128
Number of observations	56	
R-squared	0.8028	

***p<0.01, **p<0.05, *p<0.1

Fig. A.18. Regression of the Log Variance on the Herfindahl for the Maintenance Industry

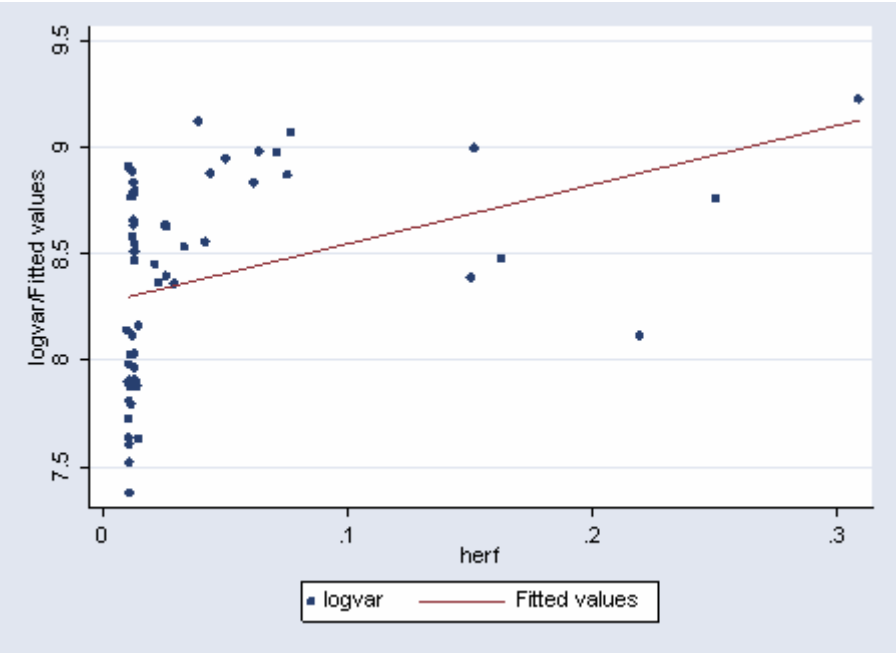


Table A.19. Farming

Variable	Coefficient	Robust Standard Error
Herfindahl	0.5652	0.448
Real national annual median (in 1000's)	0.4200***	0.000
Year 2000	0.3001*	0.159
Year 2001	0.1206	0.133
Year 2002	0.0343	0.204
Year 2003	0.1663	0.126
Year 2004	0.0661	0.204
Year 2005	0.205	0.146
Some college percentage	-0.0572	0.039
College or more	0.0425	0.029
Constant	7.9393***	0.490
Number of observations	78	
R-squared	0.4203	

***p<0.01, **p<0.05, *p<0.1

Fig. A.19. Regression of the Log Variance on the Herfindahl for the Farming Industry

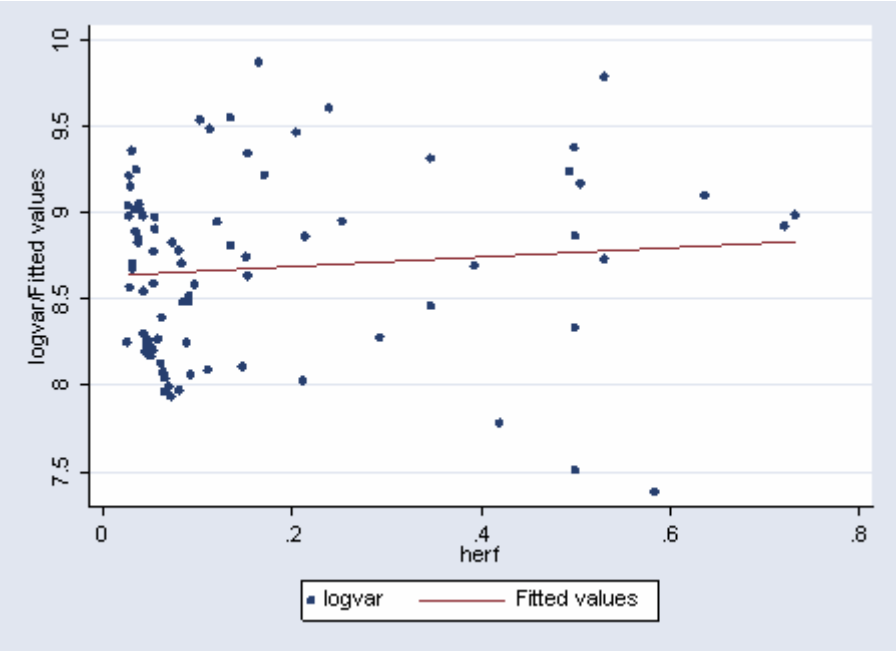


Table A.20. Repair

Variable	Coefficient	Robust Standard Error
Herfindahl	0.4252**	0.201
Real national annual median (in 1000's)	0.1500***	0.000
Year 2000	0.1902***	0.051
Year 2001	0.0478	0.050
Year 2002	0.0012	0.057
Year 2003	0.0662	0.049
Year 2004	0.0726	0.046
Year 2005	0.1236**	0.050
Some college percentage	0.0030***	0.001
College or more	0.0146***	0.004
Constant	7.9885***	0.075
Number of observations	328	
R-squared	0.4527	

***p<0.01, **p<0.05, *p<0.1

Fig. A.20. Regression of the Log Variance on the Herfindahl for the Repair Industry

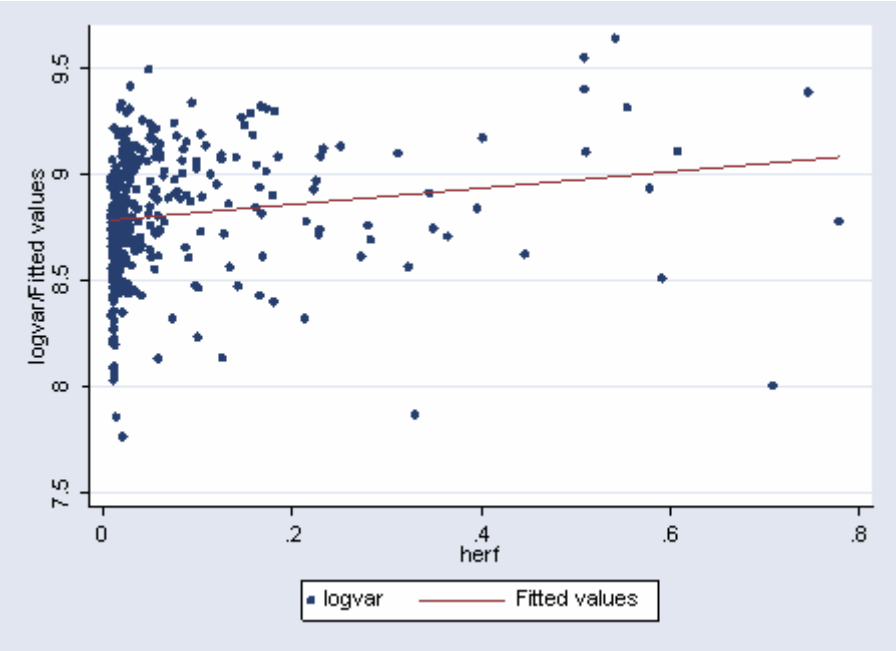


Table A.21. Production

Variable	Coefficient	Robust Standard Error
Herfindahl	0.3136	0.262
Real national annual median (in 1000's)	0.2420***	0.000
Year 2000	0.2287***	0.041
Year 2001	0.0077	0.041
Year 2002	-0.0403	0.040
Year 2003	-0.0115	0.039
Year 2004	0.0404	0.040
Year 2005	0.0355	0.044
Some college percentage	0.0028*	0.002
College or more	0.0008	0.002
Constant	7.8105***	0.047
Number of observations	729	
R-squared	0.4123	

***p<0.01, **p<0.05, *p<0.1

Fig. A.21. Regression of the Log Variance on the Herfindahl for the Production Industry

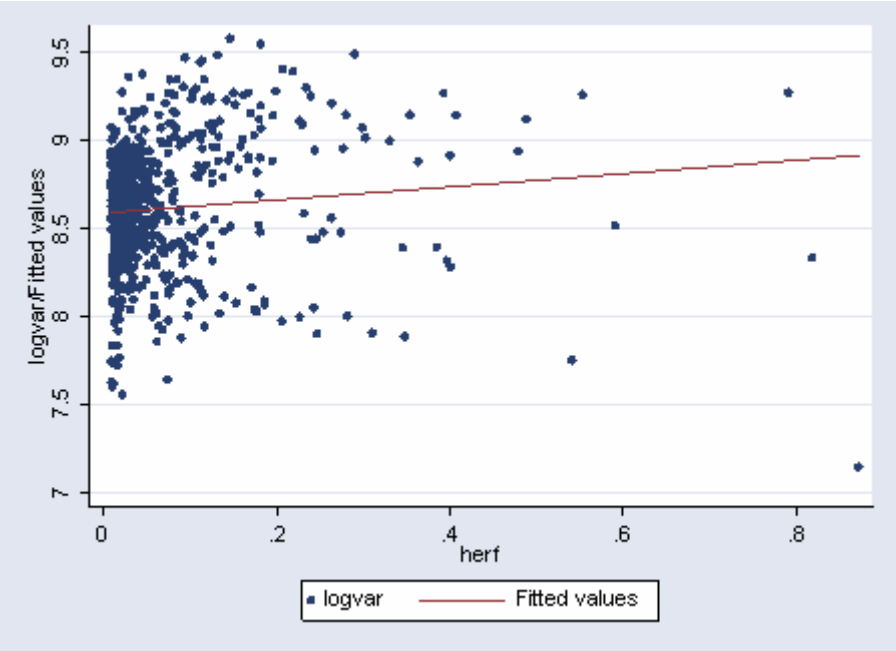
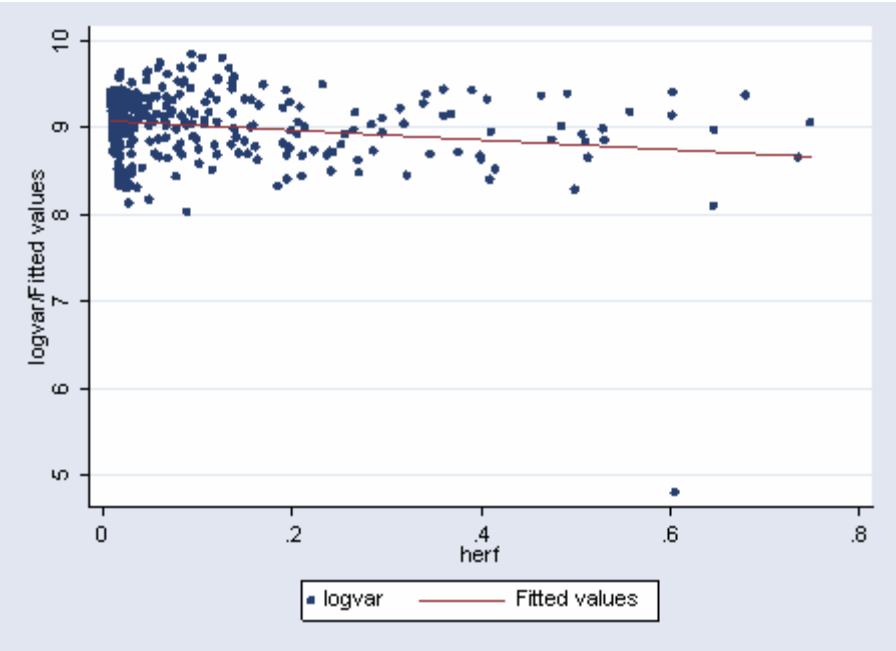


Table A.22. Construction

Variable	Coefficient	Robust Standard Error
Herfindahl	-0.4433	0.330
Real national annual median (in 1000's)	0.2400***	0.000
Year 2000	0.2139***	0.061
Year 2001	-0.0127	0.059
Year 2002	-0.0539	0.059
Year 2003	-0.0351	0.056
Year 2004	-0.0336	0.055
Year 2005	-0.0876	0.105
Some college percentage	0.0016	0.002
College or more	-0.0230	0.004
Constant	8.3610***	0.112
Number of observations	357	
R-squared	0.3031	

***p<0.01, **p<0.05, *p<0.1

Fig. A.22. Regression of the Log Variance on the Herfindahl for the Construction Industry



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